MEASURING THE EFFECT OF LOW-SKILLED WORKERS ON INNOVATION

RACHEL HARRIS

A DISSERTATION
SUBMITTED TO THE FACULTY OF GRADUATE STUDIES
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
for the degree
DOCTOR OF PHILOSOPHY

GRADUATE PROGRAM IN ECONOMICS
YORK UNIVERSITY
TORONTO, ONTARIO
APRIL, 2020

Abstract

While the effects of high-skilled immigration and labour on an economy have been well studied, the effects of low-skilled immigrants have not. In particular, this effect is presumed to be negative. This Dissertation seeks to examine the relationship between low-skilled immigration and innovation and in particular, patenting behaviour. In the first study, I provide novel empirical evidence to show how the Mariel Boatlift, an exogenous influx of low-skilled labour to south Florida, had an economically and statistically significant impact on individual patenting behaviour. I argue that this is because following the influx of low-skilled immigration, high-skilled inventors are now able to hire these low-skilled immigrants to help them with domestic work. This allows the individual inventors to free up their time and spend more time inventing, and thus we see an increase in individual patenting. My second study aims to see if these results hold in different circumstances. I choose to look at the share of low-skilled immigrants in a city and whether this share affects individual patenting levels across time. However, I do not find that there is an effect. Finally, my third study provides a theoretical backing for the mechanism I argue in my first study.

Contents

1 Introduction

The central thesis of this dissertation is that low-skilled workers can have a significant impact on innovation. This is interesting for two key reasons. The first has to do with the current political climate in the United States. As immigration laws are being scrutinized, more research on the potential positive effects of low-skilled immigrants on the American economy is needed. The second is that this relationship is not obvious and under-researched. There is a small body of research about the impact of low-skilled workers on high-skilled labour supply, which finds that, under certain circumstances, an increase in the supply of low-skilled workers does cause an increase in time worked by the high-skilled that hired them. There has been little research on whether or not an increase in the supply of low-skilled workers can cause the high-skilled to produce more, and none has looked at patents specifically. If conclusive evidence is found to support this hypothesis, these papers could become an important contribution to the literature that changes the way that researchers and policy makers think about the relationship between low-skilled immigrants and innovation.

I explore this relationship in three different essays. The first looks at a natural experiment, the Mariel Boatlift, which was the unauthorized immigration of hundreds of thousands low-skilled Cubans to southern Florida in 1980. I explore the following mechanism: as low-skilled immigrants enter an area, the unskilled wage in that area drops. This allows high-skilled individuals to hire unskilled workers for jobs around the house. This allows the high-skilled to spend less time doing jobs around the house and more time working (inventing, patenting, etc.). I find that the Mariel Boatlift caused an increase in individual patenting but had no effect on the patenting behaviour of corporations or government agencies.

The second essay looks at whether the results of the first essay hold more broadly across the United States by looking at whether the percentage of a city's population that is low-skilled affects individual patenting behaviour. By looking at the largest cities across The United States in 1980 and 1990, I am able to examine whether the supply of unskilled immigrants had an impact on different types of patents. My main regressions show that the percentage of low-skilled immigrants does not affect patenting behaviour.

The third essay proposes a theoretical model that puts both of the empirical chapters into context and provides a theoretical backing for the proposed mechanism. The main result of the model is that as the supply of low-skilled workers increases, high-skilled inventors will choose to hire more help around the house and spend more time on their own work. This model is consistent with the empirical findings of other work that shows that as the volume of low-skilled workers increases, the wage among them does not materially change.

Overall, my findings support a relationship between low-skilled immigration and innovations in subtle and indirect ways, and under certain circumstances. The rest of the dissertation is laid out as follows: chapter 1 provides an over-arching introduction to the remaining chapters, chapter 2 examines the impact of the Mariel Boatlift on patenting, chapter 3 looks at the relationship between unskilled immigration and patenting in American cities across time, chapter 4 provides a theoretical backing for the empirical work, and chapter 5 concludes.

2 Effects of Low-Skilled Immigration on Innovation: Evidence from The Mariel Boatlift

This chapter examines the effect of low-skilled immigration on innovation using the Mariel Boatlift as a natural experiment. 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) and George Borjas (Borjas 2015).

This chapter finds that the Mariel Boatlift sparked an increase in individually assigned patents in some technological categories. Specifically, the results show that The Mariel Boatlift caused an increase of 153.94 individually assigned patents in Florida (compared to the comparison group) and found no evidence of a statistically significant increase in government or corporate patents.

These main results are not only statistically and economically significant but also withstand a large number of robustness checks. This paper contends that the main mechanism behind this phenomenon is that, following the Mariel Boatlift, individual inventors had access to a large supply of low-skilled labourers and were able to hire them to perform housework, child care, etc. As a result, these inventors were able to move away from housework and spend more time inventing, thus leading to an increase in patenting. This mechanism does not increase corporate patenting as I contend that the return to innovation is bigger when you are the residual claimant of the work.

Figures 1 and 2 offer motivation for examining the Mariel Boatlift. Figure 1 shows the number of patents individuals filed for in Florida compared with the rest of the U.S. over time. In this figure, patents are averaged over states. Figure 2 shows the number of patents corporations or governments filed for in Florida compared to the rest of the U.S. over time (again, averaged over states). The vertical red line in each graph signifies the year of the Mariel Boatlift (1980).

In Figure 1, Florida experiences a large increase in patents compared to the rest of the U.S. In Figure 2, Florida and the U.S. follow a more similar time path. These two pose an interesting question: what was happening in Florida in 1980 that affected individual patenting behaviour but had no effect on government or corporate assigned patents?

2.1 The Mariel Boatlift

Following unrest among the Cuban population, culminating in an incident in which 10,000 people sought asylum at the Peruvian embassy, Fidel Castro allowed anyone who wanted to leave Cuba to do so via the port of Mariel. Previously, not all Cubans were free to leave as they pleased. Many took advantage of this opportunity, and hundreds of boats left Cuba and travelled to the American port of Miami. This wave of immigration began on April 15, 1980 and ended on October 31, 1980 (Hawk, Villella, de Varona, and Adolfo 2014).

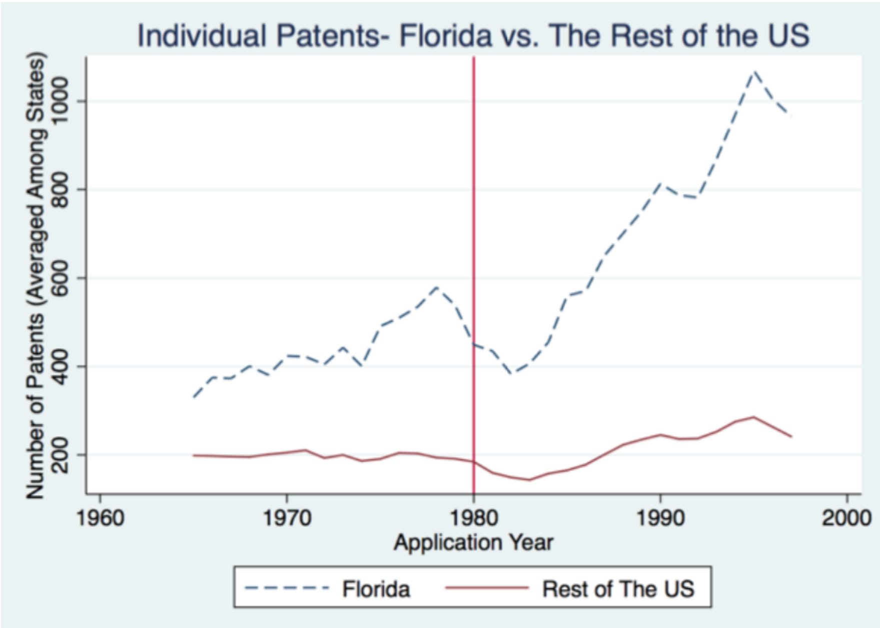

Figure 1: Individual Assignees

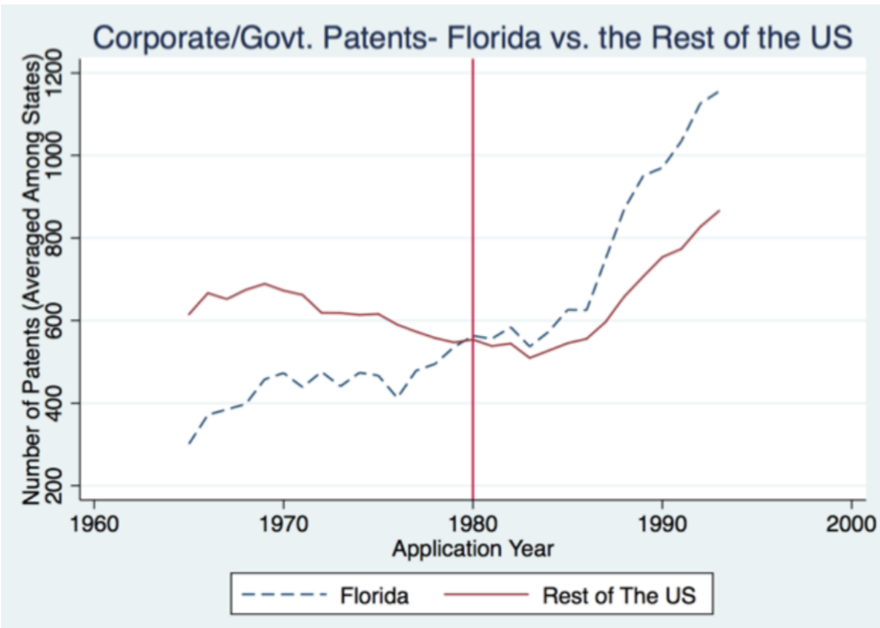

Figure 2: Government/Corporate Assignees

Characteristic	Percentage
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 Participation	22.81
Former Participation	54.19
Never Participated	23
Educational Attainment	
Less Than High School	74.56
High School	7.69
Beyond High School	17.75

Table 1: Mariel Boatlift Summary Statistics

Notes: these are the summary statistics of 514 Marielitos residing in Southern Florida, interviewed in 1983, 1985 and 1986

Since the Mariel Boatlift was unauthorized and unexpected by Americans, little information is available on how many people came to the United States or exactly where they settled. According to the most reliable sources, between April 1980 and October 1980 somewhere between 120,000 and 126,000 Cubans entered the U.S. labour market (Card 1990). About half settled in Miami, and the other half dispersed to the rest of Florida(Hawk, Villella, de Varona, and Adolfo 2014) .

Three groups of people left Cuba for America. The first group consisted of people with relatives in the United States, who rented boats and sailed to the port of Mariel in Cuba to collect their family members. The second group consisted of refugees from the Peruvian embassy. The third group consisted of those who petitioned for visas from the government. People granted visas were sometimes referred to by the government as “escoria,” which included homosexuals, prostitutes, drug users and "enemies of the revolution". Castro used this third category to cleanse Cuba of “scum” (Ojita 2005). According to David Card, many of the immigrants were low-skilled and had a low level of English competency (Card 1990).

The Center for Migration and Development (CMD) conducted a survey and compiled summary statistics of the Mariel immigrants (Marielitos). In 1983 and then again in 1985 and 1986, it interviewed 514 Marielitos residing in southern Florida. Although the CMD study focuses exclusively on Marielitos living in southern Florida, it provides a general idea of the overall characteristics of this group. Table 1 shows the summary statistics produced from the CMD data.

These summary statistics are very similar to what Card suggests in his 1990 paper(Card 1990). Over half of the respondents stated that their self-evaluation of the English language was bad, while only 10% of the respondents said they had a fairly or very good understanding of English. Furthermore, 77.19% of the Mariel immigrants in the sample indicated that they had used the food stamp program at some point. It should be noted that labour scholars consistently use participation in the American food stamp program as a proxy for household income, since participants must be below a certain income to qualify. The fact that 77% of these participants used food stamps at some point indicates low levels of income among the group of Marielitos. In addition, almost three quarters of the sample did not have a high school degree.

In conclusion, the Marielitos surveyed had a low educational attainment and limited ability to speak or understand English and were low-income earners. Based on these characteristics, Marielitos likely had difficulty finding a traditional job in southern Florida and might have had a better time obtaining a job as a domestic worker, where English proficiency and educational attainment are less important.

2.2 American Patenting in the 1980s

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

The legislation standardized patent law by removing the Court of Claims and the Court of Customs and Patent Appeals and replacing them with the U.S. Court of Appeals for the Federal Circuit and the U.S. Claims Court.

The purpose of this restructuring was to increase decisional uniformity across the country in certain areas of the law, specifically patent, tax and environmental (Jaffe 2000).

Prior to 1982, the U.S. patent office was perceived as administratively cumbersome; the office was overworked and understaffed. Furthermore, the courts were unlikely to enforce patent rights when issues were brought to court. These two effects combined led people to believe that filing a patent was an inefficient process and that patents offered little protection to innovations. The *Federal Courts Improvements Act* of 1982 increased the power of patents to the point that they became a favourable way of protecting inventions(Jaffe 2000).

Another shift in patenting policy during the 1980s involved publicly funded research. Until that time, there was no consistent policy across all states. Beginning in the early 1980s, however, a set of policy changes made almost all public research eligible for private patents. Prior to these changes, university patenting would have been done under the university's name, not the individual's name(Jaffe 2000). Since individuals could now be credited for their inventions, university patenting became much more attractive.

Concurrently, a vast change in what could be patented occurred. 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 is genetically altered mice: prior to 1980, this novel idea would probably not have been granted a patent (Jaffe 2000).

In summary, right around the time of the Mariel Boatlift, a dramatic change occurred in patenting behaviour. As a result, the United States saw a huge surge in patenting during the early 1980s. Figure 3 shows the number of domestic patents granted across the U.S. from 1970 to 2000. As the graph illustrates, during the early 1980s domestic patenting spiked. This figure differs from Figures 1 and 2 because it shows the number of patents summed across states. Figures 1 and 2 paint a different picture because they show the number of patents averaged among states. Despite these changes to patenting behaviour across the U.S., this paper argues that Florida saw a much larger increase in individual patents, and in some technological industries, than any comparable states following the Mariel Boatlift.

