SCHOOL OF
ECONOMICS AND
MANAGEMENT

LUND UNIVERSITY

Master's Program in Economic Demography

They ain't One of Us

Anti-Immigration Sentiment and Labor Market Assimilation of Central American Immigrants

by

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This thesis investigates the impact of rising resentment against immigrants on the labor market assimilation of Central American Immigrants in the United States from 2014 to 2019. During the 2016 presidential campaign, Donald Trump made anti-immigration rhetoric a core part of his campaign. A likely correlated rise in hate crimes against immigrants could be observed in the aftermath. Since immigrants from Central America have been demonized the worst, they are consequently the main focus of this investigation. The results based on analysis from a cross-sectional dataset, constructed from several American Community Survey waves, do indicate that immigrants who were exposed to higher rates of hate crime assimilated better into the American labor market. Possible explanations are a high proportion of illegal immigrants and possible differences between high and low population states.

Program Code: EKHS02
Master's Thesis (15 credits ECTS)
June 2021
Supervisor: Ingrid van Dijk
Examiner: Kirk Scott
Word Count: 15569

Acknowledgements

First of all, I want to thank my supervisor Ingrid van Dijk. Like in the first year, she was always supportive and assisted me in this often-stressful process. I could never have wished for a better supervisor. In addition, I thank the other members of my master thesis group for their valuable comments and support. As I had to switch topics twice, I got great help from several members of the University to develop these ideas as well. They could not be realized, but I still want to thank them anonymously for helping me in the first steps of these projects.

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American Community Survey	ACS
The United Nations High Commissioner for Refugees	UNHCR
ordinary least squares	OLS
Federal Bureau of Investigation	FBI

1 Introduction

During the last decade, industrialized countries saw a rapid increase in immigration towards their countries. With the climate crisis worsening and in expectation of new conflicts this trend is expected to most likely even accelerate. The United Nations High Commissioner for Refugees (UNHCR) estimates that the inglorious limit of 100 million people displaced from their homes was breached for the first time. 40 million of them searching refuge in another country than their original home country (UNHCR, 2022). The latest example is the war in Ukraine which led to an influx of people into the European Union, not experienced since the end of the second world war.

With this rise in immigration, right-wing parties that oppose this trend gained more popularity. During the primary phase and the following presidential election, Donald Trump rose from a political outsider to become the 45th president of the United States of America (Chinni, 2016). One main strategy in his rhetoric to gain support among Republican voters is to target immigrants (Finley & Esposito, 2020). He especially targeted immigrants from Central America, calling them rapists, murderers, and competition for native American jobs (Finley & Esposito, 2020). In the same period, other industrialized western countries saw a rising influence of right-wing populist parties that also gained support through anti-immigration rhetoric (Bredtmann, 2020; Dustmann, Vasiljeva & Damm, 2019; Campo, Giunti & Mendola, 2021). The rhetoric of these parties is very similar to the one of Donald Trump. The caucus leader of the German right-wing party Alice Weidel implies in a speech in front of the German parliament that Germany is flooded by Muslim immigrants, suggesting an increase in violence with the neologism “Messermänner” [direct meaning: knife men] (Schuler, 2018). In the case of Italian elections Campo, Giutni and Mendola (2021) find evidence that this right-wing propaganda also helped gain support in the population.

Additionally, Edwards and Rushin (2018) argue that this threatening and harsh language may have played a vital role increasing hate crimes in the United States which followed the 2016 presidential election. That the rise in hate crime against immigrants might also be a visible part of the overall rising resentment against immigrants will be elaborated on in theory. There were other events where resentments against a particular group of immigrants rose. Most of them started with a violent attack and then caused a rise in discrimination against the group the individuals were affiliated to. Like Muslim immigrants after 9/11 or against Japanese immigrants after the attack on Pearl Harbor (Dávila & Mora, 2005; Saavedra, 2021). This time the rise in resentments is not caused by a violent attack but by the rhetoric and election of Donald Trump. Due to this, the thesis contributes to the knowledge how harmful, anti-immigration rhetoric can harm the assimilation of immigrants. Because of this and the fact that no study has been published that is looking at this case study, the paper will contribute valuable insights into the connection between immigration resentments, discrimination, and assimilation.

As the victims of this rhetoric are real humans it is essential to study its impact on them, especially immigrants that arrive at these times, since they are the primary target, and how they are able to assimilate in the country under these conditions. Here the research of the impact of local sentiment against immigrants on their labor market assimilation is a field were further evidence seems necesarry.

