THE EFFECTS OF THE NOVEMBER 2015 PARIS ATTACKS ON LABOR MARKET OUTCOMES OF ARABS AND MUSLIMS IN THE UNITED STATES

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Abstract

This thesis studies the impact of the November 2015 Paris attacks on the labor market outcomes of Arabs and Muslims living in the United States. With a difference-in-differences approach, I use the Current Population Survey's monthly outgoing rotation group files and find that hours worked for Arab and Muslim men decreased by at least 1.08 and 1.11 hours when compared to other immigrants and US-born individuals classified as "Whites", respectively. Employment rates for Arab men also decreased by 2% due to the attacks when compared to other immigrants and US-born individuals of any race. Furthermore, there is evidence that in the aftermath of the attacks, Muslims and Arabs shifted from higher paying industries and occupations to ones with lower pay.

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Chapter 1: Introduction

1.1 Discrimination towards Arabs and Muslims in the 21st century

The turn of the century came with a set of unfortunate events related to terrorist attacks around the world. Dreadful incidents such as September 11th in New York, the 2004 Madrid and 2005 London Bombings, and the November 2015 Paris attacks changed the lives of millions of people in an undesirable manner. Inevitably, this not only affected those directly related to the devastating attacks but also individuals more likely to be seen as Arabs or Muslims. Immediately after the September 11th attacks, it appears that the presence of Muslims in America went from being invisible (Naber, 2000) to one of the most targeted groups regarding discrimination practices and hate crime events (Cainkar, 2002).

In September 2002, in an attempt to have better tracking records about travelers from countries associated with Islam[1], the United States Department of Justice introduced the National Security Entry-Exit Registration System (NSEERS). This was one of the strategies used to combat the war on terrorism. The nature of this program was, arguably, dubious. While it is true that terrorist attacks are mostly associated with individuals coming from countries included in the NSEERS' list, thousands of individuals, who may or may not even have been Muslims at all, were also thrown into the same basket. This program created 93,000 cases in which some, according to the American Civil Liberties Union (ACLU), were not terrorism-related convictions (Rickerd, 2011). Although the ACLU does not precisely quantify the number of cases created that were not directly linked to terrorism, NSEERS' existence reflects part of the reaction that the US had in response to the unfortunate set of events of 9/11. These terrorist attacks inevitably changed the social and political context for Muslims in America (Byng, 2008). This, combined with the government's response and the rising anger and animosity against Muslims and Arabs inevitably led to discrimination towards individuals associated with such groups.

It is important to also take into account the potential effects that terrorist events occurring in one nation would have on immigrants living in other countries. It has been reported that Muslim communities and other vulnerable groups in the European Union became targets of hate crimes right after 9/11 and that an increasing feeling of fear from the general population inevitably exacerbated the pre-existing and not necessarily accurate notions about Muslims in Europe (Nielsen & Allen, 2002). In Australia, incidents of racial attacks or denigrations became more frequent immediately after the September 11th attacks. The same phenomenon has been recorded in the aftermath of the 2002 Bali bombings (Poynting & Noble, 2001). Meanwhile in

[1] These countries are Iran, Iraq, Libya, Sudan, Syria, Afghanistan, Algeria, Bahrain, Eritrea, Lebanon, Morocco, Oman, Qatar, Somalia, Tunisia, United Arab Emirates, Yemen, Pakistan, Saudi Arabia, Bangladesh, Egypt, Indonesia, Jordan and Kuwait. North Korea was also included there but obviously not for the same reason as the other countries.

the United Kingdom, there has been a significant increase in hate crimes towards Muslims that happened in the aftermath of not only the 2005 London bombings but also the September 11th attacks (Hanes & Machin, 2014). On the other hand and interesting in its own right, a certain part of the European population discovered a new interest in Islamic culture and thus started practicing inter-faith initiatives (Nielsen & Allen, 2002).

In this thesis I focus on the changes in labor market outcomes of Arabs and Muslims in the United States in response to the 2015 Paris attacks that occurred between November 13th and 14th. I use this event as a source of exogenous variation in discrimination towards individuals associated with this group. With a difference-in-differences approach, I use the Current Population Survey Outgoing Rotation Group Files (CPS-ORG) from 2010 to 2019 to track individuals associated with Islam and with the Arab world and compare them with three comparison groups: Immigrants without Arab and Muslim background (Comparison Group 1), US-born individuals of any race (Comparison Group 2), US-born Whites (Comparison Group 3). I use these three comparison groups in order to fulfill the following two conditions: First, the individuals belonging to the comparison groups should not be affected by the adverse changes in labor market outcomes due to the attacks. Second, unobserved characteristics that are contemporaneous to such attacks equally affect both the target group (Arabs and Muslims) and the comparison groups (CG1, CG2, and CG3).

By analyzing the potential effect that terrorist attacks that occurred outside of a nation could have on the local labor market outcomes of a specific target group (in this case, Arabs and Muslims), this thesis contributes to the literature across different fields that focuses on discrimination not only towards Arabs and Muslims but also to immigrants as a whole. I find that Arab and Muslim men worked at least 1.08 and 1.11 hours less when compared to other immigrants and US-born individuals classified as "Whites" by the CPS. The employment rates for Arab and Muslim men went down by 2% when compared to other immigrants and US-born individuals of any race. There is evidence that, due to the attacks, Arabs and Muslims shifted from high paying industries and occupations to ones with lower pay; suggesting that discrimination is not only channeled through income and employment but also through other variables such as industry and occupation. Importantly, there is some evidence of a decrease in wages and weekly earnings for both Arab men and women.

The rest of this thesis is organized as follows: Chapter 2 provides an in-depth review of existing literature in this area. Chapter 3 is divided into two sections: Data and Methodology. In the first section, I present the data used to run my analysis and how I categorize observations based on their nativity profiles. In the second section, I discuss the difference-in-differences model used in this thesis. Chapter 4 presents the main results. First, I present summary statistics for all the variables used in the analysis. Then I display and interpret the results obtained from the difference-in-differences (DD) analysis using a variety of approaches (long- vs. short-term and with vs. without industry controls). In Chapter 5, I perform robustness checks such as testing for pre-trends and running pseudo-intervention analyses with a period prior to the 2015 Paris attacks. In Chapter 6, I summarize the main results, discuss the limitations of the analysis and conclude.

Chapter 2: Literature Review

2.1 Discrimination in the same country after a terrorist attack

There is evidence that Muslims appear to have experienced a decline in wages and weekly earnings of between 9 to 11 percent below what they would have gotten had 9/11 not occurred at all (Kaushal et al., 2007). Shortly after the 9/11 attacks, it has been found that the employment-population ratios and hours worked of young Muslims between the ages of 16 and 25 have decreased; these effects, however, quickly began to dissipate by the end of 2004 (Rabby & Rodgers, 2011). More literature related to this topic indicate that Muslims struggled to integrate to local populations in the US after the events mentioned the previous chapter (Gould & Klor, 2016). Inevitably, this led Muslims immigrants living in US states with the highest increase in rates of hate crime (after 9/11) to become more likely to marry within their own ethnic group, have higher fertility, lower female labor participation rates and lower levels of English proficiency (Gould & Klor, 2016). It has been found that Muslims were less prone to set up their own businesses after 9/11; especially when considering industries that are associated with high levels of capital investment (Wang, 2016). Using a correspondence study methodology, there is some evidence that Arab Americans were negatively affected in the American labor market due to a hiring bias against them (Widner & Chicoine, 2011). However, such study does not isolate the discrimination that would solely be aimed towards Arabs and Muslims than to immigrants in general. Meanwhile in the United Kingdom and right after the 2005 London bombings, a 10 percentage point decrease in employment of young Muslim men as opposed to non-Muslim immigrants has been found and was also accompanied by drops in real earnings and hours worked (Rabby & Rodgers III, 2010).

While there is strong evidence that Arab Americans and non-US citizens associated with Islam were adversely affected by 9/11, evidence suggests that there is within variation in changes of labor outcomes in the Muslim population not only in terms of gender (Kaushal et al., 2007), but also regarding country of origin and age category[2]. These relative declines worsen if one focuses on a narrow target group that is more likely to face discrimination[3] (Rabby & Rodgers, 2011).

Discrimination towards minorities in different countries is not only reflected in labor market outcomes such as employment, hours worked and wages but also in the sharing economy. A 41-month long analysis of hosts using Airbnb in Paris, France shows that before the November 2015 Paris attacks there was no statistically significant difference of occupancy rates of hosts with French or Arab/Muslim names. Just a month after the attacks, however, the latter group showed lower rates. This effect lasted for almost two and a half years (Wagner & Petev, 2019). In Germany's carpooling market, it has been found that drivers with Arab/Turkish/Persian names (and the ones that would most likely be associated with these sets of groups) would have to offer their rides €4.20 cheaper than the average German driver to obtain the same demand; this represents 32% of the price decline compared with an average ride (Tjaden et al., 2018).

[2] Individuals from the Middle East were worse off than others and those who were 26 years old or less faced relative declines in employment as opposed to older workers.

[3] This group would closely match the profiles of those who initiated the 9/11 attacks in terms of age category and country of origin.

What is also important are the adverse effects that terrorist attacks have on immigrants who are not linked to Islam and Arab culture. It is not clear how much 9/11 may have affected the labor market outcomes of male immigrants from Latin America in the United States. This group encompasses the vast majority of illegal immigrants in the US. There is some evidence, however, that Hispanic immigrants who have been in the US for less than 5 years experienced a decline in employment and earnings in comparison to other Hispanics who have been in the US for longer (Orrenius & Zavodny, 2005). What makes this finding even more interesting is that after 9/11, Hispanic immigrants who have been in the US for longer than 10 years experienced increases in earnings and employment relative to White and non-Hispanic natives (Orrenius & Zavodny, 2005). It can be argued that these relative gains in the aforementioned labor market outcomes of Hispanic immigrants who have been in the US for longer can be attributed to employers substituting away from recent Hispanic immigrants or Muslims and Arabs towards Hispanic workers who have been in the United States for longer, which gives them more certainty about what workers they are hiring given their longer tenure in America.

2.2 Discrimination in a different country after a terrorist attack

Although literature related to discrimination in countries where terrorist attacks took place documents significant changes in attitudes towards the Muslim population and their labor market outcomes such as weekly earnings and wages (Kaushal et al., 2007), it is also important to look at the effects such events would also have on minorities living in other countries.

While one would assume that these effects would be stronger in the country where the event took place, there is no reason to believe other countries would be isolated from such effects; specially in the age of heavy media consumption, as it was highlighted in Hanes & Machin (2014). Furthermore, the effects of the 2002 Bali attacks were shown to have considerable variation regarding the magnitude and temporal duration of labor market discrimination across nine European countries and their subregions (Legewie, 2013). The same researcher found that events taking place in geographically distant places from the countries in the study have smaller effects than geographically closer incidents. In this case, Legewie (2013) was comparing the effects of the 2002 Bali bombings against the ones from the 2004 Madrid bombings. The latter had stronger a stronger impact regarding discrimination in European labor markets than the former did.