2.3 What Else was Happening in Florida at this Time?

From 1972 until 1981, the United States Immigration and Naturalization Service (INS) documented that over 55,000 Haitians arrived in Florida. The INS also noted that it was possible that over half of these immigrants avoided detection, so the actual number was more likely above 100,000. However, the story of the Haitian "boat people" differs from that of the Mariel emigrants, since the Haitians were often literate and skilled. Approximately 85% settled in Miami (for Migration and Development).

This Haitian immigration into southern Florida may have contributed to the increase in patenting, although it is unlikely for one main reason: the Haitian immigration happened over nine years. If one assumes at least 110,000 Haitian boat people arrived, then on average just over 12,000 Haitians arrived in Florida each year. However, if instead one assumes the recorded number of 55,000 Haitian boat people, this number shrinks to 6,000 Haitians arriving in Florida each year. Conversely, approximately 125,000 Mariel immigrants arrived in Florida in one year, while between 6,000 and 12,000

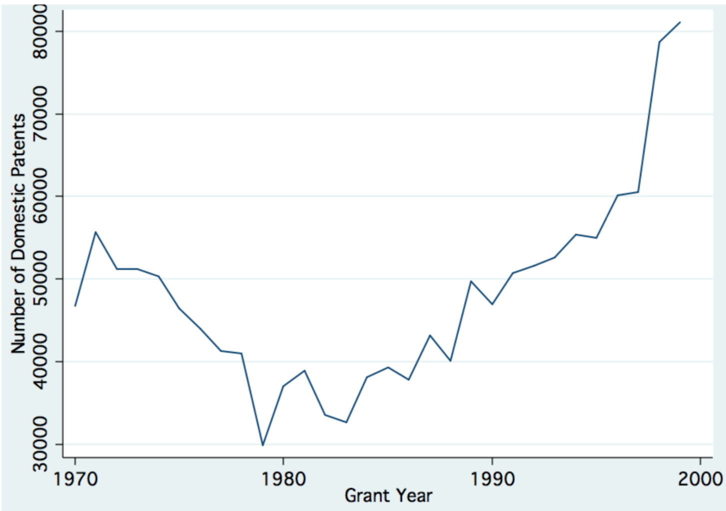

Figure 3: U.S. Patenting Behaviour between 1970 and 2000

Haitians arrived in Florida that same year. If the Haitians were to have caused the increase, we likely would have seen a gradual increase of patents increasing over time in Florida (compared to the rest of the US). Instead, we see a large spike in a single year.

Another key event was the Miami riots of 1980. In December 1979, police killed an African American man after a high-speed chase. The victim, Arthur McDuffie, was a Marine Corps veteran and prominent salesman. At first, the information released suggested that McDuffie had died due to injuries sustained in a motorcycle crash. However, an elaborate cover-up was later exposed, and the public eventually learned that police officers had beaten him to death. Despite the evidence, the officers were cleared of all charges after a court hearing before an all-white jury. The community was outraged by the court's decision and began rioting on May 17, 1980, burning cars and attacking whites. The riots lasted for roughly three days, with 17 dead, 100 arrested and over $100 million in damages.

Despite the protests, the McDuffie family and black community never received justice (Herald 2016). This event may have affected innovation; indeed, it may have actually hindered innovation during this period, since 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 the patenting estimates in Florida, and specifically Miami, to be conservative.

Finally, there was a large economic downturn in the United States that started in 1981 and ended in 1982 when things bottomed out. Indeed, this effect can be seen in all patenting behaviour. Figure 3 shows a dramatic drop in overall patenting in 1981 with a local minimum occurring around 1982. Following 1982 we see a steady increase. This recession is of concern to these results, if it had a different effect on Florida as it did on other states. However, almost all states saw this drop in patent behaviour following 1981, suggesting it affected all states.

2.4 Card vs. Borjas

As previously mentioned, the Mariel Boatlift has been used as an exogenous treatment effect in previous studies. David Card published an influential paper titled "The Impact of the Mariel Boatlift on the Miami Labor Market" in 1990, using the Mariel Boatlift as the exogenous treatment to discern the effect that low-skilled immigration had on wages and unemployment (Card 1990). Card found that this large influx of low-skilled workers had virtually no effect on Miami wages or unemployment and hypothesized that this was due to the fact that Miami had experienced so many previous waves of immigration that it was able to quickly absorb the workers into the labour force (Card 1990). These results were largely left uncontested until recently.

In late 2015, George Borjas published a paper entitled "The Wage Impact of the Marielitos: A Reappraisal" (Borjas 2015). In this paper, Borjas argues that Card's initial findings do not tell the entire story because he did not divide the population into different subsections when conducting his analysis. Using this new method, Borjas found that wages among low-skilled workers in Miami was negatively affected. In fact, he found that the wage of these workers dropped by as much as 20% following the Mariel Boatlift (Borjas 2015).

2.5 Literature Review

This section provides an overview of the current literature on immigration and technological innovation. Most of the literature focuses on the entrepreneurship of immigrants, either high or low skilled, and neglects the way low skilled immigrants may complement innovation by higher skilled natives (or immigrants). For example, Mueller (Mueller 2011) investigates technology entrepreneurship possibilities with and without immigration. He specifically examines how immigrants from southern and southeast Europe with low education levels have contributed to entrepreneurship in Germany. His results show that immigrants are less than half as likely as German locals to found a knowledge-intensive company. Mueller suggests that education is a barrier to entry into knowledge-intensive industries (Mueller 2011) .

There is also a large body of literature documenting other potential gains from high-skilled immigration. In theory, an immigrant surplus (when immigrants enter the labor force, they increase the productive capacity of the economy and raise GDP and thus wages for all) should have a significant economic impact since it can cause a large redistribution of wealth from labour to capital (Borjas 1995). Using 2000 Census data, Card finds that immigrants assimilate well in the U.S. and that their children generally outperform the children of natives (Card 2005).

A study conducted by the National Domestic Workers Alliance titled "The Invisible and Unregulated World of Domestic Work" provides a summary of the importance of domestic workers (Burnham and Theodore 2012). Domestic workers help families operate more efficiently and can free 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 productive pursuits with undistracted focus and commitment"(Burnham and Theodore 2012). This finding is very similar to the key finding in my paper.

Another related body of literature focuses on highly skilled immigration and patenting. Hunt et al. (Hunt and Gauthier-Loiselle 2010) examine 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 displaced native inventors and understated if there were spillover effects. They also show that immigrant inventors do not crowd out natives and that there are in fact positive spillovers (Hunt and Gauthier-Loiselle 2010). Blit et al look at the Canadian landscape and examine the effects of changes in skilled-immigrant population share on patents per capita. They find results that are much smaller than those seen in the US and suggest that these results may be exceptional (Blit, Skuterud, and Zhang 2019).

This paper also adds to the time-use literature, which centers on how women and men change their leisure and labour supply decisions based on certain factors. For example, Lisa Dettling found that access to high-speed internet increases female labour force participation, especially for those with high levels of education (Dettling 2015). The proposed mechanism is that time saved in home production could cause women to return to work.

The paper that comes closest to documenting a causal 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 (Bratti and Conti 2018). They find a positive relationship between high-skilled immigration and patents and a negative relationship between low-skilled immigration and patents. However, their paper differs from this one in several ways. First, they study Italian immigration and patenting. Arguably, immigrants who choose to settle in Italy may not be similar to immigrants who exogenously move to America. This may be because they are more risk-averse. Secondly, Italian patenting behaviour may not be comparable to American patenting behaviour. Finally – and most importantly – their paper does not separate individual patents from other types of patents (Bratti and Conti 2018). Therefore, the present paper can be interpreted as a more comprehensive look at low-skilled immigration and innovation. Ultimately, there is a gap in the literature regarding low-skilled immigration and innovation that this paper hopes to fill.

2.6 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 the technological classification to which it belongs and details on the owner of the invention. The assignee category outlines who applied for the patent: the government, a corporation or an individual. It also reveals whether a foreign or domestic entity applied for the patent (Hall, Jaffer, and Trajtenberg 2001).

Of course, patent data have certain limitations. The first is that not everyone chooses to patent their invention, since patent applications can be expensive and time-consuming. However, since not every piece of technology is patented, using patents as a proxy for innovation will not bias the results unless inventors in the comparison group are more likely to file patents than are people in the treatment group (or vice versa).

Patent Number	Description of Innovation
4354144	Transmissionless drive system
4359870	Apparatus for producing a solar electricity from solar
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 hear exchanger
4385672	Feed level indicator
4395975	Method for desulfurication and oxidation of carbonaceous
4386480	Simulated tree trunk for supporting vines
4388185	Electric oil refiner
4391706	Filer element dealing device for filter pan
4393150	Adhesive bandage material
4393986	Surfboard carrying rack
4395030	Quick action vise

Table 2: Patent Examples

Note: this table shows a 5% sample of patents applied for in 1982 by individual and shows an example of what sort of innovation was happening in Florida two years after the Boatlift

Another potential problem with using patents as a proxy is that not all inventions are granted a patent. All potential patents must meet strict criteria, and patents are often rejected for seemingly arbitrary reasons (Hall, Jaffer, and Trajtenberg 2001). This issue would bias the results only if patents in the comparison group were more likely to be granted than patents in the treatment group (or vice versa). As long as patenting behaviour and application and grant percentages are the same in each state, neither of these potential drawbacks of using patent data will bias the results. This is likely to be the case as patent laws are applied uniformly across the US and there are not different laws from state to state.

In 1982, individuals filed for 383 patents in Florida. Table 2 lists a 5% sample of these patents. This table provides examples of what sort of innovation was happening in Florida two years after the Mariel Boatlift.

2.7 Data

This paper utilizes data from the National Bureau of Economic Research (NBER) "Patent Citation Data File," which contains information on under three million United States patents granted between January 1963 and December 1999. It contains all utility patents filed during this period but does not include three other minor patent categories (design, reissue, and plant patents). The majority of patents filed fall into the utility category. In 1999, for example, 153,493 utility patents were granted, while only 14,732 design, 448 reissues, and 421 plant patents were granted. This dataset also includes all citations made to these patents between 1975 and 1999 (Hall, Jaffer, and Trajtenberg 2001).

This dataset also contains detailed information on the object of the patent, the assignee type, the name of the individual or organization that filed the patent, and the place of residence of this person or entity. The assignee type classifies all patents into one the following seven categories: Unassigned, U.S. non-government organizations (mostly corporations), Non-U.S., Non-government organizations (mostly corporations), U.S. individuals, Non-U.S.

individuals, The U.S. Federal Government and Non-U.S. governments (Hall, Jaffer, and Trajtenberg 2001).

The dataset also includes several other variables, including technological category and number of citations made and received. The United States Patent and Trademark Office (USPTO) classifies each patent into one of 400 main patent classes. The authors of the NBER Patent Citation Dataset construct a higher-level classification that aggregates these patent classes into six main technology categories and 36 subcategories. These six main categories are Chemical (excluding drugs), Computers and Communications, Drugs and Medical, Electrical and Electronics, Mechanical and Others.

2.8 Empirical Strategy

In this paper, I estimate the following difference-in-differences regression, where Y_{it}= the number of patents.

$$Y_{it} = \beta 0 + \beta 1 Post1980_t + \beta_2 Florida_i + \theta Post1980_t * Florida_i + \epsilon_{it} \quad (1)$$

To discern the treatment effect (theta), a proper comparison group needs to be chosen. A valid comparison group should have followed the same pre-treatment time trend as Florida with respect to the number of individual patents produced. This paper will use the synthetic control method (SCM) to choose a comparison group. In this case, Florida is the treatment group, but 49 states and one district serve as potential comparison states.

The SCM uses matching variables to choose a weighted average of states that form the control group. This control group should best match the time path of Florida before the treatment. Without the SCM, a control group with similar characteristics to the treatment group would be arbitrarily selected. This decision is not explicitly driven by data, and it is left to the author to justify their chosen control group. This paper will use the SCM to remove the arbitrariness associated with choosing a control group

Abadie et al. first propose the synthetic control method in a 2003 paper that examines terrorism in Basque Country (Alberto Abadie 2003). In a more recent paper, Abadie et al (2010) refine the SCM method and study the effects of *Proposition 99* on smoking rates in California. *Proposition 99* was a 1988 California law that added a 25-cent excise tax to each package of cigarettes. The authors constructed a weighted average of states that could be considered a synthetic California, or suitable comparison group, because, up until the time of the treatment, the time trend in cigarette sales was almost identical to California's. They then compared the two timelines to see what would have happened in California had Proposition 99 not passed(Alberto Abadie 2003).

This paper will follow a slightly different method; specifically, the SCM will be used to choose the comparison group, but a difference-in-differences 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 limit the potential for human error.

Following the work done by Abadie et al in 2003 (Alberto Abadie 2003) and in 2010 (Alberto Abadie and Hainmueller 2010), I will now describe the general 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. 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 and that the subscript 1 denotes Florida. 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.