The research question for this thesis is, therefore:

How does the increase in discrimination against Central American Immigrants during and after the Trump presidency influence their labor market assimilation?

The assimilation theory, which describes the process of immigrants and natives getting more similar over time (Alba & Nee, 1995), will be combined with the theory of labor market discrimination, which explains the mechanism behind the varying performance of groups in the population. These two concepts can explain why cohorts who arrive in the host country than the resentments against immigrants are higher should also perform worse in the labor market. Furthermore, the link between hate crimes and discrimination will be explained so the reader can follow why the number of hate crimes is used as a proxy for the more general sentiment against certain immigrant groups. The methods used are an ordinary least squares (OLS) model will be used for earnings and a probit model for the chances of being unemployed. The data, the research will rely on, comes from the American Community Survey (ACS).

2 Theory

This chapter will introduce the crucial theoretical concepts for this research question. First, the assimilation theory will explain how immigrants develop in the host country. Secondly, the discrimination theory sets the framework for the question of why ethnic minorities often perform worse in the labor market. The human capital theory helps develop the most critical cases made and links both theories together. As an additional important source of information, hate crime and the underlying prejudice will be explained. This will help with the argumentation that discrimination and hate crime are closely related and that hate crime can be used to measure the overall development of resentment against immigration. A review and discussion of the previous literature on the mentioned topics will highlight the research frontier and insights already made in this field.

2.1 The Theory of Immigrant Assimilation

As a first theoretical framework, the immigrant assimilation theory will be introduced. Economic assimilation was first introduced by Chiswick in 1978 and Borjas in 1985 (Borjas, Chiswick & Elsner, 2019). As their foundation, they use the human capital theory introduced by Becker (Becker, 2009; Chiswick, 1978; Borjas, 1985). In the following, the theory of human capital will be introduced shortly as it helps to explain the assimilation theory later.

The human capital theory was developed in the ‘60s by Becker (Becker, 2009). He distinguishes this form of capital from the known ones in that time, such as factors of production and monetary assets. Becker (2009) established the concept of human capital, which is not like the other forms of capital bound to an individual and cannot be transferred. He defines *human capital* as the skills and knowledge an individual accumulates over a lifetime and can generate wealth. He argues that a person that has accumulated more skills and knowledge is more productive and that employers have a higher utility from his work (Becker, 2009). Consequently, the chances of getting employed and wages are higher than for an individual with less human capital.

The acquiring of human capital is also of interest since it explains a crucial part of immigrants' assimilation problems and processes in the host country. Human capital can be acquired in two ways. The first is from (school) education. It consists of general skills like language-, math-, and problem-solving skills. These skills are not tied to a specific job or task but define the baseline productivity and ability to learn new skills (Becker, 2009). The second type of accumulation is on-the-job training which is more bound to a specific job or task and cannot be transferred easily if switching jobs or tasks (Becker, 2009). As Becker (2009) describes it, this particular knowledge is most likely even of higher worth for employers but will get worthless for the owner if he will no longer proceed with the task he needs the skills for, for instance, upon changing jobs. This problem of transferability is also the core of immigrant assimilation. Because an immigrant is expected to lose some of their human capital when immigrating

Immigrant assimilation in the host country is a complex phenomenon. A very general definition was done by Alba and Nee (1997). In their view, "*assimilation* can be defined as the decline, and at its endpoint the disappearance, of an ethnic/racial distinction and the cultural and social differences that express it" (Alba & Nee, 1997, p 863). So, at the start, when immigrants arrive in the host country, there are differences between them and the native population. Nevertheless, both sides adapt their social norms until these differences disappear as time progresses. As this definition shows, the scope of this is much broader than the economic perspective I will lastly focus on. However, as the thesis focuses on labor market indicators, further explanation will also focus on this part of assimilation.