Geographic distance, however, may not be the only relevant variable regarding this issue. It can be argued that Western nations may be more sensitive to attacks in countries similar to them in terms of culture, history and their economies. For example, Swedish longitudinal survey data indicates that 9/11 significantly changed attitudes towards a group of minorities in Sweden. This change, however, did not lead to changes in labor market outcomes of these minorities (Åslund & Rooth, 2005). This is in conflict with various theories of labor market discrimination both from neoclassical and non-neoclassical viewpoints[4]. Furthermore, Australian data shows that immediately after the 9/11 attacks took place, Muslim men and those who were more likely to be associated with such group experienced a larger increase in religious and racial intolerance and discrimination when compared to other immigrants (Goel, 2010). Additionally, an Australian report argues that Arab and Muslim women in Australia are more prone to be victims of racism[5] (Poynting & Noble, 2001). While this increase in discrimination deserves attention in its own right, the goal of Goel (2010) and Poynting and Noble (2001) was not to analyze whether this increased perception of discrimination translated into adverse changes in labor market outcomes for Muslim minorities in Australia; thus one

[4] In neoclassical economic theory, discrimination in the labor market can be attributed to inconsistencies in the treatment of two individuals who are equally productive but may differ in terms of sex, ethnicity, age, religious beliefs, etc. (Honig et al., 1987). In non-neoclassical economics, labor market discrimination is more broadly defined than its neoclassical counterpart; it is seen as a multi-faceted interlinkage of several variables such as economic, social, political and cultural forces not only in the workplace but also outside of it, which leads to different labor market outcomes such as earnings and employment (Figart, 1997).

[5] The use of the headscarf has been mentioned as the main cause for experiences of racism.

cannot conclude whether such phenomenon is consistent with labor market discrimination theories such as the ones mentioned before. In contrast, in the UK, a decrease in employment of the very young immigrants from predominantly Muslim countries has been found in the aftermath of 9/11 (Rabby & Rodgers III, 2010). Data from the police force from areas in the UK with significant Asian and Arab immigrants showed how individuals belonging to such groups were victims of an unusual high number of hate crimes not only after the 2005 London bombings but also after the 9/11 attacks (Hanes & Machin, 2014).

Despite the evidence of Muslim immigrants being victims of discrimination both in the labor market and in other areas due to terrorist-related events that happened in another country, data from the German labor market using difference-in-differences estimates shows that 9/11 did not severely decline labor market opportunities for immigrants coming from predominantly Muslim countries (Braakmann, 2009). One could interpret this as employers behaving rationally during the hiring process of potential new employees or that discrimination towards Muslims relies on other preferences that were not affected by events such as 9/11. Nonetheless, there is no reason to believe that the overall perceptions about Muslim immigrants is the same in Germany as it is in other nations of the West such as the United States, the United Kingdom, Sweden and Australia; the literature reviewed shows such differences in perceptions.

Chapter 3: Data and Methodology

3.1 Data

3.1.1 Current population survey - Outgoing rotation group

To estimate the effect that the November 2015 Paris attacks may have had on the labor market outcomes of Muslim immigrants in the United States, I use the Current Population Survey (CPS) from the years 2010 to 2019. More specifically, I use the CPS Merged Outgoing Rotation Group records (CPS-ORG). The CPS is one of the most important sources of labor force statistics in the United States. It covers topics such as employment, income, and demographic data. Households are being interviewed for the survey eight times in total. First for four months in a row, then they go eight months without an interview, and finally another four consecutive months of interviews. I use the CPS-ORG, which is a subsample of the broad

CPS, due to its richness in data describing hours worked per week and income such as weekly earnings and wages. I focus on the years 2010 to 2019 (inclusive) for the following reasons: First, it allows me to go back several years before the shock occurred; providing the possibility to test for pre-trends. Second, such an extensive time-range allows me to test the longevity of different effects by using various combinations of years such as 2010-2019 (for long-term effects) or 2010-2016 (for short-term effects).

The CPS is rich in variables describing the interviewees' demographic background such as country of birth, parents' country of birth and race[6]. This is of huge importance since it allows researchers to identify most individuals with Arab or Muslim background[7]. In an ideal scenario, I would only treat those individuals that are Muslims or Arabs (or have such backgrounds) as the target group. However, given the variables offered by the CPS-ORG, the closest one can get to creating such group is by using the nativity profiles of the interviewees and of their parents. More specifically, one can create a target group composed of individuals with backgrounds from nations belonging to the Arab world or from Muslim-majority countries. A key problem with this approach is that not all individuals that come from these countries are necessarily Muslims or Arabs, nor all Arabs and Muslims come from those countries. This is important to take into account when estimating and interpreting the effects of the 2015 Paris attacks, since what is being estimated is the average effects for the target group as a whole. However, just part of such group may be affected by the shock.

Consistent with existing literature that did similar studies but with respect to previous terrorist attacks such as September 11th (Kaushal et al., 2007; Orrenius & Zavodny, 2005; Rabby & Rodgers, 2011; Wang, 2016), the main criteria I use to determine whether a first- or

[6] The Current Population Survey (CPS) categorizes the concept of race in 5 groups: White, Black (or African American), Hispanic, Asian, Native American, and Mixed.

[7] The CPS tracks the nativity profiles of the interviewees' parents. However, it could be the case that some of the interviewees are third generation immigrants from an Arab or Muslim-majority country and that they identify themselves as 'Whites'. In this case and given the information provided by the CPS, it would be virtually impossible to distinguish these individuals from, say, White Americans with European descent.

second-generation immigrant belongs to the target group is whether they come from the countries that were included in the NSEERS program which was described in Chapter 1. The NSEERS is a valuable indicator of the countries that are most likely to be associated with terrorism. However, North Korea was also included in such list, but it is not obvious that it was for similar reasons as the other countries. Therefore, I include all first- and second- generation immigrants from all the countries included in the NSEER program (with the exception of North Korea) to be part of the target group that is used in this analysis. These countries are Afghanistan, Algeria, Bahrain, Bangladesh, Egypt, Eritrea, Indonesia, Iran, Iraq, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Pakistan, Qatar, Saudi Arabia, Somalia, Sudan, Syria, Tunisia, United Arab Emirates, and Yemen. Furthermore, and consistent with previous literature, I also include immigrants with Turkish and Malaysian backgrounds. While they were not included in the NSEER program, these are two Muslim-majority nations. It is possible that immigrants from such countries are just as likely to be victims of terrorist-related discriminations as the individuals from the NSEER's country list. Lastly, the case for India is special since it has the largest population of Muslims excluding Muslim-majority countries. 14.2% of its inhabitants practice Islam, which translates into 172 million people (Census of India, 2011). Also, Sikhism is practiced by 1.7% of Indians, who, due to some aesthetic similarities in clothing between Sikh and Islam, may also be victims of discrimination. Due to the likely differences in discrimination that these two groups may have as opposed to the rest of the Indian population, I decided to drop Indian immigrants from my analysis altogether.

All in all, I claim the resulting target group is an adequate proxy for determining if a worker is Muslim or not. According to Allen & Nielsen (2002), in the aftermath of 9/11, the most determining aspect regarding who was a victim of discrimination or hate crime was how close their phenotype was to those from the Arab world and Islam. In other words, it is possible that those who are neither Muslims nor Arabs but look like them may just be as likely as them to be victims of discrimination.

I compare the labor market outcomes of the target group with three different comparison groups. The main criteria behind creating each comparison group is to choose individuals who have similar observable characteristics such as age, educational attainment, occupation, etc. to those belonging to the target group. It is important to mention that under an ideal setting, the unobserved characteristics of both the target and comparison groups during the time range of interest (around the November 2015 attacks) should equally affect the labor market outcomes of both the groups (target vs. comparison). The following three comparison groups are being used throughout this analysis to test the relative effects of the November 2015 Paris attacks on the target group versus a comparison group.

1. Comparison Group 1 (CG1 hereafter): It is made of first- and second-generation immigrants coming from countries that do not have Islam as its most practiced religion and that do not belong to the target group. Individuals with nativity profiles associated with India, Mexico, Central America, the Caribbean and countries classified as "Other Africa" are also excluded. Again, India is excluded from this analysis altogether due to its Sikh population. I exclude individuals from Mexico, Central America and the Caribbean due to their particular educational attainment and language proficiency characteristics, which is not the same as for other immigrants (Kaushal et al., 2007).
2. Comparison Group 2 (CG2 hereafter): Comprised of individuals born in the United States that are not second-generation immigrants from any of the countries included in the target group. Second-generation immigrants from India, Mexico, Central America, the Caribbean and countries classified as "Other Africa" are also excluded.
3. Comparison Group 3 (CG3 hereafter): Contains all American citizens born on US soil that are classified as "White" by the CPS and that do not belong to the target group.

3.1.2 Two samples: States with 85% of the Arab population and the most aware states

By looking at the CPS files, it can be seen that the majority of Arabs and Muslims tend to be concentrated in particular regions as opposed to the comparison groups, which are more dispersed across the country. To minimize this problem, half of my analysis focuses on the states that contain 85% of the Arab and Muslim population in the United States. Furthermore, doing this also allows me to minimize the negative effects of heterogeneity in business cycle effects across the states. For this part of the analysis, I end up with 22 states[8].

The other half of my analysis will focus on the states that were the most aware about the November 2015 Paris attacks. Since the degree of awareness about this event and the subsequent impact of it on the labor market varied across states, I use Google Trends to find the states that were the most aware about such incident. This service allows its users to quantify the popularity of the top search queries using Google's web search engine, which lets me get an approximation of which US states were the most aware about these Paris 2015 attacks. A valuable feature of Google Trends for researchers is that it allows to track search data not only by region (in our case, US states) but also by time period. I can adjust the time period of the search queries about the Paris attacks to bring it in line with the time period of interest for my research. For long-term effects I use the time period November 2015 – October 2019 and for short-term effects November 2015 – October 2016. It is important to mention that Google Trends does not show the actual number of search queries about a certain topic, what it shows instead is the popularity of a topic in proportion to all searches on all topics in a region during a particular time period. This means that there will be some regions in which even though the search volumes (total number of search queries) are not the same, the population-adjusted

[8] The states (+ DC) that contain 85% of the Arab and Muslim population are Arizona, California, Colorado, Connecticut, Florida, Georgia, Illinois, Maryland, Massachusetts, Michigan, Minnesota, Nevada, New Jersey, New York, North Carolina, Ohio, Oregon, Pennsylvania, Texas, Virginia, and Washington.

popularity (or state-wide search interest) could still be the same. Lastly, while it is true that the popularity of searches on Google does not necessarily represent the actual level popularity of a topic for the whole population of a state, it can be argued that it can serve as a good proxy for it.

For the analysis where I use Google Trends, I am limiting my analysis to the effects of the Paris attacks on 22 of the states (+ DC) that were the most aware about the Paris attacks during the long-term and short-term periods. Because the states of Oregon, Georgia and Texas were amongst the 25 most aware states for the long-term but not the short-term and the states Wyoming, North Dakota and South Dakota were in the short-term but not the long-term, I decided to drop all these 6 states from the analysis to make the long-term and short-term effects comparable[9].

3.1.3 Overlap between both state classifications

When interpreting the results that are presented in the next chapter, it is important to know what fraction of observations are present in both samples. One sample is comprised of the most aware states and the other of states with 85% of the Arab population. Some states are present in one group but not in the other; this will lead to differences in estimated coefficients. Table 11 in the Appendix provides detailed information about the fraction of the total observations that are present in both samples.