Define α_{it} to be the treatment effect, and assume that $\alpha_{it} = Y_{it}^I - Y_{it}^N$. 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:

$$Y_{it} = Y_{it}^N + \alpha_{it} D_{it}. \tag{2}$$

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

$$\alpha_{1t} = Y_{1t}^I - Y_{1t}^N = Y_{1t} - Y_{1t}^N. \tag{3}$$

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:

$$Y_{it}^N = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \epsilon_{it}. \tag{4}$$

Where δ_t is common to all units, Z_i are observed covariates not affecting the intervention, θ_t is a vector of unknown parameters 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 be attached to a potential synthetic control state and thus the synthetic control unit will be a weighted average of each potential state. Following Equation 4, the value of the outcome variable for each synthetic control is the following:

$$\sum_{j=2}^{J+1} w_j Y_{jt} = \delta_t + \theta_t \sum_{j=2}^{J+1} w_j Z_j + \lambda_t \sum_{j=2}^{J+1} w_j \mu_j + \sum_{j=2}^{J+1} w_j \epsilon jt \tag{5}$$

Assume that there are weights such that:

$$\sum_{j=2}^{J+1} w_j^* Y_{j1} = Y_{11}, ..., \sum_{j=2}^{J+1} w_j^* Y_{jT0} = Y_{1T0}, \text{ and } \sum_{j=2}^{J+1} w_j^* Z_j = Z_1 \tag{6}$$

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:

$$Y_{1t}^N - \sum_{j=2}^{J+1} w_j^* Y_{jt} = \sum_{j=2}^{J+1} w_j \sum_{s=1}^{T0} \lambda_t (\sum_{n=1}^{T0} \lambda_n^{'} \lambda_n)^{-1} \lambda_s^{'} (\epsilon_{js} - \epsilon_{1s}) - \sum_{j=2}^{J+1} w_j^* (\epsilon_{jt} - \epsilon_{1t}) \tag{7}$$

As an estimator of α_{it}, Abadie et al. suggest using:

$$\hat{\alpha_{1t}} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{8}$$

Equation 7 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 8 will hold exactly, so the fact it holds approximately is enough (Alberto Abadie and Hainmueller 2010). 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. A detailed explanation of this method can be found in Abadie et al's 2010 paper (Alberto Abadie and Hainmueller 2010).

The outcome variable is the number of patents. To construct a synthetic Florida using the SCM, indicator variables that predict the number of patents must be chosen. Patent levels in previous years will be used to predict future values of patents. Therefore, the predictors for the number of patents are the number of patents in 1965, 1966, 1967, etc., including every year up until the year of the treatment in 1980. The data is separated into two samples based on assignee, and each separate sample has its own comparison group, calculated using the SCM.

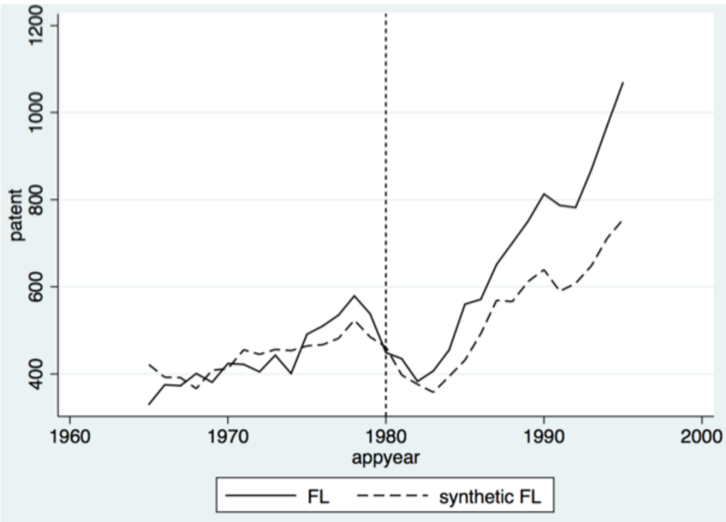

Figure 4: SCM- Individual Assignees

State	Weight
AZ	0.837
CA	0.163

Table 3: State Weights- Individual Assignees

I estimate by baseline specification on two subsamples: individual assignees and corporate and government assignees. The states and weights that form the synthetic control group for these two categories are shown in Tables 3 and 4. Figures 4 and 5 show how well the comparison group matches

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

Table 4: State Weights- Corporate and Government Assignees

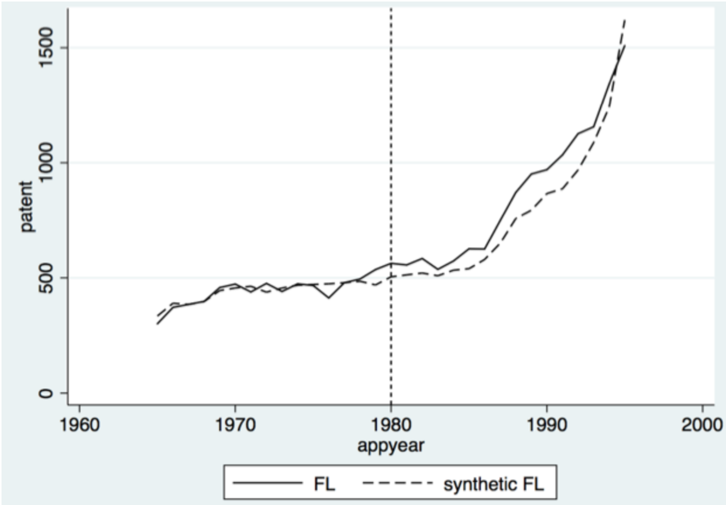

Figure 5: SCM- Corporate and Government Assignees

the pre-treatment time trend of the treated group.

A potential issue with this specification is data truncation. However, since all samples use data from 1963-1999, and the treatment is in 1980, this is likely to be an issue as the years span far past the date of the treatment.

2.9 Results

The purpose of this paper is to measure the impact of the Mariel Boatlift on patenting in Florida. The entire sample of patents is divided into many different categories to see where exactly this natural experiment had an effect. First, the sample is split into (1) patents assigned to individuals and (2) patents filed by government agencies and corporations. Throughout this paper, I label sample (1) as individually assigned patents and (2) as corporate assigned patents. Sample (1) includes patents assigned to individuals and patents that are unassigned. Sample (2) includes patents assigned to US corporate and government agencies. Next, the sample is divided into six different technological categories: Chemical, Computers and Communications, Drugs and Medical, Electrical and Electronics, Mechanical and Other. The "Other" category contains patents filed in the following sub-categories: Agriculture, Husbandry, Food; Amusement Devices; Apparel & Textile; Earth Working & Wells; Furniture, House Fixtures; Heating; Pipes & Joints; Receptacles; and Miscellaneous-Others (Hall, Jaffer, and Trajtenberg 2001).

The United States Patent and Trademark Office (USPTO) classifies each patent into one of six technological categories. The authors of the NBER patent dataset then split each of these six categories into more granular subcategories(Hall, Jaffer, and Trajtenberg 2001). After estimating the effect of the Mariel Boatlift in each of the six main categories, I will determine in which subcategories the effect is the greatest.

Table 5 includes estimated treatment effects for all six categories. I estimate the treatment effect using a difference-in-differences estimator. This method compares patenting in each category in Florida with patenting in the same category in the counterfactual (found using the SCM). The first important point to note is that, for patents filed by individuals, the treatment effect (the coefficient on post*treatment) is statistically significant. This coefficient can be interpreted as follows. The Mariel Boatlift increased the number of individual patents by 153. On average, between 1965 and 1995, individuals filed approximately 555 patents per year. An increase of 153 patents is not only statistically significant at the 1% level but also economically significant. The estimated treatment effect for patents filed by government agencies and corporations was not statistically significant.

The top row of Table 5 lists the six technological categories. For each category, a different counterfactual was used that best captures its history. The weights attached to states in each counterfactual can be found in the appendix (tables 15 to 22). Each counterfactual has been calculated using the SCM. Again, the variable of interest is Post*Florida. The only technological categories that have statistically significant coefficients are Drugs and Medical, Mechanical, and Other. The interpretation of this finding is: (1) the Mariel Boatlift caused patenting in each of these categories to increase, and (2) the Mariel Boatlift had no statistically significant effect on patenting in the Chemical, Computers, and Electrical categories.

The only technological categories with a statistically significant and positive treatment effect in table 5 are Drugs and Medical, Mechanical, and Other. Tables 7, 8 and 9 estimate treatment effects for the subcategories of each of these technological categories.

Table 7 looks at the subcategories of Drugs and Medical. These subcategories are Drugs, Surgery & Medical Instruments, Biotechnology, and Miscellaneous. The only categories that are statistically significant are Surgery & Medical Instruments and Miscellaneous. Although some patents for surgery and medical instruments do require FDA approval, one can apply for this after the initial patent application, with the FDA guaranteeing a 90-day turn-around period for most approvals(Emergo).

	Assignee		Technical Category					
	Individual	Government/ Corporate	Chemical	Computers	Drugs	Electrical	Mechanical	Other
Post	130.57	190.13	45.88	161.52	116.54	164.22	38.36	87.94
	(40.66)***	(32.38)***	(10.88)***	(32.26)***	(19.35)***	(22.88)***	(16.47)**	(25.17***)
Florida	0.8251	-42.67	-2.41	-0.1103	0.8378	0.1812	1.38	-0.2672
	(37.24)	(8.14)***	(9.97)	(29.54)	(17.72)	(20.95)	(15.08)	(23.05)
Post*	153.93	33.01	4.84	-18.09	47.36	-49.69	64.43	100.44
Florida	(57.5)***	(22.63)	(15.39)	(45.62)	(27.37)*	(32.36)	(23.29)***	(35.59)***
Obs.	62	62	62	62	62	62	62	62
R-Squared	0.53	0.99	0.4	0.44	0.66	0.57	0.47	0.56
Standard errors are listed in brackets								
* - 10 percent significance level, ** - 5 percent significance level, *** - 1 percent significance level								

Table 5: All categories tested

OLS estimates using a difference-in-difference approach. The first two regressions seperate the two assignee groups compared to their synthetic control group. The next six regressions look at each different technical category and compare it to its synthetic control group

Medical devices are not subject to the same rigorous approval process as drugs. In addition, Class 1 medical devices that are generally defined as low risk, such as gauze, do not require FDA approval. Manufacturers of 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, have a more stringent approval process. Therefore, for the majority of medical devices, FDA approval is given and is not an extremely time-consuming or capital-intensive process. (Emergo). Table 7 provides a sample of patents in the Surgery & Medical Instruments subcategory.

Table 8 shows results for the mechanical subcategories. The subcategories are: Materials Processing & Handling, Metal Working, Motors, Engines & Parts, Optics, Transportation and Miscellaneous-Mechanical. The categories that are statistically significant are Metalworking, Motors, Engines & Parts, Transportation and Miscellaneous-Mechanical.

Patent Number	Description of Innovation
483531	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 6: Sample of Surgery & Medical Instruments Subcategories

Notes: this table provides a small sample of patents in the surgery and medical instruments subcategory

	Drugs	Surgery and Medical Instruments	Biotechnology	Miscellaneous
Post	25.72	54.28	16.63	8.26
	(6.22)***	(10.22)***	(3.22)***	(1.84)***
Florida	-18.28	8.36	-1.66	1.78
	(5.69)***	(9.36)	(3.22)	(1.69)
Post*Florida	6.42	48.8	-5.48	8.25
	(8.79)	(14.45)***	(4.73)	(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				

Table 7: Subcategories of Drugs & Medical

OLS estimates using a difference-in-difference approach. Each column is a subcategory of the Drugs and Medical technical category

	Materials	Metalworking	Motors, Engines and Parts	Optics	Transportation	Miscellaneous
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)**
Florida	-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*Florida	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	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 8: Mechanical Subcategories

OLS estimates using a difference-in-difference approach. Each column is a subcategory of the Mechanical technical category.

	Agriculture	Amusement	Apparel	Working	Furniture	Heating	Pipes	Receptacles	Misc.
Post	5.91	9.33	4.87	1.45	13.43	-2.29	-0.26	14.66	40.99
	(3.32)*	(3.78_**	(2.17)**	(2.77)	(3.51)***	(2.32)	(1.31)	(3.52)***	(10.69)***
Florida	22.85	5.22	8.91	-56.38	12.28	-2.64	-9.64	3.57	13.19
	(3.04)***	(3.46)	(1.98)***	(2.54)***	(3.21)***	(2.12)	(1.2)***	(3.22)	(9.79)
Post*	4.6	11.51	1.52	6.63	14.07	8.12	7.82	10.03	35.99
Florida	(4.7)	(5.34)**	(3.06)	(3.92)*	(4.96)***	(3.28)**	(1.86)	(4.97)**	(16.12)**
Obs.	62	62	62	62	62	62	62	62	62
R-Squared	0.67	0.47	0.48	0.93	0.69	0.11	0.58	0.57	0.58
*- 10 percent significance level, ** - 5 percent significance level, *** -,1 percent significance level									

Table 9: Other Subcategories

OLS estimates using a difference-in-difference approach. Each column is a subcategory of the Other technical subcategory.

Finally, Table 9 shows results for the subcategories of "Others." The subcategories are: Agriculture, Husbandry, Food, Amusement Devices, Apparel & Textile, Earth Working & Wells, Furniture, House Fixtures, Heating, Pipes & Joints, Receptacles, and Miscellaneous. The subcategories that are statistically significant are Amusement Devices, Earth Working & Wells, Furniture, House Fixtures, Heating, Receptacles, and Miscellaneous.

Table 10 tests individual and corporate and government patenting using a slightly different method. Here, a differences-in-differences-in-differences design is used. This approach is used to provide a more convincing analysis. This is done by further refining the definition of the treatment and control groups by looking at the effects between individual and non-individual inventors. 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, Regressions 1 and 2 are run separately.

In the first regression, the synthetic control group is a weighted average of Arizona and California, while a separate synthetic control group (shown in table 4) is used in Regression 2. In Table 10, the results from the difference-in-differences in Table 5 are validated. The treatment effect is determined by the coefficient on the variable Post*Individual*Treatment. In Regression 3, the estimate can be interpreted to mean 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, a negative number would be

	Individual (1)	Gov./Corp. (2)	Individual (3)	Gov./Corp. (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)***
Florida	-355.04	255.51	-355.04	255.51
	(75.24)***	(56.05)***	(16.99)***	(16)***
Post*Florida	-122.46	198.93	-122.46	198.93
	(116.19)	(86.53)**	(93.35)	(53.84)***
Post*Individual	-471.13	365.57	-471.13	-253.68
	(116.19)**	(86.53)***	(109.61)***	(20.47)***
Individual*Florida	355.87	-253.68	355.87	-253.68
	(106.41)***	(79.25)***	(22.19)***	(64.01)***
Post*Individual*	276.39	-195.72	276.39	-195.72
Florida	(164.32)*	(112.38)	(116.79)**	(72.65)***
Year Dummies			Yes	Yes
Robust SEs			Yes	Yes
Observations	124	124	124	124
R-Squared	0.65	0.68	0.9	0.94

* - 10%, ** - 5%, *** - 1%

Table 10: Triple DID

OLS estimates using a difference-in-difference-in-difference approach. The first two columns do not have year dummies or robust standard errors. The second two columns have year dummies and robust standard errors.

expected.