Nevertheless, how do we define the labor market assimilation of immigrants? As a first step, immigrants experience a drop in earnings after they arrive in the host country because the skills they acquired in the host country are not fully transferable (Chiswick, 1978). This leads to a disadvantage, which translates into lower-paid jobs and lowers unemployment rates than native peers. Therefore, the economic assimilation of migrants can be defined as immigrants reaching the same unemployment rates and income levels as the native population by reaching the same skills level (Borjas, Chiswick & Elsner, 2019). Borjas and Chiswick (2019) argue that immigrants overcome these disadvantages by investing in human capital over time. This is done by getting new degrees, learning the local language, and acquiring the requested skills in the host country's labor market. Consequently, they will become more comparable with the native population and therefore also converge in employment rates and earnings. A graphical illustration is a U-shape curve over time and is shown, for earnings, in a stylized way in figure

1. Here the wage in period 1 is the wage the immigrant earns before immigrating. After immigrating to the new country, the earnings drop in period 2 before recovering once again.

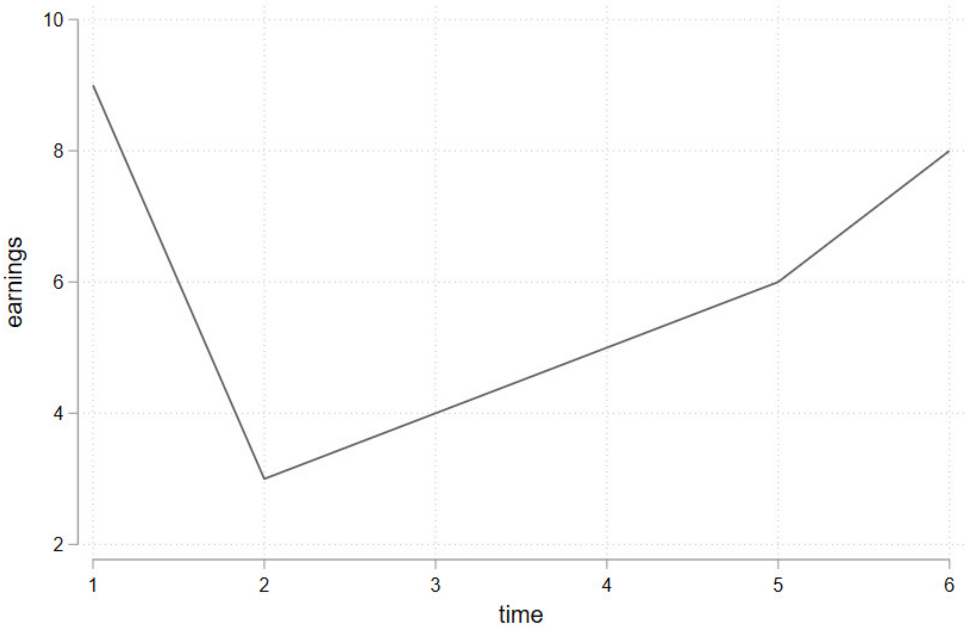

Figure 1:Stylized assimilation process

Note: Not based on calculations. Only a visulisation of the assimilation process

In summarizing, it can be said that the assimilation theory predicts that the performance of immigrants does depend on the skills they bring with them to the host country and the time they are in the country to accumulate host country-specific skills.

2.2 Labor Market Discrimination

The second theoretical cornerstone for this thesis is the theory of labor market discrimination. The theory was also established by Becker in 1957 (Stiglitz, 1973). In this theory, *discrimination* is defined as different treatment of individuals that are equal in skill and should be treated equally from a purely economic standpoint (Stiglitz, 1973). Human capital is considered the as determent of an individual's skill level. So if the education and labor market experience for an individual is not the explanation of the wage differential, other factors like ethnicity, religion, gender, or age are possible drivers for a different treatment (Rodgers, 2009). Therefore, the unequal treatment is not justified by a difference in productivity.

The economic explanation for discrimination is signaling. Stiglitz (1973) argues that in a market of imperfect information, as the labor market is, employers use the observable characteristics to predict the actual productivity of an applicant. Ethnic or religious discrimination is if the ethnic heritage or religious beliefs are falsely used to predict the individual's skill level. An example is that prejudices against some ethnicities could cause them to be systematically lazier or less reliable than natives. The ethnic heritage signals to a potential employer that the individual is less productive. When all other observable characteristics are considered equal, the individual from the ethnic minority has a lower chance of getting hired. Moreover, as they would be seen as less productive, they will get paid less on average as the work is seen as less valuable.