The main takeaways from Table 11 are as follows: First, more than half of the observations are present in both samples. Second, the subsample "Arabs versus CG1" is the one with the biggest fraction of common observations (around 66% of the observations in the states with 85% of the Arab population are also present in the most aware states sample and around 75%

[9] The 22 states (+ DC) I will use for my analysis when taking Google Trends into account are: Alaska, Arizona, California, Colorado, Connecticut, Hawaii, Idaho, Illinois, Iowa, Maine, Massachusetts, Michigan, Minnesota, Montana, New Hampshire, New Jersey, New York, Rhode Island, Utah, Vermont, Washington and Wisconsin.

of the observations in the latter group are also present in the former). Third, the two subsamples that have the lowest fractions of common observations are Arabs versus CG2 and Arabs versus CG3 from the perspective of the sample containing states with 85% of Arabs (shown in Panel A); just around 53% of the observations from such samples are common observations.

3.2 Econometric method

The goal of this thesis is to estimate the effect that the November 2015 Paris attacks may have had on wages, weekly earnings, hours worked per week and employment of Muslims and Arabs in the United States and find out how these outcomes change compared to other groups who have similar observable characteristics as Muslims and Arabs but whose labor market outcomes were not affected by the Paris attacks. In order to capture such changes, it is important to control for variations of the several characteristics of the observations. Moreover, seasonality and business cycle fluctuations need to be taken into account. Lastly, it is highly likely that there are unobservable factors that vary over time. To address these issues, I run a multivariate regression analysis which allows me to take the observable characteristics into account and do comparison group analysis so that unobservable characteristics can be controlled for.

In order to determine whether causality can be proven in this analysis (that is, if the November 2015 Paris attacks had any impact whatsoever on labor market outcomes of Arabs and Muslims in the United States), I need to consider the potential confounding variables that may exist and what can be done about them. During the period of interest and specially around the time of the shock, there was a presidential election campaign in which immigration was a hot topic among the presidential candidates. The outcome of the election was Donald Trump becoming president, which may have had an impact on labor market decisions of immigrants in general. This may or may not be problematic for my analysis if the labor market decisions of immigrants varied across immigrant groups. That is, if Arab and Muslim immigrants reacted differently to, for example, European immigrants. Moreover, the US economy was booming, leading to an increase in the demand for labor. This may make the interpretations of the estimates inconclusive unless I am able to control for these unobservable characteristics. A difference-in-differences approach is ideal to control for such characteristics and other unmeasured variables. The comparison groups (CG1, CG2 and CG3) mentioned in Section 3.1.1 are consistent with the ones used in similar literature that focused on other events such as 9/11 (Kaushal et al., 2007; Rabby & Rodgers, 2011). These comparison groups are equivalent to the target group of interest (Arabs and Muslims) in terms of variables that affect labor market outcomes (age, education, language proficiency, years of experience, etc.). Importantly, it can be argued that the comparison groups were not adversely affected by the November 2015 events. For a difference-in-differences model to be identifiable we need to assume that if the November 2015 events did not happen, the individuals classified as Arabs and Muslims would have been affected in the same way as individuals belonging to the comparison groups. In order to get rid of the effect of unobserved variables that changed around the November 2015 attacks (i.e. pre-Nov. 2015 to post-Nov. 2015), I take advantage of the labor market outcome changes of the control group. Thus, assuming that those unmeasured changes were of the same magnitude for both the target- and comparison-groups, the DD would effectively be getting rid of such effects.

Using difference-in-differences, the influence that changes in labor supply, labor demand and other variables may have on labor market outcomes are removed. The labor market outcomes are described by the equation below:

$$\begin{aligned} Y_{ist} = {} & \beta_0 + \beta_1 November15_t + \beta_2 Arab_{ist} + \beta_3 (November15_t * Arab_{ist}) \\ & + Time_d \delta + X_{ist} \Gamma + (X_{ist} * Arab_{ist}) \widetilde{\Gamma} + Month_m \Omega \\ & + (Month_m * Arab_{ist}) \widetilde{\Omega} + State_s Z + (State_s * Arab_{ist}) \widetilde{Z} + \mu_{ist} \end{aligned} \tag{1}$$

Y_{ist} denotes the labor market outcome of one of the four dependent variables of interest (employment, hours worked, weekly earnings and hourly wage) for individual *i* living in state *s* at time *t*. The time range covered by this DD analysis goes from November 2010 to October 2019 (for the long-term effects) and November 2010 to October 2016 (for the short-term effects). This allows me to test for pre-trends but also to look for the (potential) longevity of the effects. $November15_t$ is a dummy variable that is zero if this observation comes from any survey that was conducted before the November 2015 Paris attacks and it equals to one if it was recorded after such attacks. $Arab_{ist}$ is a dummy variable that indicates whether the individuals belong to the target group or not. X_{ist} is a vector of individual characteristics that consists of age category, educational attainment, race, marital status, citizenship status, amount of years spent in America, living in a rural area or not, occupation type and industry sector. $Time_d$ is a set of dummy variables for month[10] (d = 1, 2, … 107). $Month_m$ is a group of month-of-the-year dummy variables that takes seasonality into account. $State_s$ is a set of dummy variables for states to control for the fixed effects of state of residence. As it can be seen in Equation (1), an interaction term of the treatment variable, $Arab_{ist}$, is included with all the other variables, which enables the effects to vary according to which group the individual belongs to. The only exception is $Time_d$, which is restricted to be the same for both groups. Lastly, μ_{ist} accounts for the unobserved (and potentially non-fixed) characteristics. Table 10 in the Appendix offers a complete description of all the variables that were used throughout this thesis.

The coefficient β_3 captures the DD influence of the November 2015 attacks on our dependent variable of interest. Depending on the model specification, it can be employment, weekly hours worked, hourly wage, or weekly earnings. I limit this analysis to focus on males

[10] This analysis uses months as time (i.e. time "d" = 1 for November 2010 and goes all the way to time = 107 for October 2019, excluding the month of November 2015, which is when the attacks occurred).

and females between the ages of 16 to 64. Due to the Arab and Muslim population being more densely concentrated in a few states rather than equally distributed across all states, half of my analysis focuses on the states (21 in total + DC) that contain 85% of the Arab and Muslim population in America. This is done with the goal to minimize the scenario in which the business cycle is not constant across states, which would be problematic for this difference-in-differences methodology. The other half of my analysis will focus on the states that were the most aware about these attacks by using data from Google Trends. Robust standard errors are clustered by state and target group: This translates to 44 clusters for the analysis that focus on the states with 85% of the Arab population and 46 clusters for the analysis using the most aware states (White, 1980).

Chapter 4: Results

4.1 Descriptive statistics

Table 1 provides summary statistics of the control variables for the samples of interest. The time range of interest goes from November 2010 to October 2019. Throughout this thesis, observations corresponding to November 2015 (the month the attacks occurred) are dropped. There are quite a few statistics worth mentioning. First, men belonging to the Arabs and Muslims group have, on average, a higher level of education than all of our three comparison groups: 46.76% of Arab and Muslim men have at least a college degree as opposed to just 35.47% of US-born "Whites". Second, the Arab and Muslim population in our sample of interest is younger than those belonging to the comparison groups. Third, Arabs tend to live more in urban areas as opposed to individuals belonging to any of the three comparison groups. Fourth, a large percentage of Arab and Muslim women are married as opposed to other women. Although there could be several reasons behind this difference, given the low levels of employment, hours of work and observations in general for Arab women, it can be argued that this is because Arab women tend to be married with men of the same background who play the breadwinner role in the household. This, however, needs more analysis with richer data related to the subject and it is not the objective of this thesis.

Table 1

Summary statistics: Control variables. CPS-ORG: November 2010 to October 2015 and December 2015 to October 2019

	Male				Female			
	Arab	CG1	CG2	CG3	Arab	CG1	CG2	CG3
Age								
16-25	21.74	18.03**	20.27**	17.72**	20.90	15.63**	18.91**	16.77**
26-35	23.77	20.77**	19.64**	19.21**	26.02	20.76**	19.79**	19.01**
36-45	20.70	21.83+	18.74**	19.02**	22.41	23.00	18.91**	18.98**
46-55	20.20	22.55**	21.97**	23.07**	18.33	22.65**	22.26**	23.42**
56-65	13.59	16.82**	19.38**	20.98**	12.34	17.96**	20.13**	21.82**
Education								
LTHS	10.29	8.67**	9.83	8.23**	12.78	8.44**	8.38**	6.89**
HS	20.38	23.07**	30.03**	28.50**	21.18	21.65	25.40**	23.81**
Some College	22.57	25.19**	28.15**	27.80**	22.42	25.04**	30.95**	30.30**
College and above	46.76	43.06**	31.99**	35.47**	43.62	44.86*	35.27**	39.01**
Citizenship								
Non-US Citizen	29.38	25.58**	-	-	30.77	26.65**	-	-
US Citizen	70.62	74.42**	100.00**	100.00**	69.23	73.35**	100.00**	100.00**
Years in the US								
Born in US	22.04	37.01**	100.00**	100.00**	21.73	33.06**	100.00**	100.00**
+18 years	32.00	30.84*	-	-	27.73	31.08**	-	-
+12 up to 18 years	12.38	10.79**	-	-	13.71	11.85**	-	-
+6 up to 12 years	12.85	9.77**	-	-	14.84	10.92**	-	-
0 up to 6 years	20.73	11.59**	-	-	21.98	13.09**	-	-
Race								
White	59.30	44.89**	77.69**	100.00**	57.11	42.27**	75.12**	100.00**
Black	9.10	8.43*	11.90**	-	10.60	8.36**	14.19**	-
Hispanic	1.44	10.85**	6.30**	-	1.54	11.10**	6.54**	-
Asian	28.93	33.64**	2.09**	-	29.42	36.10**	1.96**	-
Native American	0.21	0.17	0.60**	-	0.19	0.19	0.63**	-
Mixed	1.02	2.02**	1.43**	-	1.14	1.97**	1.55**	-
Area								
Urban	98.61	97.72**	89.09**	87.83**	98.76	97.59**	89.13**	87.68**
Rural	1.39	2.28**	10.91**	12.17**	1.24	2.41**	10.87**	12.32**
Marital Status								
Married	56.31	55.39+	48.65**	52.79**	60.63	57.40**	48.57**	54.45**
Number of Observations	11,665	81,598	466,767	362,500	10,731	91,357	493,649	370,762

Notes: If there is a difference in means between the outcome of the target group and the comparison group, the mean of the latter group will be marked as follows: ** implies significant at 1 percent, * implies significant at 5 percent and + implies significant at 10 percent.