Finally, this paper will estimate the treatment effect of the Mariel Boatlift by comparing individual inventors in Florida to individual inventors in the rest of the U.S. This regression is meant to provide further evidence that the Mariel Boatlift caused individual inventors in Florida to increase their patenting. This regression will also show that the baseline results are driven by individual inventors choosing to invent *more*, and not by entry of new inventors ("moonlight inventors").

Year	Inventor	Patent
1975	1	.
1976	1	.
1977	1	.
1978	1	.
1979	1	1
1980	1	0
1981	1	0
1982	1	2
1983	1	0
1984	1	0

Table 11: Data Summary

To do this, I create an individual-level panel by linking inventors across time by last name and city. An example of what this dataset looks like is given in Table 11. For example, Inventor 1 had his first patent in 1979, zero patents in 1980 and 1981, and two patents in 1982. I assign 0's in each year before an inventor's first patent is filed. This process has been followed for every single individual inventor in the U.S. from 1965 to 1995.

The main equation used for this regression is below:

$$\begin{aligned} Y_{itx} =& \beta 0 + \beta 1 Post1980_t + \beta 2 Florida_i + \beta 3 Repeat_x + \\ & \beta 4 Post1980_t * Florida_i + \beta 5 Post1980_t * Repeat_x + \\ & \beta 6 Repeat_x * Florida_i + \theta Post1980_t * Florida_i * Repeat_x + \epsilon_{itx} \end{aligned} \tag{9}$$

This is a differences-in-differences-in-differences design, where repeat inventors in Florida are compared to 1. non-repeat inventors in Florida and 2. all inventors in the rest of the U.S. Repeat inventors are inventors who have patented more than once in the sample, while non-repeat inventors are those who have only patented once. By separating repeat and non-repeat inventors, this regression is able to disentangle the treatment effects on inventors who only patent once in the sample from the effect on those who patent many times. Whether the mechanism I describe affects the extensive or intensive margin in patenting is an empirical question, which I try to answer with this regression.

Table 12 shows the results from this regression. The estimated treatment effect is the coefficient on Post*Florida*Repeat in both regressions. This coefficient is 0.0390 and is statistically significant at the 1% level. The economic significance of this variable is easier to interpret if it is presented in terms of a percentage change. If the dependent variable is changed to log (patent), this coefficient becomes 0.0162 and is still statistically significant at the 1% level. This coefficient can be interpreted as follows: the Mariel Boatlift caused repeat individual inventors in Florida to increase their patenting behaviour by 1.62% more than non-repeat inventors in Florida, relative to the analogous difference in the rest of the U.S. Again, this regression provides additional support for the conjecture that, when the number of low-skilled immigrants in an area increases, individual inventors are able to hire them for household jobs and reallocate time from household chores to innovating or patenting.

While this paper provides a well researched and justified argument for low-skilled immigration having a statistically significant and positive effect on patents, there are still limitations. Future research could look at importance of patents, by looking at citation weighted patents, to determine whether the impact on patents is beneficial to society or not. It could also examine

Number of Patents	(1)	(2)
Post	-0.1468	-0.8425
	(0.0011)***	(0.0455)***
Florida	0.0107	0.0202
	(0.0013)***	(0.0020)***
Repeat	2.6404	2.2467
	(0.0056)***	(0.0059)***
Post*Florida	-0.0027	-0.012
	(0.0011)***	(0.0016)***
Post*Repeat	-0.1336	-0.1203
	(0.0047)**	(0.0049)***
Repeat*Florida	-0.0168	-0.0225
	(0.0056)***	(0.006)***
Post*Florida*Repeat	0.0333	0.0390
	(0.0047)***	(0.0050)***
Year Fixed Effects	No	Yes
Observations	2,266,471	2,266,471
R-Squared	0.0501	0.0684

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

Table 12: Repeat Inventors

OLS estimates. The second regression has year fixed effects.
Both show the effect that the Mariel Boatlift had on repeat inventors (those that have patented more than once).

whether smaller corporations see similar results to individuals, to help and strengthen the results.

2.10 Mechanism

This section will justify the proposed mechanism and provide supporting evidence. To reiterate, the mechanism is as follows. A large number of low-skilled Mariel immigrants exogenously arrived in southeast Florida. This influx increased the supply of unskilled labour in Florida, which allowed more individual inventors to hire low-skilled workers to perform household tasks. See chapter 4 for a more detailed explanation of the theory behind this mechanism.

Examples of such activities include: housekeeping, babysitting, lawn maintenance, etc. Now, these individual inventors were able to spend less time on tasks around the house and allocate more time to innovating or patenting.

To justify this mechanism, two things need to be shown. The first is that the Mariel immigrants were largely engaged in housework. The second is that individual inventors were spending more time working after the Mariel Boatlift. Figure 6 shows that right after the treatment (1980) there was a sharp increase in the number of Cubans working in the domestic service industry in Florida. This figure serves as reasonably strong evidence that the Marielitos did in fact enter domestic work after arriving into southeast Florida.

One might worry that this could just be a trend nationwide, and that

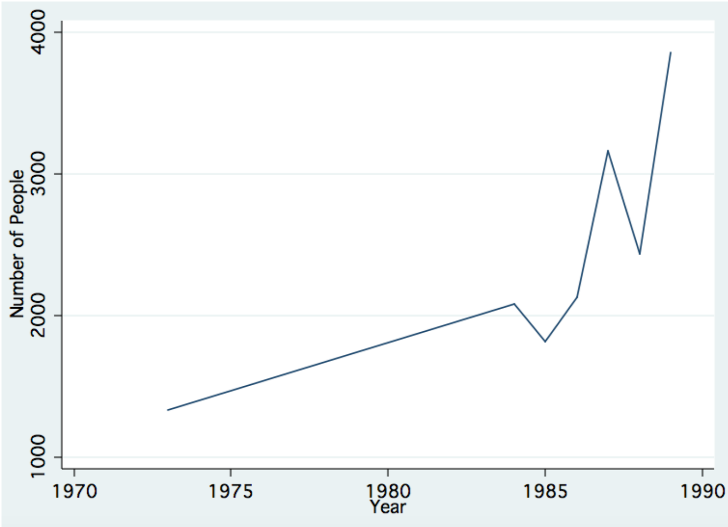

Figure 6: Cuban Workers in Domestic Service in Florida

more people were choosing to go into domestic housework everywhere in the U.S. However, Figure 7 shows just the opposite. In fact, the number of workers in domestic service has been decreasing in the U.S. since 1970. Note that Figure 2.6 shows Cuban workers, and Figure 7 shows all workers in the U.S. (during this period the rest of the U.S. did not have large concentrations of Cubans).

Figures 8 and 9 will be used to show strong evidence for the fact that the set of "potential inventors" in Florida started working more hours per week in Florida relative to the comparison group. Figure 8 compares hours worked per week among workers with a college degree or higher for Florida and the synthetic control group. When Ejermo and Jung look at Swedish inventors, they find that the number of inventors who are at least college educated is around 50% around this time period (Ejermo and Jung 2015). It is difficult to know exactly who these potential inventors are in the census; however,

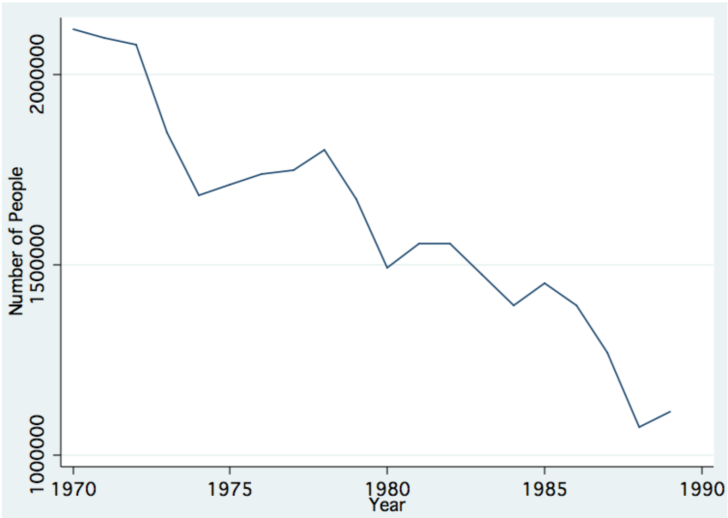

Figure 7: All Workers in Domestic Service in The U.S.

it is reasonable to assume that at the very least they had at least a college degree, but presumably also an advanced degree. Figure 9 compares hours worked per week among workers with an advanced degree (six or more years in post-high school studies) in Florida with the synthetic control group. Both of these figures show that workers in Florida with at least a college degree started working more hours per week right around the time of the treatment, relative to the synthetic control group.

Cortes and Tessada (2011) argue a very similar mechanism in their paper "Low-Skilled Immigration and the Labor Supply of Highly Skilled Women". They find that as the percentage of low-skilled immigrants in a city increases, women with a Ph.D. degree work more hours per week. They advance the following mechanism: these women are now able to hire workers to help them with household work and are thus able to spend more time working and less time engaged in housework (Cortes and Tessada 2008) .

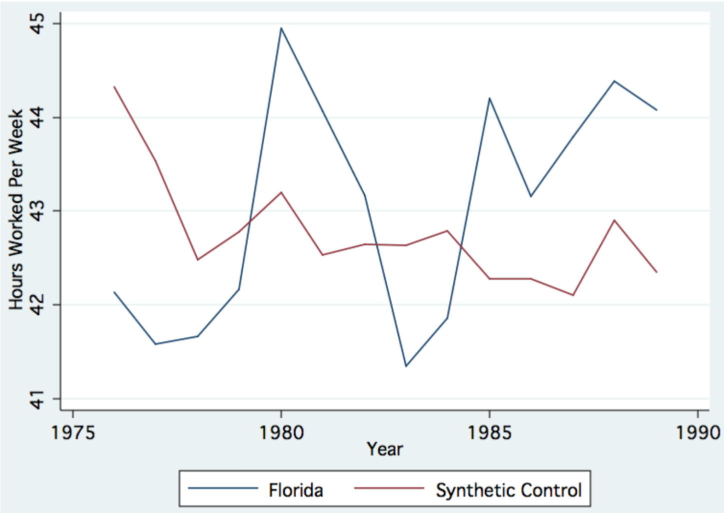

Figure 8: Workers with a College Degree

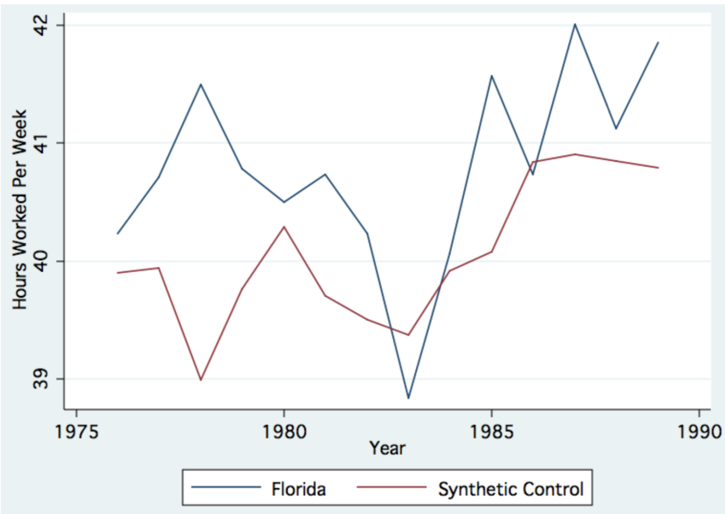

Figure 9: Workers with an Advanced Degree

More recently, Patricia Cortes published a similar paper with Jessica Pan in which they examine the effect that hiring a domestic helper has on labour-force participation and employment decisions of native women in Hong Kong. They found that part of the increase in the labour force participation over the last twenty years can be attributed to these women receiving domestic help (Cortes and Pan 2013). Barone and Mocetti also find a similar result when looking at the labour supply of Italian women (Cortes and Tessada 2008).

Finally, Tiago Freire provides similar results to the existing literature (Freire 2010). Using data from Brazil, he found that as low-skilled migration increases, the wage of domestic workers decreases, which causes the labour supply of highly skilled women to increase. Given that the existing literature finds only a causal link between low-skilled immigration and hours worked or labour-force participation, this paper contributes by showing a causal link between low-skilled immigration and production or innovation.

This section considers other plausible mechanisms that could have caused a relative increase in patenting in Florida after the Mariel Boatlift. The first potential mechanism is that the Cuban immigrants arrived in America – the land of opportunity – and were able to pursue their dreams of inventing. To test this mechanism, 400 of the most common Cuban last names in Florida were gathered and matched to the last names in the sample of patents. Over 1,000 of the most common Spanish last names in the United States were collected and matched with the sample. Figure 10 displays the results. As a comparison, the number of patents filed by individuals is also included.