For immigrants, this explanation is tricky. When considering the assimilation theory, immigrants are expected to perform worse when arriving in the host country, as their skills do not match perfectly. For example, it may be harder for an American employer to evaluate how a college degree abroad can be compared with an American college degree. Quality in education varies between countries, especially comparing rich industrial countries with poorer emerging ones. This is shown by Hanushek and Woessmann (2007), who compare international standardized test results between countries. The results show that after 7th grade, less than ten percent of American students can be considered illiterate. In Columbia and Jordan, the percentage lies around 40 percent, while Mexico has a 55 illiterate rate. Therefore, years of schooling are not accurate in predicting students' cognitive skills from different countries (Hanushek & Woessmann, 2007). Due to this, the existing discrimination is often hard to measure if the immigrant status is considered a signal for the skill level; the employer's calculation might justify some difference in treatment. Nevertheless, as this is more a matter of the empirical analysis later, this is only mentioned shortly here.

Overall, it can be said that the economic theory of discrimination does predict that if prejudice against certain ethnic groups exists, the labor market performance of this group should be worse. Following this elaboration, it is evident that if the attitude against a specific group shifts, the group should perform worse after this shift happens. This research focuses on the time of the presidential vote and the success of Donald Trump around 2016. Other researchers are suggesting that sentiments against immigrants in general and especially against groups from central America rose due to the harsh rhetoric from Donald Trump, calling them rapists and thieves (Edwards & Rushin, 2018; Finley & Esposito, 2020). Due to this change in prejudice against an ethnic group, the theory would predict a change in labor market performance against immigrants.

2.3 Political Attitude and Discrimination

An important aspect when talking about discrimination is the link to hate crime. As this study will use hate crime statistics with ethnic motivation, it has to be argued that hate crime can be seen as a form of discrimination. The broad definition of *hate crime* is "unlawful conduct directed at a wide array of different target groups" (Green, McFalls & Smith, 2001, p 481). Hate crimes are motivated by specific individuals' characteristics like ethnicity, religion, sexual orientation, or skin color, and thus, the motivation behind discrimination and hate crime is the same. Still, it appears that the literature studying the development and impacts of hate crime across different fields of science makes a distinction between hate crime and discrimination across many fields of social science and medicine (Nikolaou, 2022; Dale et al., 2016; Rees et al., 2019; Fouka, 2017). However, all authors handle them as closely related at the same time. Therefore, the close but distinct handling is reasonable as they are two different actions. This is reasonable because the motivation comes from the same source, having negative associations with a specific group.

One additional strain of argumentation is how electoral support for parties and people who speak out against immigrants transfers to discrimination. One way to think about this is how electoral support for right-wing parties is correlated with local hate crimes against ethnic minorities, as the anti-migrant rhetoric of Donald Trump is very similar to the rhetoric of right-wing parties in general. Right-wing parties are trying to increase the fear by threatening replacement[1] and increasing crime caused by immigration (Rees et al., 2019). Trump also brought up these arguments, and more hostile rhetoric against certain ethnic groups is also expected to increase resentment against them in public (Edwards & Rushin, 2018)[2]. In their study, Rees et al. (2019) try to make precisely this link in Germany. They find a statistically significant, positive effect between regional election results for the far-right party Alternative für Deutschland (AFD) and the share of hate crimes against immigrants, after accounting for the density of immigrants in the regions. In addition, unemployment and the density of ethnic minorities in a region still have a much more significant influence. While unemployment increases the likelihood of hate crimes, the density decreases it (Rees et al., 2019).

Summed up, people who elected Trump are more likely to conduct hate crimes and therefore are likely to have more resentments against immigrants in general. It also seems likely that the rhetoric against certain groups of immigrants from prominent figures can increase the number of hate crimes against them. As discrimination is a phenomenon with the same source as a hate crime, a possible correlation between hate crime and discrimination can be drawn. Due to this, hate crime seems to be a good indicator of measuring discrimination. This implies for this research that measuring the change in hate crime over time will be a possible way to estimate

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[1] In brief, the replacement theory is a talking point of far-right movement, which in its core stresses the threat that the native white population in the United States will be replaced by other ethnic groups coming from abroad to make themselves a minority (The Associated Press & NORC, 2022)

[2] There are many different theories on what causes hate crime. Psychological theory assumes that a hate crime is the most extreme form of prejudice. Conducted by individuals with affective disorder and most often authoritarian tendencies (Green, McFalls & Smith, 2001). Social psychology has two main strains: The first attributes the causes to peer pressure and social norms in racist subcultures, while another strain sees the main cause in unbalanced media coverage creating a narrative, which functions as motivation for hate crime (Green, McFalls & Smith, 2001). Economic theory sees the competition for scarce resources in the center. New immigrants are seen as getting already strained resources, which is why hate crimes are expected to be higher in regions and communities with higher unemployment (Green, McFalls & Smith, 2001). A common theme is that the characteristics always have high correlation with rights wing party preferences.

the overall change in sentiments against immigrants from Central America. As the rhetoric is primarily targeted against newly arriving immigrants, it will be interesting to see how immigrants who come to the United States assimilate differently. Suppose the resentment against immigrants from Central America increases the time around the presidential election. In that case, immigrants arriving at this point should also experience worse labor market conditions than immigrants that arrived before.