Similarly, Table 2 provides summary statistics of the labor market outcomes of interest for this analysis. Both wages and weekly earnings are consumer price index-adjusted to 2015 prices. For both the pre- and post-November 2015 periods, it can be seen that Arab and Muslim men and women worked less than their counterparts from the comparison groups. The

Table 2

Summary statistics: Labor market outcomes. CPS-ORG: November 2010 to October 2015 and December 2015 to October 2019

	Male				Female			
	Arab	CG1	CG2	CG3	Arab	CG1	CG2	CG3
Pre-November 2015								
Employment	71.27	75.03**	72.17	75.59**	47.74	64.27**	64.97**	67.19**
Hours worked last week	28.813	30.615**	29.540**	31.270**	16.252	23.232**	23.121**	23.855**
Log real weekly earnings	6.668	6.781**	6.735**	6.794**	6.349	6.484**	6.422**	6.453**
Log real wage	3.015	3.092**	3.045*	3.093**	2.862	2.917**	2.870	2.905**
Post-November 2015								
Employment	72.68	77.34**	74.70**	77.53**	51.07	66.48**	67.40**	69.00**
Hours worked last week	29.578	31.598**	30.755**	32.283**	17.422	24.263**	24.444**	24.992**
Log real weekly earnings	6.737	6.842**	6.782**	6.848**	6.403	6.560**	6.495**	6.535**
Log real wage	3.063	3.155**	3.087*	3.142**	2.909	2.981**	2.925+	2.968**
Observations (Pre-Nov 2015)	6,364	45,706	268,368	209,393	5,779	51,146	284,351	214,019
Observations for Earnings Analysis (Pre-Nov 2015)	3,656	29,473	169,187	136,753	2,457	29,961	172,714	133,373
Observations (Post-Nov 2015)	5,017	33,633	184,583	141,878	4,707	37,724	194,694	144,981
Observations for Earnings Analysis (Post-Nov 2015)	2,987	22,623	122,254	96,578	2,196	23,073	123,093	93,072

Notes: Employment is represented in percentage of the group being employed. If there is a difference in means between the outcome of the target group and the comparison group, the mean of the latter group will be marked as follows: ** implies significant at 1 percent, * implies significant at 5 percent and + implies significant at 10 percent.

difference is quite substantial if one looks at the case for females, not only for employment but also for hours worked and weekly earnings. By comparing the pre- and post-November 2015 periods, it can be seen that all labor market outcomes of all groups across both genders have improved. This is consistent with the positive GDP growth statistics of the United States during the time period of interest (Bureau of Economic Analysis, 2020), which also facilitated the increase in labor demand, which increased the overall level of employment.

4.2 Difference-in-differences results (long run, states with 85% of Arab population)

Tables 3, 4, 5 and 6 show estimates of the target group mean (β_2) and difference-in-differences estimates for the interaction between target group and the November 2015 attacks (β_3). Both estimates are included so that we can better understand the relative magnitude of the treatment effect (i.e. the attacks) on the treatment group.

Table 3 shows the long-term effects that the November 2015 attacks may have had on labor market outcomes (hence the time period goes all the way up to October 2019). The estimated coefficients are differentiated by gender, meaning that for this analysis I am estimating the effect of terrorist attacks on labor market outcomes separately for males and females. This table focuses on the 21 states (+ DC) that contain 85% of the Arab and Muslim population in America. For the DD models that have the dependent variables as hourly wage and weekly earnings, I am running two different models for each. Models (3) and (5) do not take industry and occupation into account while models (4) and (6) do so. This is to consider if wages and earnings are affected by changes in industry and occupation of workers, which would imply that discrimination can be channeled through these two factors.

With the exception of employment for Arab females, Table 3 suggests a negative long-term effect of the Paris 2015 attacks on wages and earnings of both Arab men and women in the 22 states of interest; however, these estimates are very imprecise due to large standard errors. Importantly, more precise estimates for hours worked are obtained when comparing Arabs against individuals belonging to CG2 and CG3 (those who were born in America). Specifically, Arab men experienced a significant but marginal decline of -0.8895 and -0.7299 in hours worked when compared to US-born individuals of any race (CG2) and US-born Whites (CG3), respectively. The magnitude of this effect in both cases is half of the effect solely attributed to being Arab during such period (-1.75 hours vs. CG2 and -1.53 hours vs. CG3), which implies that the attacks had a relative significant effect on hours worked for Arabs. The negative but marginally insignificant effect of the attacks on weekly hours worked on Muslims versus other immigrants that belong to CG1 may be due to other events that may have also changed the sentiment towards other immigrants at the same time. Such events may be the 2016 elections and the travel restrictions towards some immigrants. Importantly, Arabs seemed to work much less (5 hours) than other immigrants (CG1) and this difference was not attributed to the attacks at all.

Models (4) and (6) shows the results of including the occupation and industry controls. While all DD estimates are negative but imprecise, virtually all estimated coefficients decreased in their absolute magnitudes, with the exceptions being wages for Arab men versus CG2 and CG3. My interpretation of this overall decrease is that the potential discrimination that could occur towards Muslims and Arabs in response to the Paris attacks may also be manifested through other channels such as shifts from higher paid occupations and industries towards ones with relatively lower hourly wages and weekly earnings.

Table 3

Difference-in-differences estimates using states with 85% of Arabs and Muslims in America (Long run: 2010-2019)						
Panel A	Currently Employed	Hours Worked	Log (Real Wage)	Log (Real Wage)	Log (Real Weekly Earnings)	Log (Real Weekly Earnings)
Females	(1)	(2)	(3)	(4)	(5)	(6)
<u>Arabs vs. CG1</u>						
Arab = 1	-0.0173	2.4296***	0.1961***	0.4675***	0.2664***	0.8151***
	(0.024)	(0.943)	(0.047)	(0.102)	(0.092)	(0.147)
Arab X Nov15	0.0049	-0.3212	-0.0234	-0.0032	-0.042	-0.0161
	(0.013)	(0.38)	(0.023)	(0.023)	(0.03)	(0.031)
Obs.	102,012	99,356	57,687	57,687	57,670	57,670
<u>Arabs vs. CG2</u>						
Arab = 1	-0.0612***	1.3119	0.1337***	0.3985***	0.2074**	0.7555***
	(0.019)	(0.834)	(0.039)	(0.048)	(0.085)	(0.143)
Arab X Nov15	0.0022	-0.6550*	-0.0133	0.0005	-0.0406	-0.0207
	(0.012)	(0.34)	(0.023)	(0.023)	(0.03)	(0.031)
Obs.	503,877	489,531	300,437	300,437	300,356	300,356
<u>Arabs vs. CG3</u>						
Arab = 1	-0.0903***	0.8685	0.1395***	0.4036***	0.2667***	0.8358***
	(0.019)	(0.835)	(0.039)	(0.050)	(0.084)	(0.152)
Arab X Nov15	0.0071	-0.5323	-0.0152	-0.0008	-0.0427	-0.0221
	(0.012)	(0.342)	(0.022)	(0.023)	(0.029)	(0.031)
Obs.	381,182	369,486	231,077	231,077	231,015	231,015
Panel B	Currently Employed	Hours Worked	Log (Real Wage)	Log (Real Wage)	Log (Real Weekly Earnings)	Log (Real Weekly Earnings)
Males	(1)	(2)	(3)	(4)	(5)	(6)
<u>Arabs vs. CG1</u>						
Arab = 1	-0.1284***	-5.0985***	0.0552	0.0755	-0.0850	-0.1465
	(0.030)	(1.210)	(0.048)	(0.235)	(0.080)	(0.251)
Arab X Nov15	-0.0099	-0.6104	-0.0259	-0.025	-0.0138	-0.0111
	(0.009)	(0.396)	(0.019)	(0.015)	(0.021)	(0.018)
Obs.	92,760	90,720	58,736	58,736	58,721	58,721
<u>Arabs vs. CG2</u>						
Arab = 1	-0.1017***	-1.7563*	0.0643	-0.0117	0.0433	-0.1806
	(0.023)	(0.992)	(0.039)	(0.218)	(0.066)	(0.242)
Arab X Nov15	-0.0137	-0.8895**	-0.012	-0.0141	-0.0075	-0.0075
	(0.009)	(0.392)	(0.015)	(0.013)	(0.019)	(0.016)
Obs.	474,257	464,332	298,098	298,098	298,038	298,038
<u>Arabs vs. CG3</u>						
Arab = 1	-0.1199***	-1.5374	0.0805**	-0.0208	0.0848	-0.1604
	(0.023)	(0.998)	(0.039)	(0.215)	(0.065)	(0.241)
Arab X Nov15	-0.0084	-0.7299*	-0.0128	-0.0144	-0.0075	-0.0071
	(0.009)	(0.391)	(0.015)	(0.013)	(0.019)	(0.016)
Obs.	370,977	362,652	239,988	239,988	239,939	239,939
Controlling for						
Occupation & Industry	No	No	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All regression specifications control for time effects using monthly dummy variables. Robust standard errors are clustered around state and type of group (target or comparison) and are shown in parentheses. Statistical significance: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

4.3 Difference-in-differences results (long run, most aware states)

As mentioned in the previous chapter, I am using a partially different set of states when running the DD analysis that takes into account the Google Trends' search queries. Table 4 shows the equivalent of the results previously displayed on Table 3. All regression specifications are the same, with the difference being the set of states taken into account. Recall that in Table 3 I use the states that contain 85% of the Arab population in the United States with the goal to minimize the negative effects of heterogeneity in business cycle effects across states and also because the Arab and Muslim population tends to be more geographically concentrated in particular regions in the US as opposed to the comparison groups being more dispersed across the country. The goal of using Google Trends in my analysis is, however, for different reasons. Primarily, it is to control for the awareness of the Paris 2015 attacks on the United States population. It is likely that states across the US were not equally aware of such event, hence Google Trends allows me to use their statistics as proxy to this awareness.

By looking at the DD-estimates without industry and occupation controls, it can be seen that most of the coefficients got smaller (when compared to the ones in Table 3) and remained insignificant. There are, however, important findings worth mentioning. First, Arab women worked 0.63 hours less (significant at the 10% level) compared to US-born individuals of all races (CG2) and 0.52 hours less (but marginally insignificant) when compared to US-born individuals categorized as Whites (CG3). Both effects are relatively important when compared to the statistically significant effects of just being Arab on its own: -1.4732 and -1.7398 hours worked, respectively. Second, the equivalent DD estimates for men regarding hours worked are significant at the 5% and the 10% levels when compared to US born individuals of all races (CG2) and Whites (CG3), respectively: Arab men seem to have worked 0.8988 hours less when compared to CG2 and 0.7683 hours less as opposed to CG3 just because of the Paris attacks. However, this difference is quite small when compared to the negative effects of being Arab male alone: -5.41 hours versus CG2 and -4.85 hours versus CG3 (both estimates significant at the 1% level). The corresponding DD estimates are not significantly different from zero when we compare Arab men with other male immigrants (CG1). This is consistent with what I found in Table 3, which could mean that during this period, the sentiments towards immigrants in general got worse and not just towards Arabs and Muslims. It is important to mention that regardless of the attacks, Arabs in general did work around 7.5 hours less than other immigrants. Overall, the significant DD effects regarding changes in hours worked due to the attacks in Table 4 are also very close to the ones found in Table 3.