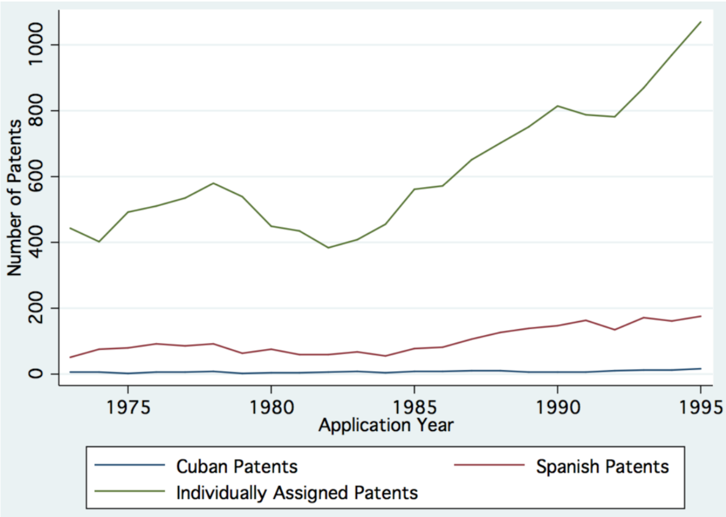

Figure 10: Hispanic Inventors

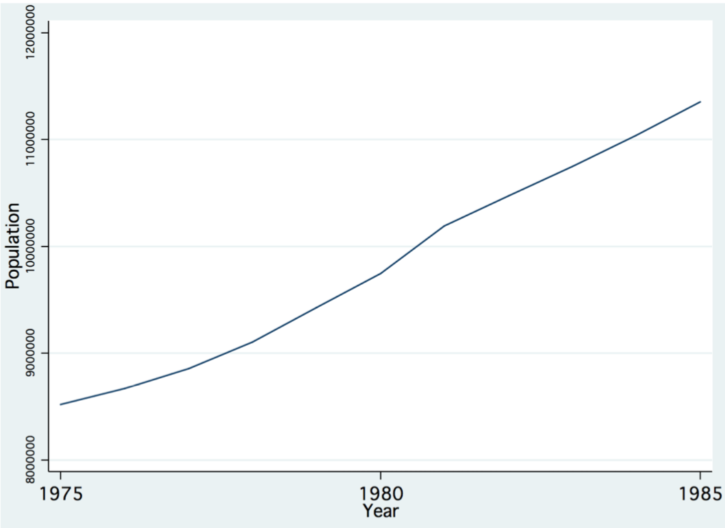

Figure 11: Florida Population

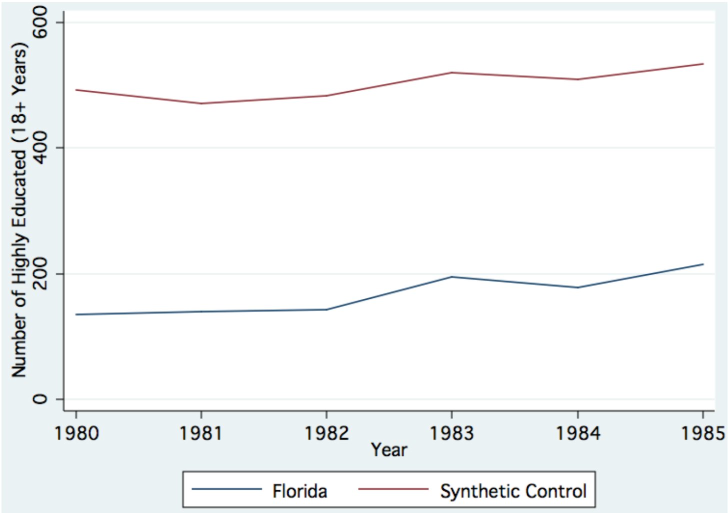

Figure 12: Number of Highly Educated in Florida vs. Synthetic Control

The number of patents filed by inventors with a Cuban last name is small and does not increase after the treatment. Patents filed 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 patents produced by individuals with a Spanish last name is trivial. This test suggests that it was not the Cubans themselves applying for patents once they arrived in Florida.

Another possibility is that during 1980, in addition to the Mariel immigrants, Florida received immigrants from either neighbouring states or other countries. These individuals could have been highly skilled and contributed to the increased patenting behaviour. If this was a viable mechanism, a significant increase in population around the time of the treatment would be expected. As can be seen in Figure 11, Florida's population steadily increased between 1975 and 1985 and did not experience a large population

	(1)	(2)
Post	-0.00000925	-0.0000438
	(0.00000372)**	(0.0000022)***
Florida	-0.0000279	-0.0000279
	(0.00000363)***	(0.000000144)***
Post*Florida	0.0000135	0.0000135
	(0.00000512)***	(0.00000204)***
Year Dummies	Yes	Yes
Observations	56	56
R-Squared	0.58	0.97

* - 10 percent significance level, ** - 5 percent significance level, *** - 1 percent significance level
All standard errors are robust

Table 13: Patents per Capita
OLS estimates. Both regressions have year dummies, robust standard errors and show the effect on logged patents.

spike around the time of the treatment.

Moreover, the results hold when patents are scaled by population. Table 13 presents results from the baseline specification, using patents per capita as the dependent variable. The estimated treatment effect is again the coefficient on post*treatment. It is both statistically significant and economically significant. Figure 11 and Table 13 indicate that population increase cannot unilaterally explain the relative surge in patenting in Florida.

A final concern is that highly skilled people may have been entering Florida at the same time that low-skilled people were leaving. This would contradict the argued mechanism as it would imply that the number of patents increased because the proportion of the population that was high skilled was also increasing. This possibility cannot be ruled out by any type of basic population analysis. Figure 12 shows the number of highly skilled workers (18+ years of school, indicating that they received a master's degree) in Florida and the synthetic control group for individual patent filers (part Arizona and part California). Were this a valid mechanism, then a spike in the number of highly skilled workers in Florida would be expected, compared to the synthetic control group, around the time of the treatment. Although there is a slight uptick around 1982 in Florida, there is a similar increase for the same group in the synthetic control. Therefore, this mechanism is likely not the main factor contributing to the increase in patenting. In sum, once examined more closely, none of these potential mechanisms appear likely to explain the large increase in individual patenting in Florida after the Mariel Boatlift.

2.11 Robustness Checks

To strengthen the argument, this section will estimate the treatment effect using several alternative comparison groups. Card also takes this approach in his Mariel Boatlift paper (Card 1990).

One concern might be that the synthetic control group is not a suitable control group. Table 14 estimates Equation 2.1 for individually assigned patents, using neighbouring states as the control group. Columns 1 to 5 use Alabama, Arkansas, Georgia, Kentucky and South Carolina as the control group, respectively. The estimated treatment effect is the coefficient on post*treatment. In each case, the variable is economically and statistically significant. This result can be interpreted as follows: after the Mariel Boatlift, Florida saw an increase in individually assigned patents compared to all neighbouring states. All of these different specifications indicate that my results are not sensitive to the choice of comparison group.

	Alabama	Arkansas	Georgia	Kentucky	South Carolina
Florida	374.56	402.5	318.38	384.5	381.81
	(38.98)***	(38.72)***	(40)***	(38.77)***	(39.13)***
Post*Florida	22.1	232.97	187.43	223.1	196.32
	(56.03)***	(55.66)***	(57.5)***	(55.74)***	(56.25)***
Observations	62	62	62	62	62
R-Squared	0.85	0.87	0.8	0.86	0.85
* - 10 percent significance level, ** - 5 percent significance level,					
*** - 1 percent significance level					

Table 14: Alternative Comparison States

Notes: OLS estimates. All regressions are done using an alternative comparative state in the difference-in-difference.

2.12 Conclusion

In conclusion, this chapter argues that the Mariel Boatlift had a positive and statistically significant effect on individual inventors' patenting behaviour. However, it had no statistically significant effect on the patenting behaviour of corporations or government agencies. The results show that The Mariel Boatlift caused an increase of 153.94 individually assigned patents in Florida (compared to the control group) and show no evidence of a statistically significant increase in government or corporate patents. This paper contends that the main mechanism behind this phenomenon is that, following the Mariel

Boatlift, individual inventors had access to a large supply of low-skilled workers and were able to hire them to perform housework, child care, etc. As a result, these inventors were able to move away from housework and spend more time inventing, thus leading to an increase in patenting.

These results are especially timely, as many governments are reviewing their immigration policies, particularly the Trump administration. In 2017, it supported a new bill – the Raise Act – that favours high-skilled immigrants over those who are low-skilled and trying to reunite their families. Although the merits of increasing highly skilled immigration are better researched, the effects of low-skilled immigration on the productivity of high-skilled workers are rarely studied and assumed to be negative.

In addition, could this same mechanism be freeing up the time of other high-skilled natives, allowing them to produce more? Are highly skilled natives able to work longer hours? In their 2011 paper, Patricia Cortes and Jose Tessada find that an increase in the supply of low-skilled immigrants leads high-skilled women to spend more time working. However, little has been done to demonstrate whether this increase in time also leads to an increase in output. Alternatively, Baker, Gruber and Milligan predict that decreasing the cost of child care causes women who are already in the workforce to work fewer hours, as long as leisure is a normal good. Although this chapter helps bolster the literature on low-skilled immigrants and their effect on the economy, more work clearly needs to be done.

2.13 Appendix A

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

Table 15: SCM: 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 16: SCM: 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 17: SCM: Drugs and Medical

State	Weight
AZ	0.351
TX	0.308
VA	0.037
WA	0.304

Table 18: SCM: Electronics

State	Weight
MI	0.043
MO	0.08
TX	0.133
WA	0.744

Table 19: SCM: Mechanical

State	Weight
AZ	0.343
CA	0.063
CO	0.436
TX	0.158

Table 20: SCM: Other

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

Table 21: SCM: Drugs

State	Weight
IL	0.11
MI	0.078
MN	0.17
NO	0.191
NC	0.06
NJ	0.142
NY	0.036
UT	0.213