2.4 Previous Research

This section will show empirical evidence of immigrants' labor market assimilation and labor market discrimination. In general, assimilation into the United States labor market seems to last at least ten years, and it is not sure that the level of native immigrants has been reached

2.4.1 General Evidence for immigrant assimilation

This section will summarize the main findings on immigrants' assimilation process. In the first phase, researchers estimated very favorable assimilation rates. For example, Chiswick (1978) predicts that the earnings of immigrants close up to native earnings after 10 to 15 years in the host economy. The cross-sectional analysis of the 1970 census was then criticized by Borjas (1985), who found significant differences in the cohort's education. Borjas (1985), therefore, argues that if the different cohorts are not very equal, a cross-sectional analysis leads to a significant bias in the results. If a later cohort is just way less educated, they already start way below the cohorts that came before them. With an analysis, looking at the assimilation rates of the different cohorts, he then also estimates much slower assimilation and even does not find a full close-up on native earnings. Immigrants do not seem to reach the native levels, even after ten to fifteen years, which could be evidence of discrimination already.

That the pattern of assimilation is not a new phenomenon is shown by Abramitzky, Boustan and Eriksson (2014). In a new approach, they construct a panel dataset of immigrants who came to the United States in the Age of Mass Migration from the 1870s to the 1910s. By observing this period, they argue that no immigration restrictions artificially sort immigrants. So, assimilation is not biased by presorting. The results show that the experience of immigrants does vary enormously by sending country. While immigrants from northern and western parts of Europe performed better from the start, southern and eastern European immigrants performed worse (Abramitzky, Boustan & Eriksson, 2014). The groups varied in two key ways. Immigrants from northern and western European countries were better educated, and the vast majority came before the ones from the south- and east Europe.

Another essential factor to consider when researching assimilation is that not all immigrants stay in the host country. As Borjas and Bratsberg (1996) argue, there are two main types of remigration. The first group is immigrants who do not find a job or are generally not as successful as planned and have incentives to remigrate. This will lead to a positive selection within a cohort over time as only the successful ones stay in the host country. Another group will be the highly educated. For them, immigration is part of a whole life cycle model where they plan to come to the US as they can earn more money there. If they achieve this goal, they will return to their country of origin (Borjas & Bratsberg, 1996). It also appears that these two types of remigrations are specific to the country of origin (Borjas & Bratsberg, 1996; Borjas, 1985; Ward, 2017). Immigrants from poorer nations that leave tend to be the least successful, and remigration from richer countries tends to be the most successful. It is essential to consider this when comparing assimilation rates from different ethnic immigrant groups, as this paper did.

An interesting question is if the assimilation process can be influenced by the economic situation in the host country at the time of arrival. A first attempt was made by Chiswick, Cohen and Zach (1997), who looked at how a recession influences the labor market assimilation of immigrants. Using a cross-sectional analysis, the research shows that the national unemployment rate at arrival does not have a significant but positive effect on labor market performance. The same is found by McDonald and Worswick (1999), who contacted similar research with Australian data. Both papers analyze the assimilation of immigrant cohorts by creating cohorts over time by combining several surveys conducted at different times (Chiswick, Cohen & Zach, 1997; McDonald & Worswick, 1999). One problem with this analysis is that in times of economic downturn, migration patterns might change. The argument is that only immigrants who still see chances of getting into the labor market will immigrate. This will lead to positive selection, and cohorts arriving in times of economic downturn might be more productive. As the estimates suggest that higher unemployment rates are positive, this is also the explanation used by the authors (Chiswick, Cohen & Zach, 1997; McDonald & Worswick, 1999).