Models (4) and (6) from Table 4 show the estimates controlling for occupation and industry. First, by looking at labor market outcomes for women, the direction of the results is unexpected for real wages. A 2.92%[11] increase in wages (significant at the 10% level) for Arab and Muslim women can be seen when comparing it with any of the comparison groups. This effect is small when compared to the significant increase in wages connected only with the happenstance of being an Arab female 42.6%, 24.7% and 24.05% versus CG1, CG2 and CG3, respectively. Furthermore, a 4.15% increase in weekly earnings for Arab and Muslim women is seen when compared to other immigrants (CG1) due to the terrorist attacks and a 50% in increase is due to just being Arab alone. These results are not intuitive and look inconsistent with labor market theories related to discrimination. One interpretation of this may be that the increase in relative wages and earnings of Arab and Muslim women may be offset by a decrease in such labor market outcomes for Arab and Muslim men. This is partially confirmed by the fact that the negative estimates for men regarding wages and earnings went up in absolute values (both for being Arab and for the terrorist attacks). However, the DD estimates related to wages are marginally insignificant and for the rest of the estimates they are highly insignificant.

[11] This estimate is essentially zero in Table 3. This difference in results could be partially attributed to the fact that for this particular subsample (Arabs vs. CG2 for females in Table 3) only has 53.15% of observations that are also present in Arabs vs. CG2 for females in Table 4.

Moreover, given the dataset limitations, there is no reason to believe with certainty that such increase in wages and earnings of Arab and Muslim females was due to (or offset) by a decrease in Arab and Muslim males.

Table 4

Difference-in-differences estimates using most aware states (Long run: 2010-2019)						
Panel A	Currently Employed	Hours Worked	Log (Real Wage)	Log (Real Wage)	Log (Real Weekly Earnings)	Log (Real Weekly Earnings)
Females	(1)	(2)	(3)	(4)	(5)	(6)
Arabs vs. CG1						
Arab = 1	0.0442	1.4158	0.0859*	0.4260***	0.0245	0.5008***
	(0.027)	(0.926)	(0.052)	(0.085)	(0.1)	(0.14)
Arab X Nov15	-0.0038	-0.3108	0.0105	0.0292*	0.0179	0.0415*
	(0.013)	(0.383)	(0.018)	(0.017)	(0.022)	-0.022
Obs.	89896	87416	51972	51972	51952	51952
Arabs vs. CG2						
Arab = 1	-0.0214	-1.4732*	0.0152	0.2470***	-0.0300	0.4550***
	(0.028)	(0.827)	(0.047)	(0.057)	(0.093)	(0.108)
Arab X Nov15	-0.0066	-0.6356*	0.0158	0.0292*	0.0111	0.0299
	(0.013)	(0.344)	(0.018)	(0.017)	(0.021)	(0.022)
Obs.	422886	409907	257929	257929	257840	257840
Arabs vs. CG3						
Arab = 1	-0.0465*	-1.7398**	0.0153	0.2405***	0.0098	0.5008***
	(0.026)	(0.852)	(0.047)	(0.059)	(0.094)	(0.108)
Arab X Nov15	-0.0024	-0.5234	0.0141	0.0281*	0.0084	0.0281
	(0.013)	(0.342)	(0.018)	(0.017)	(0.021)	(0.021)
Obs.	340898	329770	212146	212146	212074	212074
Panel B	Currently Employed	Hours Worked	Log (Real Wage)	Log (Real Wage)	Log (Real Weekly Earnings)	Log (Real Weekly Earnings)
Males	(1)	(2)	(3)	(4)	(5)	(6)
Arabs vs. CG1						
Arab = 1	-0.1456***	-7.5521***	-0.0243	-0.0112	-0.3544***	-0.3770**
	(0.04)	(1.661)	(0.061)	(0.157)	(0.092)	(0.188)
Arab X Nov15	-0.0007	-0.5389	-0.0220	-0.0231	-0.0120	-0.0114
	(0.008)	(0.445)	(0.018)	(0.015)	(0.020)	(0.016)
Obs.	81593	79688	51786	51786	51768	51768
Arabs vs. CG2						
Arab = 1	-0.1616***	-5.4128***	0.0301	-0.0349	-0.1767**	-0.3069*
	(0.030)	(1.348)	(0.049)	(0.143)	(0.077)	(0.173)
Arab X Nov15	-0.0096	-0.8988**	-0.0120	-0.0171	-0.0039	-0.0076
	(0.007)	(0.433)	(0.015)	(0.012)	(0.017)	(0.015)
Obs.	405815	396397	257270	257270	257212	257212
Arabs vs. CG3						
Arab = 1	-0.1731***	-4.8546***	0.0352	-0.0328	-0.1482*	-0.2826
	(0.029)	(1.349)	(0.049)	(0.143)	(0.077)	(0.174)
Arab X Nov15	-0.0054	-0.7683*	-0.0132	-0.0179	-0.0041	-0.0075
	(0.007)	(0.435)	(0.015)	(0.012)	(0.018)	(0.015)
Obs.	333591	325480	216572	216572	216523	216523
Controlling for						
Occupation & Industry	No	No	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All regression specifications control for time effects using monthly dummy variables. Robust standard errors are clustered around state and type of group (target or comparison) and are shown in parentheses. Statistical significance: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

4.4 Difference-in-differences results (short run, states with 85% of Arab population)

Up until now, all DD estimates shown were related to the long-term effects of the Paris attacks on labor market outcomes of Arabs and Muslims in America. It is likely that the adverse effects of the attacks were stronger during the months that were closer to the time of the event. To test for this, I now focus on a much shorter period: November 2010 to October 2016. Table 5 focuses on the short-term effects using the states with 85% of the Muslim population.

For females, there are several findings worth mentioning: First, Arab women seem to have worked at least three quarters of an hour less than US born women (CG2 & CG3) right after the attacks; the treatment mean also indicates that both groups would have worked the same amount of hours per week if the attacks did not happen. Second, weekly earnings estimates for Arab females decreased by at least 7% when compared to any of the comparison groups. However, the target group mean indicates that Arab and Muslim women had a 21% increase in earnings when compared to US-born White women. Third, after controlling for industry and occupation, the DD weekly earnings estimates go down to around 6.3% and remain significant only when comparing the target group to US-born individuals (with such decrease once again suggesting other channels through which discrimination may occur).

Regarding the DD estimates for males, the main findings are as follows: First, highly significant DD estimates indicate that Arab men worked at least 1.1 hours less per week when compared to any comparison group; the decrease in hours attributed to just being an Arab man was of 4.98 hours (vs. CG1, significant), 2.09 hours (vs. CG2, significant) and 1.70 hours (vs. CG3, marginally insignificant). Second, because of the attacks, employment went down by around 2% for Arab men when compared to CG1 and CG2 (the results are marginally insignificant when compared to CG3); the difference in employment due to just being an Arab man is of at least -10% versus any comparison group. Third, adding industry and occupation controls decreases the magnitude (in absolute terms) of the DD estimates and also for the target group mean for men; this is consistent with what I found in the DD analysis focusing on the long-term effects.

Table 5

Difference-in-differences estimates using states with 85% of Arabs and Muslims in America (Short run: 2010-2016)

Panel A	Currently Employed	Hours Worked	Log (Real Wage)	Log (Real Wage)	Log (Real Weekly Earnings)	Log (Real Weekly Earnings)
Females	(1)	(2)	(3)	(4)	(5)	(6)
Arabs vs. CG1						
Arab = 1	-0.0640*	0.3810	0.1672***	0.5095***	0.1786	0.7947***
	(0.036)	(1.336)	(0.064)	(0.142)	(0.126)	(0.184)
Arab X Nov15	0.0092	-0.4394	-0.0223	-0.0061	-0.0742***	-0.0576
	(0.012)	(0.421)	(0.019)	(0.022)	(0.028)	(0.037)
Obs.	70591	68814	39326	39326	39315	39315
Arabs vs. CG2						
Arab = 1	-0.0721***	0.8627	0.1132*	0.4410***	0.1641	0.6474***
	(0.024)	(1.003)	(0.066)	(0.095)	(0.127)	(0.147)
Arab X Nov15	0.0048	-0.7937**	-0.0117	-0.0056	-0.0701**	-0.0625*
	(0.012)	(0.401)	(0.018)	(0.021)	(0.029)	(0.037)
Obs.	356740	346713	210179	210179	210130	210130
Arabs vs. CG3						
Arab = 1	-0.0976***	0.552	0.1163*	0.4444***	0.2174*	0.7112***
	(0.024)	(1.009)	(0.065)	(0.095)	(0.126)	(0.148)
Arab X Nov15	0.0077	-0.7728*	-0.0132	-0.0065	-0.0732***	-0.0649*
	(0.012)	(0.408)	(0.018)	(0.021)	(0.028)	(0.036)
Obs.	270529	262288	162572	162572	162534	162534
Panel B	Currently Employed	Hours Worked	Log (Real Wage)	Log (Real Wage)	Log (Real Weekly Earnings)	Log (Real Weekly Earnings)
Males	(1)	(2)	(3)	(4)	(5)	(6)
Arabs vs. CG1						
Arab = 1	-0.1188***	-4.9809***	0.0085	0.1499	-0.0584	0.0117
	(0.034)	(1.388)	(0.059)	(0.303)	(0.092)	(0.355)
Arab X Nov15	-0.0218*	-1.0843**	-0.0453*	-0.0341	-0.0436*	-0.031
	(0.011)	(0.430)	(0.025)	(0.024)	(0.024)	(0.022)
Obs.	64173	62781	40193	40193	40182	40182
Arabs vs. CG2						
Arab = 1	-0.1022***	-2.0950*	0.0441	0.0435	0.0966	-0.0425
	(0.026)	(1.081)	(0.053)	(0.292)	(0.077)	(0.343)
Arab X Nov15	-0.0220**	-1.2073***	-0.0292	-0.0230	-0.0292	-0.0209
	(0.011)	(0.416)	(0.024)	(0.023)	(0.023)	(0.022)
Obs.	335493	328524	207876	207876	207835	207835
Arabs vs. CG3						
Arab = 1	-0.1184***	-1.7077	0.0601	0.0255	0.1395*	-0.0312
	(0.026)	(1.086)	(0.053)	(0.289)	(0.076)	(0.342)
Arab X Nov15	-0.0178	-1.1156***	-0.0279	-0.0211	-0.0286	-0.0195
	(0.011)	(0.415)	(0.024)	(0.024)	(0.023)	(0.022)
Obs.	263443	257526	168341	168341	168308	168308
Controlling for						
Occupation & Industry	No	No	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All regression specifications control for time effects using monthly dummy variables. Robust standard errors are clustered around state and type of group (target or comparison) and are shown in parentheses. Statistical significance: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

4.5 Difference-in-differences results (short run, most aware states)

Table 6 shows the DD estimates focusing on the short-term effects (Nov. 2010 – Oct. 2016) using the states that were the most aware about the attacks (according to Google Trends).

For females, the following findings are worth mentioning: First, it seems that due to the attacks, relative weekly earnings of Arab and Muslim women went down by 5% when compared to US-born White women only (with no differences attributed to the target group mean when compared with any comparison group). When controlling for occupation and industry the DD estimate is not significant anymore (again suggesting that discrimination may be channeled through these two variables as well). Second, DD estimates regarding hours worked versus CG2 and CG3 are negative but marginally insignificant due to large standard errors. Third, by looking at the treatment means, wages for Arab females are 46% higher than other immigrants (CG1) and around 29% higher versus US-born individuals (CG2 & CG3). Fourth, the target group means for weekly earnings are at least 38% higher for Arab females versus any comparison group.