Table 22: SCM: Surgery and Medical Instruments

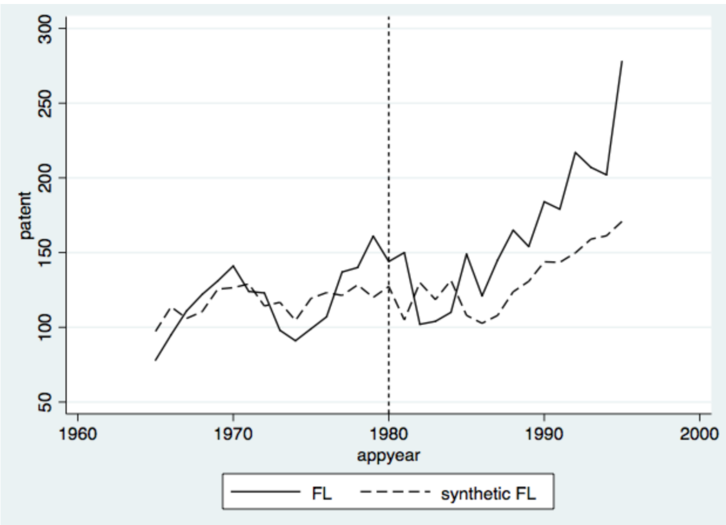

Figure 13: SCM- Chemical

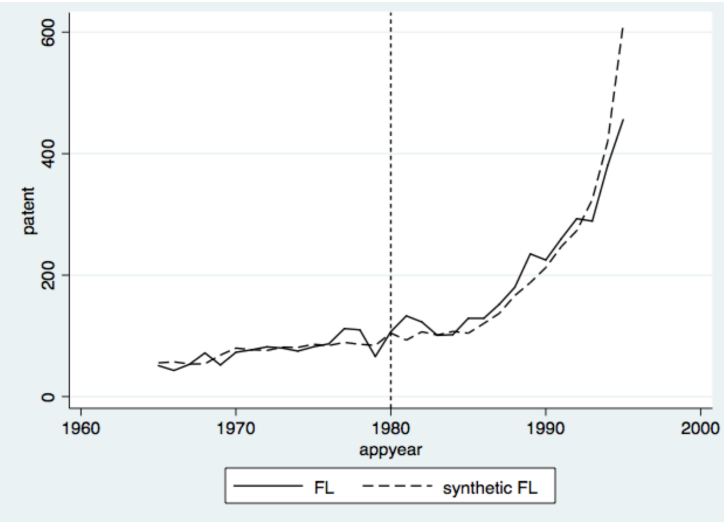

Figure 14: SCM- Computers and Communications

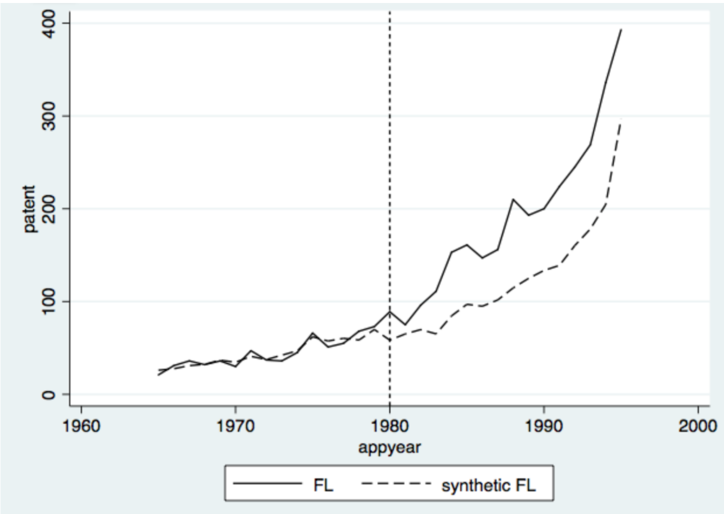

Figure 15: SCM- Drugs and Medical

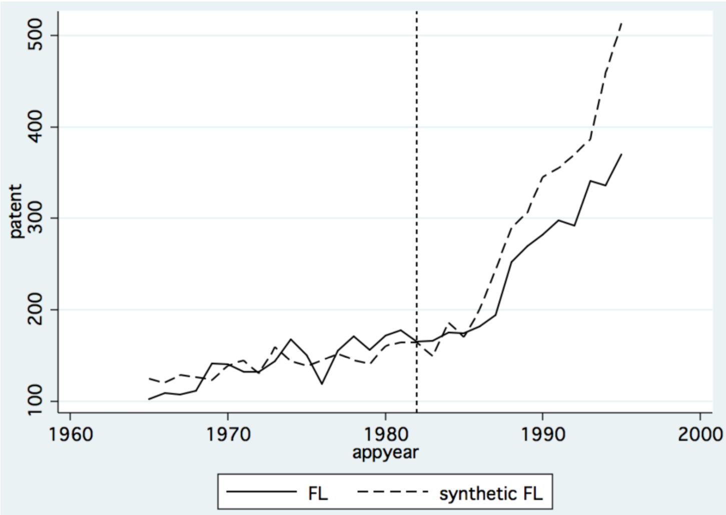

Figure 16: SCM- Electronics

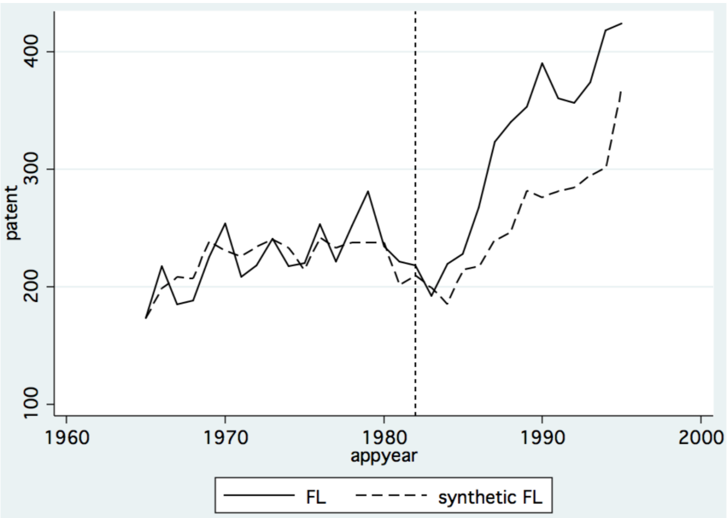

Figure 17: SCM- Mechanical

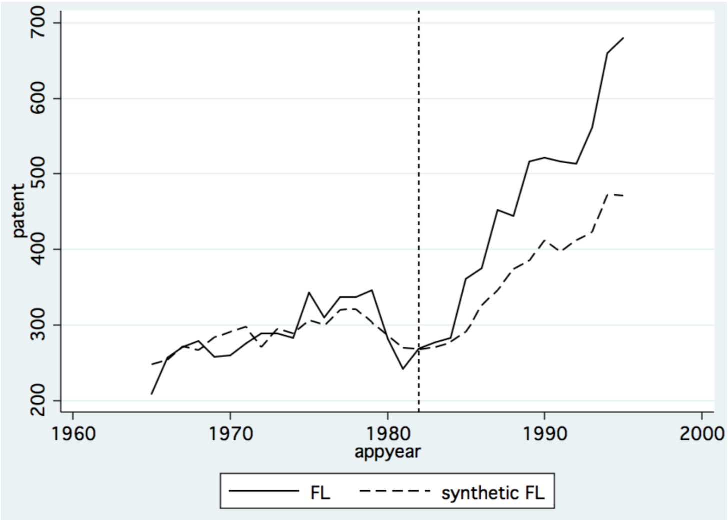

Figure 18: SCM- Other

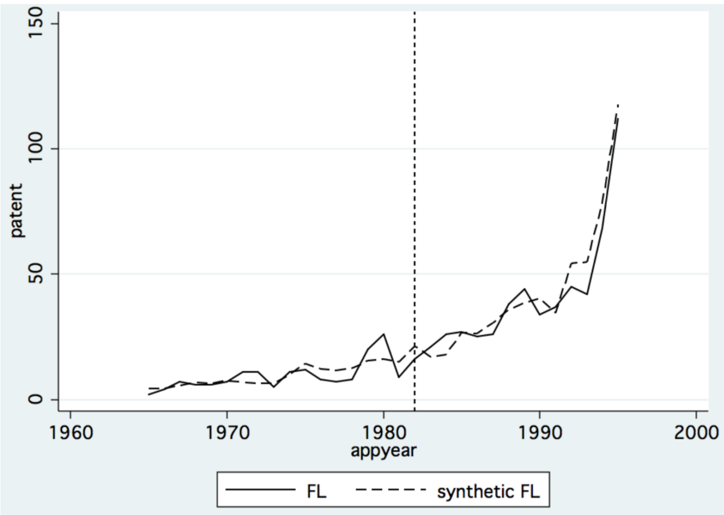

Figure 19: SCM- Drugs

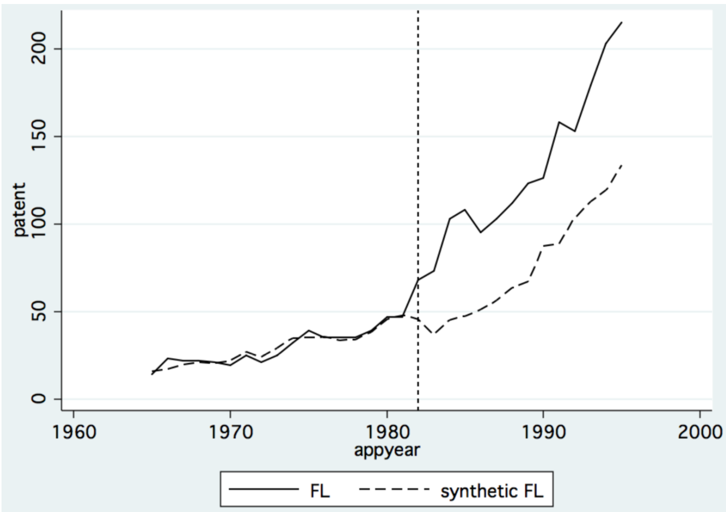

Figure 20: SCM- Surgery and Medical Instruments

3 Low-Skilled Immigration: Enabling Innovation Among Individual Inventors

This chapter examines 74 of the largest cities in the U.S. across two periods (1980 and 1990) to investigate whether a causal relationship exists between the percentage of a city's workforce that is low skilled and the number of patents applied for and granted in that city. This paper does not find that there is a statistically significant effect on patents filed by corporations or government agencies, or on individually assigned patents.

Although this chapter is asking a similar question to that of chapter 2, the empirical approach is different. This chapter uses decennial population census data to calculate the percentage of low-skilled immigrants in each major U.S. city and the NBER U.S. Patent Citations Data File dataset to calculate the number of patents filed in each city. The methods used in this chapter vary from those used in Chapter 2 in several ways. First, Chapter 2 exploits an exogenous immigration shock and uses a difference-in-differences estimator for its main regression. It exploits a real "natural experiment" but the assumptions need to interpret the results as causal are strong. This chapter uses a different empirical setting to see if the key results hold up in a very different setting and thus, offers complementary evidence.

While the methods in this chapter are adapted to the available data (city-year panel data), the results are not as well identified as those in Chapter 2, which uses an exogenous immigration shock that reduces the likelihood that the change in patenting was driven by other factors. This chapter has no exogenous shock and, therefore, is not as cleanly identified.

This chapter shows contrasting results to Chapter 2. Although this chapter does not find a statistically significant – and positive – effect of low-skilled immigration on the number of patents filed by individuals, it also does not find a statistically significant effect of the percentage of the population that is composed of low-skilled immigrants on patents filed by corporations or government agencies, which is similar to Chapter 2.

Figure 21 provides some motivation for this chapter. This Figure uses census and U.S. patent data from 1980 (Hall, Jaffer, and Trajtenberg 2001). The vertical axis shows the number of individually assigned patents filed, by city, in 1980. The horizontal axis shows the percentage of the workforce consisting of low-skilled immigrants, by city, in 1980. For this analysis, a low-skilled person is defined as a high school dropout. Each data point represents one U.S. city.

This figure indicates that a positive relationship exists between the percentage of the population consisting of low-skilled immigrants and the number of individually assigned patents. The remainder of this chapter will determine if this relationship is causal.

3.1 Data

This chapter uses a combination of two datasets. The first is the NBER Patent Database (Hall, Jaffer, and Trajtenberg 2001). This database contains information from under three million patents that were filed and granted This

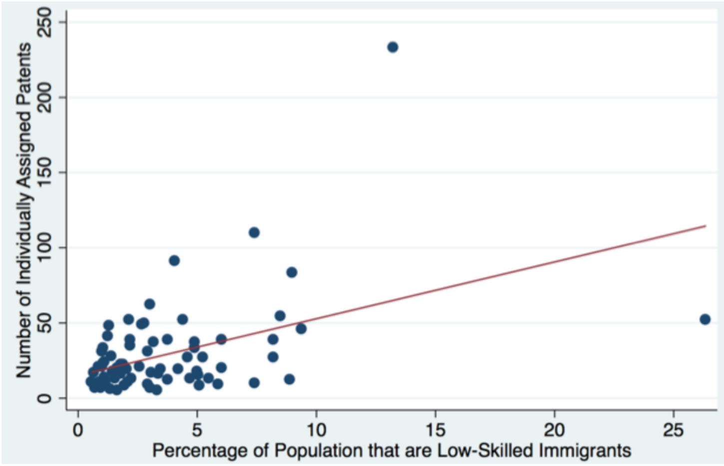

Figure 21: Proportion of Low-Skilled Immigrants vs. Number of Patents (1980)

chapter uses two datasets. The first is the NBER Patent Database. This database contains information about almost three million patents that were filed and granted between January 1963 and December 1999. This dataset has a high level of granularity, and most observations include the city and zip code of the inventor (Hall, Jaffer, and Trajtenberg 2001). This database is used to calculate the number of patents at the city level.

The second database used for this chapter is the decennial census data taken from the Integrated Public Use Microdata Series (IPUMS). This database provides a large number of variables and observations and is used in this setting to provide population data regarding low-skilled workers. The data needed to construct this measure are only collected every 10 years; consequently, this chapter only looks at city-level data in 1980 and 1990. It does not include 1970 data as not all population data is available for that year.

3.2 Empirical Approach and Results

This chapter will use a fairly simple empirical strategy and will exploit variation in the percentage of the population that is unskilled across cities and over time. The baseline regression model is shown in Equation 3.1, where LSIMM represents the percentage of the population that is unskilled.

$$Y_{it} = \beta 0 + \beta 1 * LSIMM_{it} + \epsilon_{it} \tag{10}$$

The cities examined in this chapter are 74 of the largest cities in the U.S. during this time and are listed in tables 23 and 24. These two tables also list the total number of patents filed and granted in that city (in 1990) and the percentage of the population consisting of low-skilled immigrants. This is measured as the number of low-skilled immigrants divided by the total population. A person is considered "low-skilled" if they have below a Grade 12 education, and an immigrant is someone born outside of the U.S. Thus, although the number shown is patents filed, it is also the number of patents that were later granted.

Table 25 contains the main results of this chapter. For the three regressions done with individually assigned patents, this includes patents that have been assigned to an individual and patents that have been unassigned. For the three regressions done with Non-Individually Assigned patents, this includes patents applied for by the US government and patents applied for by US corporations. This table shows separate regressions for each type of assigned patent, with the final and most robust regression for each type

City	Number of Patents	Low Skilled Immigration (Percentages)
Abilene, TX	5	1.3301
Akron, OH	172	0.4318
Albany, GA	67	0.7496
Albuquerque, NM	226	1.1257
Alexandria, LA	109	0.2184
Allentown	145	1.1022
Ann Arbor, MI	293	0.5300
Atlanta, GA	144	0.7138
Bakersfield, CA	53	3.2753
Baltimore, MD	162	0.6022
Baton Rouge, LA	348	0.2610
Boise City, ID	274	0.3982
Canton, OH	113	0.3402
Charleston, SC	119	0.4529
Charlotte	172	0.3858
Chicago, IL	424	2.0779
Cincinnati	623	0.3028
Cleveland, OH	98	0.9349
Colorado Springs, CO	126	1.1746
Dallas-Fort Worth, TX	538	1.9362
Danville, VA	93	0.1067
Dayton-Springfield, OH	174	0.3142
Denver-Boulder, CO	136	0.9788
Des Moines, IA	53	0.5806
Detroit, MI	51	1.0187
Erie, PA	85	0.5401
Eugene-Springfield, OR	49	0.4438
Flint, MI	24	0.3752
Fort Lauderdale, FL	46	2.8566
Fort Wayne, IN	130	0.3859
Fresno, CA	40	5.9380
Gainsville, FL	164	0.7168
Greensboro, NC	70	0.2846
Indianapolis, IN	350	0.3255
Jacksonville, FL	93	0.7331
Kansas City, MO/KS	77	0.4423
Knoxville, TN	87	0.2444

Table 23: City Summary

City	Number of Patents	Low Skilled Immigration (Percentages)
Las Vegas, NV	69	2.2909
Lexington-Fayette, KY	288	0.3486
Lincoln, NE	103	0.2713
Manchester, NH	98	1.1858
Memphis, TN	92	0.2864
Miami, FL	158	8.3157
Minneapolis, MN	231	0.8122
Nashville, TN	77	0.2995
New Orleans, LA	86	0.8655
New York, NJ	559	4.2143
Odessa, TX		2.5412
Omaha, NE	78	0.6056
Orlando, FL	83	1.6183
Philadelphia, PA	183	1.1056
Phoenix, AZ	345	1.6257
Pittsburgh, PA	424	0.3780
Portland, OR	221	1.0935
Raleigh-Durham, NC	253	0.4836
Reno, NV	55	2.4086
Richmond- Petersburg, VA	280	0.4644
Riverside- San Bernadino, CA	81	3.5168
Rochester, NY	1446	1.0531
Rockford, IL	199	0.6480
Sacramento, CA	69	2.1500
Salem, OR	92	1.3948
Salt Lake City, UT	262	0.7592
San Antonio, TX	160	2.2676
San Diego, CA	701	3.5791
San Francisco, CA	299	3.2955
San Jose, CA	851	4.0392
Santa Barbara, CA	134	3.4291
Sarasota, FL	49	0.9891
Shreveport, LA	34	0.2962
Tampa, FL	64	1.4465
Tucson, AZ	342	1.9769
Tulsa, OK	155	0.4485
Washington, DC	135	1.8443

Table 24: City Summary

appearing in the third and sixth column.

Assignee Type						
	Individually Assigned			Non-Individually Assigned		
Low Skilled Immigrants (%)	1.4269	1.357	0.3374	-1.9949	-3.0401	-9.7743
	(0.5762)**	(0.7485)**	(2.0596)	(5.0197)	(4.3719)	(21.8226)
City Population	0.00002	0.00002	-0.000003	0.00003	0.000028	0.000107
	(0.00000)***	(0.00000)***	(0.00002)	(0.00001)**	(0.00001)***	0.00007
Year Dummies	No	Yes	Yes	No	Yes	Yes
City Dummies	No	No	Yes	No	No	Yes
SEs Clustered at Metropolitan Area	No	Yes	Yes	No	Yes	Yes
Observations	142	142	142	142	142	142
R-Squared	.6766	.6766	.9592	.0326	.0888	.7987
*-10 percent significance level, **-5 percent significance level, ***-1 percent significance level						

Table 25: Regression Split by Assignee Type

OLS estimates.This table shows separate regressions for each type of assigned patent, with the final and most robust regression for each type appearing in the third and sixth column.