As argued by Åslund and Rooth (2007), this selection bias does make it hard to see the real impact of the economic downturn on immigrants' labor market performance. Due to this reason, they researched the performance of refugees in Sweden during a time when a sudden economic collapse happened. Because this downturn was hard to predict beforehand, they argue that migration decisions are not as influenced as if the shift was more slowly (Åslund & Rooth, 2007). In addition, the choice to observe refugees does also have the same effect as theory predicts that this sub-group of immigrants does not have economic calculation at the core of their decision to migrate (Fiddian-Qasmiyeh et al., 2014; Åslund & Rooth, 2007). They conducted these estimates two times, one time with national numbers on the economy and a second time looking at the economic performance in the single regions of Sweden. The estimates indicate that immigrants coming in times of fewer job opportunities perform worse over the whole assimilation process. After eight years, the differences still appear (Åslund & Rooth, 2007). As this research is dealing with possible selection bias, these results should indicate that the economic conditions influence immigrants' assimilation process.

The initial labor market conditions at the arrival might influence economic outcomes for immigrants also in an indirect way as well. All three approaches used times of recession to spot possible differences in cohorts that came before and after it (Chiswick, Cohen & Zach, 1997; McDonald & Worswick, 1999; Åslund & Rooth, 2007). At the same time, a change in attitude towards immigrants might also have accrued. Evidence suggests that in times of economic downturn, resistance against immigrants increases in the host population (Hatton, 2016; Neumayer, 2004). So besides possible changes in economic opportunity, the arriving immigrants might also have been facing fewer opportunities due to more discrimination. The next chapter will show that evidence that immigrants experience discrimination in the labor market is available. So, the possible worse job opportunities for immigrants found by Åslund and Rooth (2007) might be part of a more hostile environment against them.

2.4.2 Evidence for the existence of ethnic labor market discrmination

The evidence and conflicting results regarding ethnic labor market discrimination will be presented in the following chapter. Research on this topic varies widely in terms of used methods and results. This synthesis will try to establish a general framework. The main difficulty in researching discrimination is finding the causal effect of discrimination on wages and unemployment. It is hard to identify if the differences between the discriminated- and the control group are due to unobserved characteristics or discrimination (Rooth, 2002). This is actually the same struggle as employers have as described in the theory part. The solutions and results are now shown in the following paragraphs.

As unobserved characteristics are one of the most crucial hurdles to overcome when researching discrimination, an experiment that would eliminate this factor would give valuable insights into this field of research. Such an experiment was firstly conducted by Bertrand and Mullainathan (2004). The experimental design looks like the following; job applications are sent to actual job offers. The names of the potential applicant are then randomly distributed on these job resumes. So, the skills and experiences are equally distributed between the compared ethnic groups and only differ in the names attached to them. The call-back rate then measures the likelihood of getting a job interview. The names for this first design were stereotypical names for white- and black Americans (Bertrand & Mullainathan, 2004). The estimates suggest a statistically significant, lower call-back ratio for job applications with names associated with Americans with black skin color. As Bertrand & Mullainathan (2004) suggest, these estimates are most likely proof of existing discrimination in the hiring process. Nevertheless, as the experiment cannot explain the further application process, it is unclear if discrimination gets higher or lower in the following steps. Still, lower call-back ratios reduce the likelihood of getting a job since this translates into fewer opportunities and, therefore, is a good measurement of existing discrimination against ethnic minorities.

An equal design was conducted by Carlsson and Rooth (2007), who now investigated if discrimination against Arab immigrants exists in the Swedish labor market. As this research is looking at immigrants and not at two different native ethnic groups as Bertrand and Mullainathan did, this research is of significant interest for this paper as it gives insights into labor market discrimination of immigrants. The estimates also suggest a significantly lower call-back rate for Arab names than applications with Swedish-sounding names (Carlsson & Rooth, 2007). Oreopoulus (2011) finds lower call-back ratios for Indian, Chinese, and Pakistani sounding names in the Canadian labor market. As can be seen, this experiment generates the same results in different countries and when comparing different ethnicities.

This experiment can detect labor market discrimination generally, as shown in the last paragraph. However, it can also generate insights into how discrimination is different between different economic sectors. Baert et al. (2015) were the first who used this experiment on the Belgian labor market, also specifying the different kinds of jobs on its labor market tightness. They argue that in sectors where labor is abundant, the recruitment behavior should be different compared to the sector with a small potential labor pool (Baert et al., 2015). They create a dummy variable indicating if the position is in a sector with an abundance of labor or not. The estimates show less discrimination in job positions where labor is scarce (Baert et al., 2015). This is in line with the theoretical assumptions of Baert et al. (2015), which indicate that firms cannot afford to discriminate on ethnicity if the options are limited.