Regarding males, these are the most important findings: First, hours worked per week for Arab and Muslim men seem to have gone down by at least 1.2% because of the Paris attacks (they are highly significant relative to any comparison group). Such decrease is not as large as the highly statistically significant decrease in hours worked due to the target group mean: -7.8, -6.0 and -5.4 less hours worked when compared to CG1, CG2 and CG3, respectively. Second, weekly earnings for Arab men seem to have gone down by at least 4%, but once I control for industry and occupation, the magnitude of such effects slightly decreases, remains significant only against CG1 and becomes marginally insignificant when using CG2 and CG3. Third, by comparing the equivalent DD estimates of the Arab * Nov15 term for men from Table 5, it can be seen that they are quite similar in magnitude.

Table 6

Difference-in-differences estimates using most aware states (Short run: 2010-2016)

Panel A	Currently Employed	Hours Worked	Log (Real Wage)	Log (Real Wage)	Log (Real Weekly Earnings)	Log (Real Weekly Earnings)
Females	(1)	(2)	(3)	(4)	(5)	(6)
Arabs vs. CG1						
Arab = 1	0.0530	0.4827	0.0129	0.4604***	-0.0997	0.4249**
	(0.037)	(1.300)	(0.071)	(0.104)	(0.142)	(0.206)
Arab X Nov15	0.0007	-0.2926	0.0029	0.0237	-0.0399	-0.0146
	(0.013)	(0.397)	(0.020)	(0.018)	(0.030)	(0.039)
Obs.	62924	61206	35869	35869	35854	35854
Arabs vs. CG2						
Arab = 1	0.0100	-1.2159	-0.0268	0.2939***	-0.0893	0.3851**
	(0.029)	(0.986)	(0.071)	(0.093)	(0.143)	(0.172)
Arab X Nov15	-0.0039	-0.6118	0.0068	0.0186	-0.0478	-0.0314
	(0.013)	(0.385)	(0.019)	(0.018)	(0.030)	(0.038)
Obs.	302365	293149	182801	182801	182738	182738
Arabs vs. CG3						
Arab = 1	-0.0123	-1.3968	-0.0269	0.2861***	-0.0486	0.4315**
	(0.028)	(0.999)	(0.070)	(0.093)	(0.144)	(0.173)
Arab X Nov15	-0.0012	-0.5629	0.0055	0.0181	-0.0510*	-0.0334
	(0.013)	(0.386)	(0.020)	(0.018)	(0.029)	(0.037)
Obs.	244752	236793	151406	151406	151357	151357
Panel B	Currently Employed	Hours Worked	Log (Real Wage)	Log (Real Wage)	Log (Real Weekly Earnings)	Log (Real Weekly Earnings)
Males	(1)	(2)	(3)	(4)	(5)	(6)
Arabs vs. CG1						
Arab = 1	-0.1314***	-7.8192***	0.0495	0.1652	-0.3576***	-0.2974
	(0.047)	(1.798)	(0.075)	(0.222)	(0.117)	(0.254)
Arab X Nov15	-0.0154	-1.2010**	-0.0474*	-0.0410*	-0.0529**	-0.0443*
	(0.012)	(0.503)	(0.026)	(0.024)	(0.024)	(0.023)
Obs.	56977	55641	35767	35767	35753	35753
Arabs vs. CG2						
Arab = 1	-0.1595***	-6.0342***	0.1023	0.1556	-0.1705*	-0.1992
	(0.033)	(1.435)	(0.064)	(0.203)	(0.097)	(0.233)
Arab X Nov15	-0.0218*	-1.3908***	-0.0379	-0.0339	-0.0420*	-0.0363
	(0.012)	(0.474)	(0.025)	(0.023)	(0.023)	(0.023)
Obs.	289185	282513	180703	180703	180657	180657
Arabs vs. CG3						
Arab = 1	-0.1696***	-5.4064***	0.1063*	0.1553	-0.1448	-0.1775
	(0.033)	(1.429)	(0.064)	(0.202)	(0.097)	(0.232)
Arab X Nov15	-0.0177	-1.2476***	-0.0368	-0.0325	-0.0409*	-0.0350
	(0.012)	(0.472)	(0.025)	(0.023)	(0.023)	(0.023)
Obs.	238909	233084	153117	153117	153078	153078
Controlling for						
Occupation & Industry	No	No	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All regression specifications control for time effects using monthly dummy variables. Robust standard errors are clustered around state and type of group (target or comparison) and are shown in parentheses. Statistical significance: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

Chapter 5: Robustness Check

5.1 Common trends assumption

When doing difference-in-differences, the most important assumption to fulfill is the common trends assumption. Such assumption implies that in the absence of the treatment, there should be no changes in the difference in discrimination between the treatment and comparison group as time goes on. For this thesis' analysis, it means that the difference between the labor market outcomes of Arabs and Muslims versus the comparison groups should have stayed constant before the November 2015 Paris attacks occurred; the change in such differences after the attacks would show the treatment effects. A violation of the common trend assumption inevitably makes the DD estimates biased and any potential causal interpretation becomes unlikely to capture.

The following model is almost identical to the one presented in Equation (1). However, there are three differences. First, the dummy $November15_t$ has been replaced by a set of dummy variables which are $\sum_k \; NovOct_{kt}$. For k = 2011, 2012, …, 2019. Such dummy variables are interpreted as follows: $NovOct_{2011,t}$ indicates the period starting from November 2010 to October 2011, $NovOct_{2012,t}$ is the subsequent period covering the months of November 2011 to October 2012 and so on. This is not to be confused with *t* which refers to time (in months) and equals to 1 for observations obtained during November 2010, 2 for December 2010 (and so on), going all the way up to 107 for October 2019. Like in Equation (1), observations from November 2015 are excluded. Second, the DD estimate and the interaction term related to the changes in labor market outcomes of Arabs and Muslims have been replaced with estimates and interaction terms represented as $\sum_k \varphi_k\ (NovOct_{kt} * \mathrm{Arab_{ist}})$. The rest of the variables are the same as in Equation (1).

$$\begin{aligned} Y_{ist} \ = \ \beta_0 + \ \beta_2 Arab_{ist} + \sum_{\mathrm{k}} \lambda_{\mathrm{k}} NovOct_{kt} + \sum_{\mathrm{k}} \varphi_{\mathrm{k}}\ (NovOct_{kt} * Arab_{ist}) \\ + \ Time_d \delta \ + X_{ist}\,\Gamma + \ (X_{ist} * Arab_{ist})\widetilde{\Gamma} \ + Month_m \Omega \\ + \ (Month_m * \ Arab_{ist})\widetilde{\Omega} + \ State_s Z \ + \ (State_s * Arab_{ist})\widetilde{Z} + \ \mu_{ist} \end{aligned} \tag{2}$$

To make the DD-estimates of labor market outcomes from Tables 3, 4, 5 and 6 valid, the coefficients φ_k (for k = 2011, 2012, 2013, 2014, 2015) should be zero. The other $\varphi_k$estimates (for k = 2016, 2017, 2018 and 2019) would reflect effects and how they change over time. In essence, what this equation does is testing the common trend assumption.

Due to space limitations, Tables 7 and 8 show models that satisfy (to different degrees) both the parallel trend assumption and that also had significant results in Tables 3, 4, 5 and 6. Nonetheless, Tables 12 and 13 in the Appendix show the results of running Equation (2) on all the models from Tables 3, 4, 5, 6 that had significant DD-estimates. For ease of reference, the model specification numbers shown in Tables 7 and 8 follow the numbers used in Tables 12 and 13[12].

[12] This is why, for example, in Table 7 the first model specification is Model (2), which is the same as Model (2) in Table 12.

Table 7 focuses on model specification candidates from Tables 3 and 4 that are the most likely to pass the parallel trend test. As it can be seen, the models that are most likely to pass such test are mostly for males (with the only exception being the DD estimates related to hours

Table 7

Parallel trends assumption test: States with 85% of the Arab population.

	Arabs vs. CG1		Arabs vs. CG2		Arabs vs. CG3	
	Male		Male		Female	Male
	Employment	Hours Worked	Employment	Hours Worked	Hours Worked	Hours Worked
	(2)	(3)	(6)	(7)	(8)	(10)
Arab = 1	-0.1161***	-4.8905***	-0.0896***	-1.4263	1.5177	-1.3204
	(0.033)	(1.236)	(0.026)	(0.919)	(0.972)	(0.928)
Arab X Nov. '11 - Oct. '12	-0.0161**	-0.2213	-0.0174***	-0.4496	-0.6007	-0.4164
	(0.008)	(0.488)	(0.007)	(0.425)	(0.474)	(0.431)
Arab X Nov. '12 - Oct. '13	-0.0028	0.2153	-0.0021	0.1716	-0.7470*	0.226
	(0.01)	(0.55)	(0.009)	(0.474)	(0.404)	(0.472)
Arab X Nov. '13 - Oct. '14	-0.0145	-0.0432	-0.0227*	-0.5618	-1.0872*	-0.4415
	(0.013)	(0.541)	(0.013)	(0.519)	(0.592)	(0.529)
Arab X Nov. '14 - Oct. '15	-0.0226*	-0.7303	-0.0196*	-0.7737*	-0.7653	-0.5457
	(0.012)	(0.509)	(0.012)	(0.464)	(0.588)	(0.474)
Arab X Dec. '15 - Oct. '16	-0.0351***	-1.3438**	-0.0394***	-1.8005***	-1.3475***	-1.5688**
	(0.012)	(0.667)	(0.011)	(0.631)	(0.502)	(0.636)
Arab X Nov. '16 - Oct. '17	-0.0234**	-0.8005	-0.0241**	-0.9133*	-1.2130**	-0.6117
	(0.012)	(0.595)	(0.01)	(0.534)	(0.558)	(0.545)
Arab X Nov. '17 - Oct. '18	-0.0213	-0.8436	-0.0212	-1.2787**	-1.4747***	-0.9702
	(0.015)	(0.668)	(0.015)	(0.628)	(0.561)	(0.629)
Arab X Nov. '18 - Oct. '19	-0.0058	-0.2084	-0.0166	-0.8517*	-0.6646	-0.5688
	(0.011)	(0.482)	(0.01)	(0.479)	(0.695)	(0.479)

Notes: All regression specifications control for time effects using monthly dummy variables. Robust standard errors are clustered around state and type of group (target or comparison) and are shown in parentheses. Statistical significance: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

worked for females[13]). Specifically, highly significant negative effects on employment can be observed in the period *Dec. 2015 – Oct. 2016* for Arab and Muslim men when compared to CG1 and CG2. Furthermore, hours worked per week for Arab men seem to have declined by at least 1.3 hours when compared to any comparison group and also for Arab females when compared to CG3. This table also shows how the negative effects change over time. It can be seen that the negative effects are generally short-lived when compared to CG1 (other immigrants). The negative effects fluctuate a bit for several periods when compared to CG2 and CG3, both of which comprise of US-born individuals. This is important because it could mean that the negative changes in labor market outcomes for Arabs were short-lived when compared to other immigrants but persisted for a much longer time when compared to US-born individuals. Admittedly, the fluctuation of the DD estimates when comparing to CG2 and CG3 could also mean that we are capturing other effects of negative antimigrant sentiment towards foreigners during such period (such as the 2016 elections). However, it can be reasonably concluded that all of the models shown above pass, albeit to different degrees, the parallel trend assumption test.