The coefficient of interest is the one for Low-Skilled Immigrants (%). For patents that have been assigned to individuals, and without any controls, the coefficient is 3.9249, and is significantly different from zero. This can be interpreted as follows: if the percentage of low-skilled immigrants in a city increases by 1 percentage point, the number of individually assigned patents in that city increases by just over 3. To put this number in perspective, in 1990 the mean number of individually assigned patents filed, averaged across cities, is 38.4189 patents. Additionally, the mean percentage of the population consisting of low-skilled immigrants, averaged across cities, is 1.3499%. So, for the mean city, almost doubling the unskilled immigrant population share leads to an increase in individual patents of almost 10%.

When fixed effects are added in for the city and year level, and standard errors are clustered at the city level, the result is not statistically significant. This result diverges from that found in chapter 2. When city fixed effects are included, the results may become insignificant because there is little variation in the unskilled immigration share across time. The rest of this chapter will look into whether the results hold across technological categories and when an instrumental variable is introduced.

For patents that have been assigned to corporations and government agencies (labelled Non-Individually Assigned), the coefficient of interest is still the one on Low Skilled Immigrants (%). However, none of these coefficients are statistically significant at the 1%, 5% or 10% levels. This can be interpreted as follows: as the percentage of the population consisting of low-skilled immigrants increases by 1 percentage point, there is no statistically significant effect on the number of patents filed in a city by corporations or government agencies.

As mentioned in Chapter 2, patents are classified into six technological categories and seven different assignee types. Assignee type is assigned by the United States Patent and Trade Office (USPTO), while the technological categories have been classified by the authors of the patent dataset. Table 26 shows the effect of the unskilled immigrant population share on patenting, separately for different technical categories. The six different technical categories are Chemical, Computers and Communications, Drugs and Medical, Electrical and Electronics, Mechanical and Other.

The parameter of interest is the coefficient on Low Skilled Immigrants (%). Each regression includes year fixed effects and clusters the standard errors at the city level. The key coefficient is not statistically significant for any of the technical categories. Again, this is likely because there is not enough variation in the percentage of Low Skilled Immigrants from 1980 to 1990 in the cities chosen for this chapter.

Each technological category is composed of several subcategories, which are classified by the authors of the patent dataset (Hall, Jaffer, and Trajtenberg 2001). Each subcategory was tested and none of the coefficients of interest were statistically significant and thus, the full tables are not shown in this chapter.

Technical Category						
	Chemical	Computers and Comms.	Drugs and Medical	Electrical/ Electronic	Mechanical	Other
Low Skilled Immigrants (%)	4.1052	1.1495	-1.4544	6.9649	-2.9899	-0.5099
	(4.4135)	(8.9922)	(4.7772)	(8.1424)	(5.4126)	(2.4405)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
City Dummies	Yes	Yes	Yes	Yes	Yes	Yes
SEs Clustered at Metropolitan Area	Yes	Yes	Yes	Yes	Yes	Yes
Observations	139	132	132	137	141	141
R-Squared	0.8542	0.7147	0.8173	0.7812	0.7768	0.9102
*-10 percent significance level, **-5 percent significance level, ***-1 percent significance level						

Table 26: Regression Split by Technological Category

OLS estimates. Each column shows results for a different technical category and includes year fixed effects, city fixed effects and standard errors clustered at the city level.

Table 27 presents results separately by assignee type. The five assignee types are: Unassigned, U.S. non-government organizations (mostly corporations), Non-U.S., Non-government organizations (mostly corporations), U.S. individuals and the U.S. Federal Government. Again, the coefficient of interest is the one for Low-Skilled Immigrants (%). Unassigned patents are those for which no rights have been granted yet to a corporation, government entity, or individual. Similar to existing literature, unassigned patents are assumed to be filed by an individual. None of the coefficients of interest are statistically significant

Assignee Type					
	Unassigned	U.S. non-govt. organizations (mostly corps.)	Non-U.S., non-government organizations (mostly corps.)	U.S. individuals	U.S. Federal Government
Low Skilled Immigrants (%)	.1483	-5.8479	0.2058	-0.3122	2.4084
	(.937)	(.781)	(.14)	(.676)	(.62)
Year Dummies	Yes	Yes	Yes	Yes	Yes
City Dummies	Yes	Yes	Yes	Yes	Yes
SEs Clustered at Metropolitan Area	Yes	Yes	Yes	Yes	Yes
Observations	142	142	61	99	93
R-Squared	0.9544	0.7919	0.8499	0.8836	0.8199
*-10 percent significance level, **-5 percent significance level, ***-1 percent significance level					

Table 27: Regression Split by Assignee Types

OLS estimates. Each column shows results for a different assignee and includes year fixed effects, city fixed effects and standard errors clustered at the city level.

3.3 Instrumental Variable

With the regressions run so far in this chapter, there is a concern that places where more innovation is happening also have more job opportunities for unskilled immigrants, so they choose to locate in these places in large numbers. In order to account for this potential endogeneity, I will use an instrumental variable (IV) identical to the one used by Cortes and Tessada (Cortes and Tessada 2008). The instrument for the number of low-skilled immigrants in city i and decade t is:

$$\sum_j \frac{Immigrants_j i1970}{Immigrants j1970} * LSImmigrants_j t \tag{11}$$

For this exercise, j includes South America, Central America and Mexico, and LSImmigrants stands for the total number of low-skilled immigrants from countries j in decade t. I choose these three countries as they make up the majority of low-skilled immigrants into these US cities during these years.

It is important to note that while this Instrumental Variable is used often in the literature, it is also criticized. Jaeger, Ruist and Stuhler find two sources of bias: (i) serial correlation in immigrant country of origin shares; and (ii) slow dynamic adjustment responses to shocks in the outcome variable (patenting). This could be considered in future research.

For this to be a useful IV, it should be highly correlated with the variable of interest (the unskilled immigrant population share in an area) but uncorrelated with the error term. The first condition is the only one that can be formally tested. This can be done by regressing "% of low-skilled" onto the

% of Low Skilled	
IV	0.0000024 (0.000000239)***
Observations	106
R-Squared	0.2045
* -10 percent significance level, ** - 5 percent significance level *** - 1 percent significance level	

Table 28: IV- First Condition

IV. The results are shown in Table 28 and indicate that the instrument and the endogenous explanatory variable are highly correlated at a statistically significant level.

Assignee Type								
	Individually Assigned				Non-Individually Assigned			
Dependent Variable	OLS	IV	IV	IV	OLS	IV	IV	IV
Low Skilled Immigrants	68.34	859.69	859.76	-186.23	-410.72	997.04	767.23	1772.84
(%)	(131.16)	(177.68)***	(339.43)**	(906.53)	(1388.66)	(770.7)	(568.34)	(2209.83)
Year Dummies	Yes	No	Yes	Yes	Yes	No	Yes	Yes
City Dummies	Yes	No	No	Yes	Yes	No	No	Yes
SEs Clustered at Metropolitan Area	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Observations	106	106	106	106	106	106	106	106

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

Table 29: IV Regressions- Split by Assignee Type

OLS and two-stage least squared (2SLS) estimates. The first and fifth columns are OLS and the rest use 2SLS. Each column includes year fixed effects, city fixed effects and standard errors clustered at the city level.

6 regressions run in table 29 are estimated by two-stage least squares (2SLS) and 2 are estimated using OLS. The second to fourth columns look at individually assigned patents and the last fifth to eighth columns look at non-individually assigned patents. The coefficient in the first column can be interpreted as follows: as the percentage of low skilled immigrants increases by 1 percentage point, the number of individually assigned patents in that city increases by just over 10 patents. Again, to put these numbers in perspective, in 1990 the number of individually assigned patents filed in the average city was 38.4189. Additionally, the mean percentage of the population consisting of low-skilled immigrants, averaged across cities, is 1.3499%

The fourth to sixth columns look at non-individually assigned patents. All coefficients of interest in the fifth to eighth columns are not statistically significant. This implies that the percentage of low skilled immigrants in a city does not affect the patenting behaviour of non-individuals (corporations and government agencies). These results are similar to those in earlier tables and those in chapter 2.

3.4 Conclusion

In conclusion, this chapter does not show a statistically significant, or positive, effect of low-skilled immigration on the number of patents filed by individuals, corporations or government agencies. I also do not find that there is an effect on any of the technological categories or subcategories of patents., In Chapter 2, I find that unskilled immigration affects patenting in a particular state (Florida) during a particular time (1980). This Chapter investigates if this result holds more broadly across the United States and does not find clear evidence to support this. This may be because identification in this chapter comes from the variation in unskilled immigration within cities, across time, which is not substantial. It may also be because unskilled immigration only positively affects individually assigned patents in certain contexts or markets. Finally, this chapter looks at changing the share of low-skilled while the first chapter just adds in more low-skilled. These are two different circumstances. The circumstances under which unskilled immigration leads to increased innovation merits further research.

Although extensive research has been done on the effects of high-skilled research and its benefits to innovation, the effects of low-skilled immigration are still unknown. This chapter attempts to shed light on some of the effects of low-skilled immigration on a host city, yet more work needs to be done. More recently, Card and Borjas have made a concerted effort to study the effects of low-skilled immigrants on natives' wages, but even those results have been largely inconclusive. In addition, this paper can be expanded upon by developing a cleaner identification strategy that allows for less measurement error and endogeneity.

4 A Model of Labour Specialization

The main purpose of this chapter is to develop a theoretical framework that formalizes the mechanism put forward in both empirical chapters. This model generates predictions about what happens when the supply of low-skilled labour increases. I will show that as the supply of unskilled workers increases, the amount of home production a skilled person will purchase increases, and that same person will increase the amount of time they spend working. These results are consistent with the mechanism described earlier: as the supply of unskilled workers increases, an individual inventor will find it easier to outsource their home production (cooking, cleaning, taking care of children, etc.) and spend more time on their own work (inventing).

This chapter models an individual inventor's decisions with respect to home production, namely whether to carry out home production themselves or to pay someone to do it. What are the conditions under which an individual would choose to carry out home production themselves, and what are the conditions under which an individual would choose to pay for home production?

After modelling the way in which an individual inventor's home production and labour supply decision depends on unskilled wages, I derive a market demand function for unskilled household labour. Because of the possibility of doing household labour themselves, inventors have a reservation price for unskilled household labour, which depends on the inventors' return to non-household work and the relative efficiency of inventors and unskilled workers in household production. If the unskilled wage exceeds this reservation wage, no unskilled labour will be demanded in this market. If the unskilled wage is equal to this reservation wage, inventors will be indifferent between hiring household workers and doing home production themselves. I show that a positive unskilled labour supply shock will increase employment in the market for household workers. However, the effect on the equilibrium wage is ambiguous, and depends on the size of the unskilled labour supply shock and the ex ante wage level. The increase in employment in the market for unskilled household labour implies an increase in skilled non-household labour supply, which implies an increase in innovation.

4.1 Model Setup

I first model the preferences and budget constraint of an individual inventor. There are two types of goods: home goods and other goods. Home goods are things like childcare, a clean house, etc. Other goods are everything else. Home goods can either be produced by the inventor, or produced by an unskilled worker for pay. Assume that L_0 is number of hours in a day; Z_1 is the quantity of home goods consumed by the inventor; Z_2 is the quantity of other goods consumed by the inventor; P_1 is the amount of home goods the inventor produces per hour if he does it himself; π_1 is the amount of home goods that an unskilled worker can produce in an hour; W_2 is the inventor's hourly wage doing market work ("innovating") and W_1 is the hourly wage the inventor must pay to an unskilled worker to produce home goods.

The inventor has Cobb-Douglas utility over Z_1 and Z_2:

$$U(Z_1, Z_2) = Z_1^{\alpha} Z_2^{1-\alpha}$$

Note that the budget constraint is different, depending on whether the inventor produces home goods himself or hires an unskilled worker to do it for him.

4.2 Budget Constraint: Inventor Produces Home Goods Himself

Assume that H_1 is the time the inventor spends producing home goods, and H_2 the time he spends working for pay. If he produces P_1 units of Z_1 per hour, then he will consume $Z_1 = P_1 H_1$. Because he is producing his own home goods, the only thing he will spend his earnings on is Z_2. So, $Z_2 = W_2 H_2$. Then,

$$\begin{aligned}
H_1 &= \frac{Z_1}{P_1} \\
H_2 &= \frac{Z_2}{W_2} \\
\Rightarrow &\frac{Z_1}{P_1} + \frac{Z_2}{W_2} = L_0 \\
\Rightarrow &\frac{W_2}{P_1} Z_1 + Z_2 = W_2 L_0
\end{aligned}$$

This is the inventor's budget constraint if he produces home goods himself.

4.3 Budget Constraint: Inventor Hires Unskilled Worker to Produce Home Goods

If the inventor spends all of his time working, he has W_2L_0 dollars to spend. He will spend some of this on Z_1, and some on Z_2. If an unskilled worker can produce π_1 units of Z_1 per hour, then the number of hours they would need to be hired to produce Z_1 units of home produced goods is Z_1/π_1. At a cost of W_1 per hour, this would cost $\frac{W_1}{\pi_1}Z_1$. So, the per unit price of Z_1 is $\frac{W_1}{\pi_1}$. Assuming each unit of Z_2 costs \$1, the budget constraint is:

$$\frac{W_1}{\pi_1}Z_1 + Z_2 = W_2L_0$$

4.4 Solution- Home Goods Decision

The two budget constraints overlap at the extreme in which $Z_1 = 0$. This implies that one budget constraint will always be strictly preferable: the one with the flatter slope. In particular, the inventor will always prefer to hire an unskilled worker to produce home goods if:

$$\frac{W_2}{P_1} > \frac{W_1}{\pi_1} \Rightarrow W_1 < \frac{\pi_1}{P_1}W_2$$

He will be indifferent between hiring an unskilled worker and doing it himself if the two sides are equal. Figure 22 is a picture of the two budget constraints, for the case in which the inventor chooses to hire someone else to produce home goods.