Following this research, Carlsson, Fumarco and Rooth (2018) applied the same experiment to the Swedish labor market but used a more accurate measurement of labor market tightness. They use a continuous variable to measure it. The estimates they get from these methods indicate the exact opposite of the finding of Baert and his coauthors, as they find a higher difference in call-back rates in jobs where labor is scarce (Carlsson, Fumarco & Rooth, 2018). The results point in the exact opposite direction, making it hard to find a final conclusion on how labor market tightness influences discrimination. As the research is done in two different countries, labor market restrictions might differ. In addition, the use of different measures for tightness adds to the lack of comparability. Both results are s indicating that the supply of labor matters still is essential when observing discrimination. As this result can also be transferred to unemployment. This also creates labor market tightness, which may influence the hiring process.

As this experiment only covers a limited part of the hiring process, other research is also necessary. It is also essential to see if ethnic differences can explain the actual employment rates and earnings. Nordin and Rooth (2009) compare second-generation immigrants to spot potential discrimination. They measure the human capital with a mandatory skill assessment test score for the Swedish military. Reducing potential unobserved characteristics, they significantly differ in unemployment rates between individuals with immigrant parents and native ones. However, they find no difference in earnings (Nordin & Rooth, 2009). Another research investigates if adopted children of Swedish native parents perform differently in the

Swedish labor market if they have a non-European appearance (Rooth, 2002). As they have the same parents as native children, Rooth (2002) argues that they should have the same characteristics despite their skin color. The results show a significantly lower employment rate for adopted individuals than natives. All of this research has the flaw that discrimination is not measured directly. It cannot be said with certainty that discrimination can explain the difference. However, the careful construction makes it the most likely case in both papers (Rooth, 2002; Nordin & Rooth, 2009).

The research on discrimination is always with caveats since it cannot be observed directly. However, the evidence presented here still points to the existence of ethnic labor market discrimination. A critical lesson from this research is that it is essential to find ethnic minorities with the most negligible difference from the native population. In the next chapter, discrimination will be approached differently since it will look at research on shifts in attitudes. So, a change in discrimination against the same immigrant groups over time.

2.4.3 Sudden Shifts in Public Opinion and Labor Market Discrmination

In this section, the focus will lay on the prejudice and discrimination against immigrants and the political environment it is happening in. This is important to understand the empirical approach of this study which combines the assimilation process of immigrants with the sentiments they are faced with when entering the host country. This chapter will focus on the shifts in sentiments and the resulting increase in labor market discrimination.

The start of this investigation will be the 9/11 terrorist attack, which saw a record increase in hate crime years after (Gould & Klor, 2016). Rabby and Rodgers (2011) researched the labor market performance of Muslim men aged 16 to 64 after the 9/11 attacks. The results do not affect the employment-population ratio when using the entire treatment group. The group that shows significant effects on employment and weekly hours is young adults aged 16 to 25. The estimates for these groups show a decrease in employment and average weekly hours that are statistically significant. The earnings are not affected in this group, but some minor statistically significant effects can be seen in the 16 to 64 group. The authors also observe a decreasing effect in higher educated groups. This means that low-educated young men are the ones that are the most affected by the event.

Rabby and Rodgers (2011) measure the discrimination by applying a difference in difference analysis, comparing immigrants from major Muslim countries with immigrants from non-Muslim countries. These control groups are close to them in other observable characteristics, like education and age structure. While the results show a significant effect, the chosen method does compare very different groups with each other. This is a significant limitation of the research. The different ethnic groups are also not included in the same policy measures, another possible explanation of the presented estimates (Rabby & Rodgers, 2011). Overall, it cannot be said with certainty that the shown effect does come from systemic discrimination from the public or the policy measures implemented after the terror attack.