Table 8 shows the equivalent results of the previous table but for the states that were the most aware about the events according to Google Trends. As it can be seen, only two candidates may pass the parallel trend test. For hours worked related to Arab males versus CG1, it can be seen that although the interaction term of being Arab and the period right after the attacks is the most significant (at the 5% level), the two periods before are also significant but at the 10% level. This lowers the credibility of this DD-estimate regarding the attacks. The other model, concerning Arab females versus CG2, seems a better candidate to pass the parallel trend test.

[13] By looking at the models for females in Table 12 in the Appendix, most of the DD estimates before November 2015 have significant coefficients at some of the previous periods; this reduces the validity of the comparison group approach for women in particular.

None of the estimates of the interaction terms before the attacks are significant at the 5% level, while the estimate for the period right after the attack is highly significant.

Table 8

Parallel trends assumption test: Most aware states.

	Arabs vs. CG1	Arabs vs. CG2
	Male	Female
	Hours Worked	Hours Worked
	(3)	(6)
Arab = 1	-6.8956***	-0.8245
	(1.628)	(1.008)
Arab X Nov. '11 - Oct. '12	-0.9827*	-0.5878
	(0.568)	(0.544)
Arab X Nov. '12 - Oct. '13	-0.8101	-0.7364*
	(0.761)	(0.433)
Arab X Nov. '13 - Oct. '14	-0.7684*	-1.1412
	(0.462)	(0.739)
Arab X Nov. '14 - Oct. '15	-1.1462*	-0.6311
	(0.645)	(0.549)
Arab X Dec. '15 - Oct. '16	-1.8783**	-1.1487**
	(0.759)	(0.582)
Arab X Nov. '16 - Oct. '17	-1.0741	-1.3480*
	(0.658)	(0.716)
Arab X Nov. '17 - Oct. '18	-0.9982	-1.3799*
	(0.72)	(0.72)
Arab X Nov. '18 - Oct. '19	-1.0368*	-1.2235
	(0.536)	(0.829)

Notes: All regression specifications control for time effects using monthly dummy variables. Robust standard errors are clustered around state and type of group (target or comparison) and are shown in parentheses. Statistical significance: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

5.2 Pseudo-intervention tests

To increase the credibility of the DD estimates on the models that did pass that the parallel trend test (i.e. meaning that the only difference in trends of labor market outcomes of Arabs and Muslims versus CG1, CG2 and CG3 is due to the November 2015 attacks), I introduce the following model:

$$Y_{ist} = \beta_0 + \beta_1 November13_t + \beta_2 Arab_{ist} + \beta_3 (November13_t * Arab_{ist}) + Time_d \delta + X_{ist}\Gamma + (X_{ist} * Arab_{ist})\widetilde{\Gamma} + Month_m \Omega + (Month_m * Arab_{ist})\widetilde{\Omega} + State_s Z + (State_s * Arab_{ist})\widetilde{Z} + \mu_{ist} \quad (3)$$

Equation (3) is identical to Equation (1) with two exceptions: First, I replaced the November 2015 dummy with an artificial event that supposedly happened in November 2013 (exactly two years before the actual attacks). Second, the time period used in this model goes from November 2010 up to October 2015 (right before the attacks took place). The validity of our DD-estimates from the models that were shown in Tables 7 and 8 depend on whether the estimates of β_3 in Equation (3) are significant or not. Such estimated coefficient should be around zero and statistically insignificant. Table 9 shows the results.

As it can be seen, the difference-in-differences estimates of labor market outcomes shown in Table 9 are around zero across all specifications (especially when compared to the actual DD-estimates for the Nov. 2015 attacks) and statistically insignificant.

Table 9

Pseudo-intervention test. Testing for the validity of the DD approach using an artificial event: Nov. 2013. Time period: November 2010 - October 2015.

	From Table 7 (Most populous Arab states)						From Table 8 - (Most Aware States)	
	(2)	(3)	(6)	(7)	(8)	(10)	(3)	(6)
	Employment	Hours Worked	Employment	Hours Worked	Hours Worked	Hours Worked	Hours Worked	Hours Worked
Arab = 1	-0.1106***	-5.6937***	-0.0911***	-2.9933***	2.5287*	-2.6004**	-7.9456***	-2.2079*
	(0.034)	(1.202)	(0.029)	(1.044)	(1.297)	(1.051)	(1.543)	(1.202)
Arab X Nov13	-0.0127	-0.1586	-0.0159	-0.3783	-0.6324	-0.2792	0.2187	-0.5455
	(0.012)	(0.399)	(0.011)	(0.371)	(0.386)	(0.377)	(0.424)	(0.373)
Obs.	52385	51246	276039	270236	216117	212170	45526	242170

Notes: All regression specifications control for time effects using monthly dummy variables. Robust standard errors are clustered around state and type of group (target or comparison) and are shown in parentheses. Statistical significance: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

Chapter 6: Conclusion

This thesis studied the relationship between the November 2015 Paris attacks and the labor market outcomes of Arabs and Muslims living in the United States. This was done by using the difference-in-differences method already applied in similar studies such as Kaestner et al. (2007), Rabby et. al (2011) and Orrenius et al. (2006). The analysis used the Current Population Survey – Merged Outgoing Rotation Groups and also Google Trends for part of the analysis that focused on the most aware states about the attacks.

As analyzed in Chapter 2 of this thesis, there is evidence that terrorist attacks such as 9/11, the 2004 Madrid incidents, and the 2005 London Bombings had an adverse impact on the labor market outcomes of Arabs and Muslims and those most likely to be associated with this group. Moreover, there is some evidence that attacks that occurred in one nation can also affect the labor market outcomes of Arab and Muslim immigrants living in other countries. This thesis extends this literature and brings the following findings:

1. Using the sample with states containing 85% of the Arab population:
    a. In the short run after the Paris attacks (December 2015 – October 2016), hours worked for Arab males decreased by 1.08, 1.20 and 1.11 when compared to other immigrants (CG1), US-born individuals of any race (CG2) and US-born Whites (CG3), respectively.
    b. By looking at the period December 2015 – October 2019, such effects (hours worked for Arab males) become insignificant versus other immigrants (CG1) and decrease in magnitude to -0.88 and -0.73 hours versus CG2 and CG3, respectively. Indicating that these negative effects were short-lived.
    c. Arab males experienced a decrease in employment in the short run of around 2% versus other immigrants (CG1) and US-born individuals of any race (CG2). There is some evidence of a similar effect when compared to US-Whites (CG3), but the DD estimates are not precise for this case. In the long run however, these effects are statistically insignificant, suggesting that the adverse effects disappear after some time.
    d. Regarding Arab females, while many estimates indicate a negative impact of the attacks on many labor market outcomes, only the following finding passed the robustness checks in Chapter 5: There is a 0.77 decrease in hours worked of Arab females compared with US-born Whites (CG3). The target group mean is zero for Arab females versus CG3.
2. Using the sample with the most aware states:
    a. For Arab males, there is some evidence of a decrease in hours worked of about 1.2 hours versus other immigrants (CG1, significant at 5%). However, the parallel trend test finds a significant DD effect at the 10% level for the two years

before the attack, which puts the validity of the effect on hours worked after the attack in doubt.

b. For Arab females versus US-born women of any race (CG2), hours worked went down by around 0.62 hours due to the attacks in the short run (2010-2016). Such effect remained at a similar level in the long run.

All findings mentioned above are robust to the two tests conducted in Chapter 5. In addition, this thesis sheds light on the following general findings:

3. General Findings
    a. Although all of the DD-estimates regarding wages and weekly earnings either did not pass the robustness checks or were not significant in the first place, many of them decreased in size after industry and occupation controls were introduced. This suggests (but does not confirm) that discrimination may have also occurred through these two variables. For example: By making workers with Arab and Muslim background switch from high paying industries and job positions to ones with lower pay.
    b. The target group means (see Tables 3, 4, 5 and 6) suggest that the employment rate of Arab females seem to be much less than US-born females (CG2 and CG3). There is no difference, however, in the number of hours they work. Importantly, Arab females enjoy higher wages and earnings. For males, the employment rate is at least 10% less for Arabs. Arab men who are employed work less hours than non-Arabs.
4. Limitations
    a. The vast majority of the DD models focusing on women did not pass the common trend test, implying that such model may not be appropriate to capture any effect of the attacks on labor market outcomes for females.

b. Related to the point above: Many of the models did not pass the parallel-trends test, which suggests that there are potentially several unobservable characteristics of the observations that are time-varying and cannot be accounted for with the use of the CPS-ORG dataset.
c. The increase in discrimination and exacerbated changes in prejudice towards Muslims from the local population could also lead to new immigration trends of individuals from the former group. Muslims may be less attracted to live in places where they not only have worse labor market opportunities than before but also face new mental challenges due to the unwelcoming reception from the locals. A decrease in immigration to nations like the United States or western European countries will inevitably lead to a subsequent decrease in the labor supply of such workers. This could counteract negative effects (lower wages, decrease in employment, etc.) of a lower demand for workers of Muslim background. In other words, the adverse effects of discrimination in labor market outcomes of immigrants may be offset by a decrease in the labor supply of such workers, leading to ambiguous results in my analysis.

All in all, this thesis raises awareness about how terrorist attacks occurring in one country can even affect Arab and Muslim immigrants living in another country through adverse changes in labor market outcomes. Research that includes individuals who moved between states (or left the country) around the time period of interest, better identifies those who actually are Arabs and Muslims, and controls for unobservable time-varying characteristics may provide better estimations about the effects of terrorist attacks on the labor market. This would guide policymakers in the right direction to minimize the alarming existence of labor market discrimination towards minorities not only in the United States, but the rest of the Western world.

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Appendix

Table 10

Thorough description of all variables used in this analysis

Variable Name	Description
Groups	
Arab (Target Group)	First- and second- generation immigrants from the following countries: Afghanistan, Algeria, Bahrain, Bangladesh, Egypt, Eritrea, Indonesia, Iran, Iraq, Jordan, Kuwait, Lebanon, Libya, Malaysia, Morocco, Oman, Pakistan, Qatar, Saudi Arabia, Somalia, Sudan, Syria, Tunisia, Turkey, United Arab Emirates, and Yemen.
CG1	It is made of first- and second-generation immigrants that come from countries that do not have Islam as its most practiced religion and that do not belong to the target group. The Caribbean, Central America, Mexico, India and "Other Africa" are also excluded.
CG2	US-born individuals that are not second-generation immigrants from any of the countries that are part of the target group. Second-generation immigrants from India, Mexico, Central America, the Caribbean and countries classified as another Africa are also excluded.
CG3	All American citizens born in US soil that are classified as "White" and do not have parents with backgrounds from countries from the target group and also not from the Caribbean, Central America, Mexico, India and "Other Africa."
Labor Market Outcomes	
Employment	Dummy variable equal to 1 if employed; 0 otherwise.
Weekly Hours Worked	Number of hours spent working during the previous week. This was set to zero if the individual did not work.
Real Wage	Expressed in log terms and CPI-adjusted to 2015 prices. Observations that have a real wage of less than $2 or bigger than $250 are excluded.
Weekly Earnings	Expressed in log terms and CPI-adjusted to 2015 prices. Observations that have a real wage of less than $2 or bigger than $250 are excluded. Observations that do not contain wage are also excluded.
Control Variables (X_{ist})	
Age Category	Ten dummy variables that categorize observations based on age as follows: 16-20 years, 21-25 years, 26-30 years, 31-35 years, 36-40 years, 41-45 years, 46-50 years, 51-55 years, 56-60 years and 61-64 years.