Note that a reduction in W_1 may push the inventor from producing home

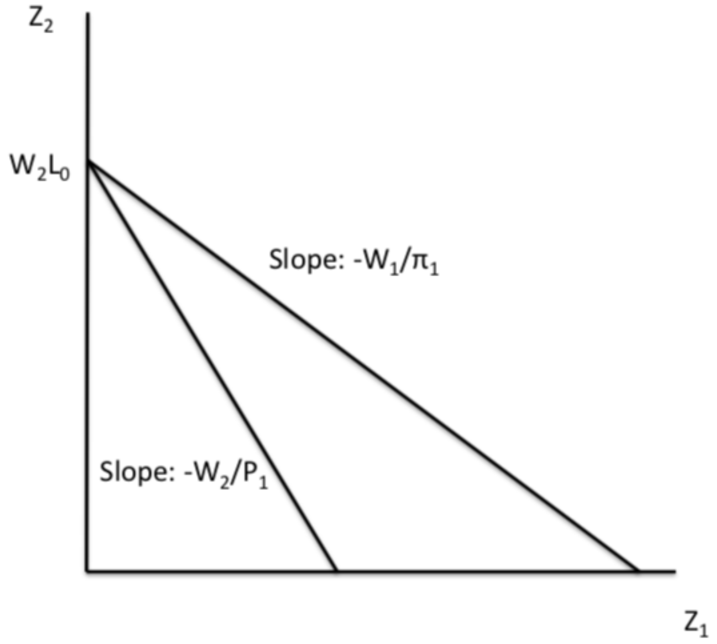

Figure 22: Budget Constraints

goods himself to hiring an unskilled worker to do it.

4.5 Solution- Inventor Produces Home Goods Himself

Here, I maximize utility subject to the budget constraint for an inventor producing home goods himself. The first order condition is:

$$\frac{\alpha}{1-\alpha}\frac{Z_2}{Z_1} = \frac{W_2}{P_1}$$

Substituting this into the budget constraint:

$$Z_1 = \alpha P_1 L_0$$

$$Z_2 = (1-\alpha) W_2 L_0$$

The amount of time spent working for pay (H_2) is $Z_2/W_2 = (1-\alpha)L_0$.

4.6 Solution- Inventor Hires Unskilled Workers

Again, I maximize utility subject to the budget constraint for an inventor hiring an unskilled worker to produce home goods. The first order condition is:

$$Z_1 = \frac{\alpha\pi_1 W_2}{W_1} L_0$$

$$Z_2 = (1-\alpha)W_2 L_0$$

Now, the amount of time spent working for pay (H_2) is L_0, and $L_0 > (1-\alpha)L_0$.

This implies that the amount of time spent working on the market is strictly higher for inventors who hire others to produce home goods.

4.7 Market for Unskilled Labor

I now determine how the supply of unskilled labour affects the amount of time inventors spend engaging in market work.

I start with an individual inventor's demand for unskilled labour. If $W_1 > \frac{\pi_1}{P_1}W_2$, then the inventor will demand zero hours of unskilled labour and he is better off producing home goods himself. If $W_1 < \frac{\pi_1}{P_1}W_2$, then the inventor will demand Z_1^*/π_1 units of unskilled labour, or $\frac{\alpha W_2}{W_1}L_0$. If $W_1 = \frac{\pi_1}{P_1}W_2$, he will be indifferent between these two quantities (or any linear combination of the two). So, if N_I^D is the quantity of unskilled labour demanded by an individual inventor:

$$N_I^D \begin{cases} = 0, & W_1 > \frac{\pi_1}{P_1} W_2 \\ \in [0, \frac{\alpha P_1 L_0}{\pi_1}], & W_1 = \frac{\pi_1}{P_1} W_2 \\ = \frac{\alpha W_2}{W_1} L_0, & W_1 < \frac{\pi_1}{P_1} W_2 \end{cases}$$

Assume there are K identical inventors in the market, which constitute the demand side of the market for unskilled workers. Aggregating the individual inventor's demand for labour up to the market level:

$$N_{MKT}^D \begin{cases} = 0, & W_1 > \frac{\pi_1}{P_1} W_2 \\ \in [0, \frac{\alpha P_1 L_0}{\pi_1} K], & W_1 = \frac{\pi_1}{P_1} W_2 \\ = \frac{\alpha W_2}{W_1} L_0 K, & W_1 < \frac{\pi_1}{P_1} W_2 \end{cases}$$

The equilibrium W_1 and N (quantity of unskilled labour hired) is given by the intersection of this labour demand function and an upward sloping labour supply function.

Assume that not every inventor has decided to outsource the production of home goods, so $W_1^* = \frac{\pi_1}{P_1} W_2$ and $N^* < \frac{\alpha P_1 L_0 K}{\pi_1}$. In this equilibrium, all inventors are indifferent between producing home goods themselves and hiring unskilled labour to do it for them. The number of inventors who actually do hire unskilled labour to produce home goods is governed by unskilled labour supply. A positive labour supply shock will increase equilibrium N^*, implying an increase in the number of inventors who choose to hire an unskilled worker to produce home goods. Depending on the size of the labour supply

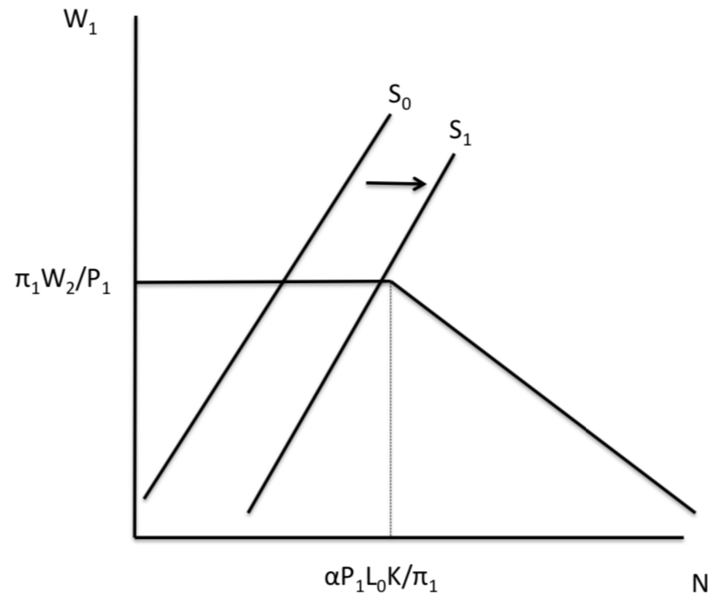

Figure 23: Supply Shock 1

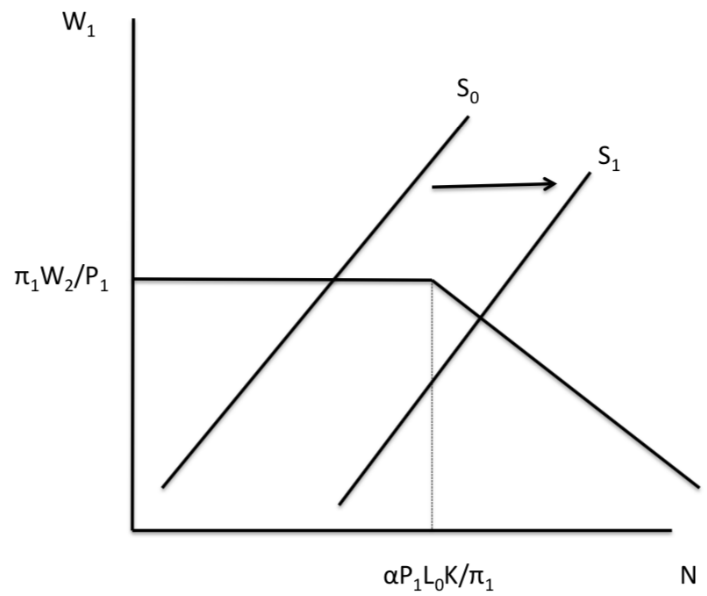

Figure 24: Supply Shock 2

shock, this may or may not lead to a reduction in equilibrium W_1^*.

If a positive unskilled labour shock causes some inventors to shift from producing their own home goods to hiring unskilled labour to produce home goods, this represents an increase in inventors' market labour supply. Assuming inventors' labour supply is positively correlated with patenting, this implies an increase in patenting following a positive unskilled labour supply shock. This can occur with or without a decline in the unskilled wage. This is illustrated in figures 23 and 24 to outline these two different circumstances.

4.8 Concluding Remarks

In conclusion, this simple model predicts that as the supply of the low-skilled increases, high-skilled hire more help around the house and are then able to devote more time to their work inventing. These results provide a theoretical backing for both of the other chapters and predict the empirical results found in them. However, there is still room for additional research as this model has many assumptions. Future research could loosen some of the constraints and have more of the variables determined inside of the model (wage, etc.) as this would be closer to mimicking real life. In addition, extensions of this model could include a search cost for finding a new employee and including a measure of work output. While this chapter strives to shed additional light on the the effects of an influx of low-skilled immigrants, there is still a lot of room for future research.

5 Conclusion

Through three separate essays, I make an argument that low-skilled workers can have a statistically significant and economically positive effect on innovation. In particular, I show that as the number of low-skilled workers in an area increases, the number of patents applied for by individual inventors also increases. I do not find that there is any effect on patents applied for by corporations or government agencies. My proposed mechanism is the following: as the number of low-skilled workers increases, it becomes easier for high-skilled inventors to hire them to help around the house. This allows the inventor to spend less time taking care of children or the house, and more time working (or inventing). Thus, we would expect to see an increase in patents applied for by individuals after a positive unskilled immigration shock.

I hope this dissertation sparks future research in the area of low-skilled workers and their effects on other parts of the economy. For the remainder of this chapter, I will speculate what effect this mechanism would have on immigration policy, automation and minimum wage with the goal that it inspires future work to be done in these areas.

Looking at this effect in a vacuum, there are implications for immigration policy. Nations should reconsider their policies to allow for more low-skilled workers to enter. While this may lower the wage among incumbent low-skilled workers, the effect on innovation and output of the high skilled is large. They are clearly doing a job that is needed and beneficial for society. The caveat to this is that more research needs to be done on what happens when the share of immigrants changes. For example, when more low-skilled are admitted, does this automatically mean that less high-skilled are admitted?

As automation increases, the effect of low-skilled workers on innovation is likely to decrease. The empirical work in this dissertation uses data from the 1980s, and lots has changed since then. As their jobs can be done by machines and robots, these workers become obsolete. That being said, there will likely always be a need for some human assistance with child care (looking after them, taking them to activities, etc.). Until a robot is able to take care of a baby, the low-skilled will still be in demand.

This dissertation would likely serve as motivation for a lower minimum wage. If the mechanism proposed in this dissertation is unable to work properly because of a minimum wage, it would neutralize the effect on innovation and patenting. The only reason this may not be the case would be if there were not enough low skilled in an area to begin with. Then, as the percentage of low-skilled increases, they would all be hired. Not because they were now more affordable but because there was a shortage.

References

Alberto Abadie, A. D. and J. Hainmueller (2010, June). Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American Statistical Association 105*(490), 493–505.

Alberto Abadie, J. G. (2003). The economic costs of conflict: A case study of the basque country. *The American Economic Review 93*(1), 113–132.

Blit, J., M. Skuterud, and J. Zhang (2019, July). Can skilled immigration raise innovation? evidence from canadian cities. *Journal of Economic Geography 86*.

Borjas, G. J. (1995). The economic benefits from immigration. *The Journal of Economic Perspectives 9*(2), 3–22.

Borjas, G. J. (2015, September). The wage impact of the marielitos: A reappraisal.

Bratti, M. and C. Conti (2018). The effect of immigration on innovation in italy. *Regional Studies 52*(7), 9340947.

Burnham, L. and N. Theodore (2012). Home economics the invisible and unregulated world of domestic work. *National Domestic Workers Alliance*.

Card, D. (1990, January). The impact of the mariel boaftlift on the miami labor market. *Industrial and Labor Relations Review 43*(2), 245–257.

Card, D. (2005, November). Is the new immigration really so bad? *The*

Economic Journal 115(507), F300–F323.

Cortes, P. and J. Pan (2013). Outsourcing household production: Foreign domestic workers and natives labor supply in hong kong. *Journal of Labor Economics 31*(2), 327–371.

Cortes, P. and J. Tessada (2008). Cheap maids and nannies: How low-skilled immigration is changing the labor supply of high-skilled american women. *Research Institute of Industrial Economics (IFN) Stockholm Conference on Family, Children, and Work*.

Dettling, L. J. (2015, February). Broadband in the labor market: The impact of residential high speend internet on married women's labor force participation. Federal Reserve Board, Washington, D.C.

Ejermo, O. and T. Jung (2015, October). Demographic patterns and trends in patenting: Gender, age, and education of inventors. *Technological Forecasting and Social Change*.

Emergo. Fda approval process for medical devices.

for Migration, C. and Development. The adaptation process of cuban and haitian refugees.

Hall, B., A. Jaffer, and M. Trajtenberg (2001, October). The nber patent citations data file: Lessons, insights and methodological tools. *National Bureau of Economic Research* (8498).

Hawk, K. D., R. Villella, L. de Varona, and Adolfo (2014). *Florida and the Mariel Boatlift of 1980: The First Twenty Days*. University Alabama Press.

Hunt, J. and M. Gauthier-Loiselle (2010, April). How much does immigration boost innovation. *American Economic Journal: Macroeconomics 2*(2), 31–56.

Jaffe, A. B. (2000). The u.s. patent system in transition: policy innovation and the innovation process. *Research Policy 29*, 531–557.

Mueller, E. (2011). Entrpreneurs from low-skilled immigrant groups in knowledge-intensive industries- company characteristics, survival and innovative performance. *Econstor* (11-030).

Ojita, M. (2005). *A Memoir of a Cuban Exodus*. The Pengiun Press.