Table 10 (*continued)*

Educational Attainment	Four dummy variables that indicate highest educational degree attained: Left High School (LTHS), High School (HS), Some College, and College and above.
Race	Six dummy variables: White, Black, Hispanic, Asian, Native American and Mixed.
Marital Status	Dummy variable equal to 1 if married; 0 otherwise.
Years in the US	Five dummy variables: Born in US; +18 years; +12 and up to 18 years; +6 and up to 12 years; and 0 and up to 6 years.
Citizenship status	Dummy variable equal to 1 if US-citizen; 0 otherwise.
Foreign Born	Dummy variable equal to 1 if foreign born; 0 otherwise.
Rural Area	Dummy variable equal to 1 if individual lives in a rural area; 0 otherwise.
Occupation	Nine classifications: Manager/Executives; Professional specialty and technicians; Services except household; Sales and Administrative Support; Farming, Forestry and Fishing; Construction and Extraction Occupations; Precision Production and Machine Operations; Transportation and Material Moving; Other.
Industry	Twelve classifications: Agriculture, Forestry and Fisheries; Mining; Construction; Manufacturing; Wholesale and Retail Trade; Transportation and Utilities; Communication; Finance and Business and Other Services, Educational and Health Services; Leisure and Hospitality; Public Administration; and Others.
$Month_m$	Month of year dummy variables.
$State_s$	Dummies for US States. 22 dummy variables when using the states with 85% of the Arab population and 23 dummy variables when using the most aware states according to Google Trends.
$Time_d$	Monthly dummy variables (107 in total for the long-term analysis and 71 for the short-term analysis)

Table 11

Panel A

Observations that are in both samples (as a fraction of total observations from the states with 85% of Arabs)

Females	Employed	Hours Worked	Log (Real Wage)	Log (Real Weekly Earnings)
Arabs vs. CG1	67.39%	67.38%	67.04%	66.99%
Arabs vs. CG2	53.39%	53.34%	53.15%	53.02%
Arabs vs. CG3	54.17%	54.12%	54.05%	53.89%
Males	Employed	Hours Worked	Log (Real Wage)	Log (Real Weekly Earnings)
Arabs vs. CG1	66.87%	66.90%	67.14%	67.05%
Arabs vs. CG2	52.78%	52.71%	53.05%	52.99%
Arabs vs. CG3	53.74%	53.67%	54.51%	54.44%

Panel B

Observations that are in both samples (as a fraction of total observations from the most aware states)

Females	Employed	Hours Worked	Log (Real Wage)	Log (Real Weekly Earnings)
Arabs vs. CG1	76.62%	76.71%	76.06%	76.10%
Arabs vs. CG2	62.39%	62.48%	61.59%	61.54%
Arabs vs. CG3	60.24%	60.30%	59.90%	59.85%
Males	Employed	Hours Worked	Log (Real Wage)	Log (Real Weekly Earnings)
Arabs vs. CG1	75.88%	76.04%	74.53%	74.51%
Arabs vs. CG2	62.88%	62.95%	61.79%	61.77%
Arabs vs. CG3	60.09%	60.13%	59.38%	59.38%

Table 12

Parallel Trends Assumption Check Using States with 85% of the Arab population.

	Arabs vs. CG1			Arabs vs. CG2				Arabs vs. CG3		
	Female	Male		Female		Male		Female		Male
	Log (Real Weekly Earnings)	Employment	Hours Worked	Hours Worked	Log (Real Weekly Earnings)	Employment	Hours Worked	Hours Worked	Log (Real Weekly Earnings)	Hours Worked
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Arab = 1	0.8096***	-0.1161***	-4.8905***	2.0808**	0.7422***	-0.0896***	-1.4263	1.5177	0.8210***	-1.3204
	(0.155)	(0.033)	(1.236)	(0.969)	(0.148)	(0.026)	(0.919)	(0.972)	(0.156)	(0.928)
Arab X Nov. '11 - Oct. '12	0.001	-0.0161**	-0.2213	-0.7146	0.0029	-0.0174***	-0.4496	-0.6007	0.0018	-0.4164
	(0.038)	(0.008)	(0.488)	(0.485)	(0.036)	(0.007)	(0.425)	(0.474)	(0.036)	(0.431)
Arab X Nov. '12 - Oct. '13	-0.0635*	-0.0028	0.2153	-0.8311**	-0.0602*	-0.0021	0.1716	-0.7470*	-0.0595*	0.226
	(0.035)	(0.01)	(0.55)	(0.402)	(0.033)	(0.009)	(0.474)	(0.404)	(0.033)	(0.472)
Arab X Nov. '13 - Oct. '14	-0.0404	-0.0145	-0.0432	-1.1166*	-0.0381	-0.0227*	-0.5618	-1.0872*	-0.0386	-0.4415
	(0.053)	(0.013)	(0.541)	(0.592)	(0.051)	(0.013)	(0.519)	(0.592)	(0.051)	(0.529)
Arab X Nov. '14 - Oct. '15	-0.0435	-0.0226*	-0.7303	-1.0037*	-0.0292	-0.0196*	-0.7737*	-0.7653	-0.03	-0.5457
	(0.054)	(0.012)	(0.509)	(0.582)	(0.054)	(0.012)	(0.464)	(0.588)	(0.053)	(0.474)
Arab X Dec. '15 - Oct. '16	-0.0775	-0.0351***	-1.3438**	-1.5544***	-0.0776	-0.0394***	-1.8005***	-1.3475***	-0.0809	-1.5688**
	(0.062)	(0.012)	(0.667)	(0.504)	(0.062)	(0.011)	(0.631)	(0.502)	(0.061)	(0.636)
Arab X Nov. '16 - Oct. '17	-0.0733	-0.0234**	-0.8005	-1.4339**	-0.0666	-0.0241**	-0.9133*	-1.2130**	-0.0674	-0.6117
	(0.06)	(0.012)	(0.595)	(0.575)	(0.06)	(0.01)	(0.534)	(0.558)	(0.059)	(0.545)
Arab X Nov. '17 - Oct. '18	-0.0369	-0.0213	-0.8436	-1.7017***	-0.0425	-0.0212	-1.2787**	-1.4747***	-0.047	-0.9702
	(0.047)	(0.015)	(0.668)	(0.566)	(0.045)	(0.015)	(0.628)	(0.561)	(0.045)	(0.629)
Arab X Nov. '18 - Oct. '19	0.0053	-0.0058	-0.2084	-1.0169	0.0073	-0.0166	-0.8517*	-0.6646	0.0097	-0.5688
	(0.056)	(0.011)	(0.482)	(0.701)	(0.054)	(0.01)	(0.479)	(0.695)	(0.053)	(0.479)

Notes: All regression specifications control for time effects using monthly dummy variables. Robust standard errors are clustered around state and type of group (target or comparison) and are shown in parentheses. Statistical significance: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

Table 13

Parallel Trends Assumption Check Using Most Aware States

	Arabs vs. CG1					Arabs vs. CG2				Arabs vs. CG3	
	Female			Male		Female		Male		Female	Male
	Log (Real Wage)	Log (Real Weekly Earnings)	Hours Worked	Log (Real Wage)	Log (Real Weekly Earnings)	Hours Worked	Log (Real Wage)	Employment	Hours Worked	Log (Real Wage)	Hours Worked
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Arab = 1	0.4241***	0.5067***	-6.8956***	-0.0387	-0.4026**	-0.8245	0.2364***	-0.1453***	-4.5827***	0.2281***	-4.0706***
	(0.083)	(0.145)	(1.628)	(0.16)	(0.191)	(1.008)	(0.057)	(0.032)	(1.32)	(0.059)	(1.322)
Arab X Nov. '11 - Oct. '12	0.0009	-0.0287	-0.9827*	0.0355	0.0135	-0.5878	-0.0025	-0.0188**	-1.0630**	-0.0017	-1.0343**
	(0.036)	(0.041)	(0.568)	(0.024)	(0.029)	(0.544)	(0.033)	(0.008)	(0.504)	(0.033)	(0.506)
Arab X Nov. '12 - Oct. '13	-0.0211	-0.0426	-0.8101	0.01	0.0526	-0.7364*	-0.0152	-0.0145	-0.8457	-0.0159	-0.8132
	(0.029)	(0.039)	(0.761)	(0.031)	(0.039)	(0.433)	(0.029)	(0.009)	(0.692)	(0.029)	(0.689)
Arab X Nov. '13 - Oct. '14	-0.0148	-0.0692	-0.7684*	0.042	0.023	-1.1412	-0.0072	-0.0303**	-1.3796***	-0.0062	-1.3084***
	(0.041)	(0.064)	(0.462)	(0.035)	(0.061)	(0.739)	(0.04)	(0.015)	(0.47)	(0.04)	(0.483)
Arab X Nov. '14 - Oct. '15	0.015	-0.005	-1.1462*	0.0466*	0.0377	-0.6311	0.0221	-0.0298**	-1.4585**	0.0211	-1.3315**
	(0.046)	(0.061)	(0.645)	(0.025)	(0.046)	(0.549)	(0.047)	(0.015)	(0.604)	(0.046)	(0.607)
Arab X Dec. '15 - Oct. '16	0.024	-0.0311	-1.8783**	-0.0233	-0.0242	-1.1487**	0.0204	-0.0446***	-2.4807***	0.0187	-2.2530***
	(0.04)	(0.068)	(0.759)	(0.038)	(0.049)	(0.582)	(0.039)	(0.013)	(0.702)	(0.038)	(0.705)
Arab X Nov. '16 - Oct. '17	0.0334	0.0064	-1.0741	0.0447	0.0497	-1.3480*	0.0413	-0.0291**	-1.3969**	0.0401	-1.2188**
	(0.039)	(0.052)	(0.658)	(0.035)	(0.047)	(0.716)	(0.038)	(0.012)	(0.571)	(0.038)	(0.578)
Arab X Nov. '17 - Oct. '18	0.0081	0.0449	-0.9982	-0.0071	0.0171	-1.3799*	0.0042	-0.0131	-1.5723**	0.0004	-1.3828**
	(0.034)	(0.044)	(0.72)	(0.022)	(0.033)	(0.72)	(0.033)	(0.015)	(0.695)	(0.033)	(0.702)
Arab X Nov. '18 - Oct. '19	0.0375	0.0511	-1.0368*	0.0033	0.0227	-1.2235	0.0514	-0.0221*	-1.8318***	0.0539	-1.6673***
	(0.043)	(0.05)	(0.536)	(0.027)	(0.041)	(0.829)	(0.043)	(0.012)	(0.496)	(0.043)	(0.496)

Notes: All regression specifications control for time effects using monthly dummy variables. Robust standard errors are clustered around state and type of group (target or comparison) and are shown in parentheses. Statistical significance: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.