Another attempt to estimate the effect of the 9/11 attack was made by Dávila and Mora (2005). They estimated how wages from Arab and other associated ethnic groups were affected in the attack's immediate aftermath. By looking at their performance from 2000 to 2002, they find a significant drop in earnings for middle Eastern Arab men, also when accounting for possible changes in cohort characteristics, like demographics and skill level. The evidence for other ethnic groups likely affected by discrimination like Iranian and north African men is unclear, and significant effects can only be partially estimated. This is in line with the findings of Rabby and Rodgers (2011). There the results are also changing when looking at different ethnic groups. A difference to the methods done by Rabby and Rodgers is that the comparison groups are now non-Hispanic, white men. (Dávila & Mora, 2005). The researchers do not consider possible policy measures that could be in place at this point, but as the research timeframe is so short, most of this is most likely not relevant to it. So, as it appears in the short run, ethnicities expected to experience a sudden increase in discrimination against them do have disadvantages in the labor market.

As Dávila and Mora only investigate the change in earnings, Kaushal, Kaestner, and Reimers's (2007) research add a more holistic picture of the labor market performance of certain immigrant groups. An essential addition to this research is that the authors try to quantify the intensity of discrimination. This is done by comparing the same ethnic groups at different stages of the assimilation process. Kaushal, Kaestner, and Reimers (2007) argue that the higher the similarities with the host majority, the less discrimination, and the more minor disadvantages in the labor market should be expected. However, this theory is not supported by the evidence since no significant difference between the groups can be observed. In addition, they also try to observe if the location matters. The effect might vary with the average level of prejudice in a region. In states where the hate crime lies below average, the labor market performance of Muslim immigrants is better at a statistically significant level (Kaushal, Kaestner & Reimers, 2007). Both methods, the difference in difference estimate and the OLS estimates indicate that Arab and Muslim immigrants experience a drop in earnings. At the same time, no significant reduction can be found in unemployment and hours worked. This change might only be a short-run effect, as indicated by the earnings recovery in the latest survey wave included (Kaushal, Kaestner & Reimers, 2007). It cannot be verified because this is not included in the two previous papers (Dávila & Mora, 2005; Rabby & Rodgers, 2011).

Widening the focus away from the US, some research also looked at how the 9/11 attack influenced the labor market performance in other western countries. Åslund and Rooth (2005) compare the Arab and Muslim immigrants with natives and other immigrant groups in Sweden before and after the terror attack. The public opinion towards these groups also worsened significantly in Sweden. Nevertheless, the estimates show no significant effect on unemployment rates against the expectation that this change in prejudice will result in worse labor market conditions (Ålsund & Rooth, 2005). The same is found in the United Kingdom by Braakmann (2010). When observing the labor market performance of Arabic immigrants in the UK, he measured, in addition to the 9/11 attacks, the effect of two other major terrorist attacks in Spain and the UK on the labor market performance of Immigrants. In all three cases, the public opinion on Arab and Muslim Immigrants took a hit, but no significant effects on wages and employment rates appear. The same can be said for the 9/11 effect in Germany (Braakmann, 2009) and Australia (Goel, 2009). Comparing all these different countries outside of America, the impact of potentially more discrimination against Arab and Muslim immigrants cannot be found.

One possible explanation for this discrepancy between the United States and the rest of the world is that the labor markets and its regulations are very different when comparing it with the United States. However, as research is done for various very heterogeneous countries, this seems to be no satisfying explanation. Another explanation might be that as America was directly affected, the backlash was most likely the most severe. Consequently, the shift in sentiments was not pronounced enough in the other countries, resulting in a not observable shift in labor market performance. Evidence for this is also the not consistent evidence for the American case as this might indicate that it only passed the threshold to observe significant shifts. What stands against this is the findings of Braakmann (2010) that a terrorist attack in

London also had no significant effect on the United Kingdom. Overall, the research on the short-run labor market effect of 9/11 indicates a worsened, measurable environment for Arab and Muslim immigrants, at least in the United States.

Looking at the long-run effects, Gould and Klor (2015) show that fertility, marriage patterns, and female labor force participation reverse from a trend towards more assimilation. This trend was most pronounced in areas with above-average hate crimes, which indicates the importance of discrimination in this process. Another finding of Saavedra (2021) indicates that the increase in discrimination against American Japanese led to a higher proportion of them giving their children American-sounding names after the attack on Pearl Harbor. This stands against the evidence of Gould and Klor since it indicates that this ethnic minority reacted by getting a higher assimilation rate to blend into the main population. It shows that the two distinct strategies are used to avoid discrimination. The first is to separate from the dominant part of society or assimilate more quickly. This is important to keep in mind as it shows that there is not only one way immigrant groups can react. As this is not a direct measurement of economic performance, its link has to be made with caution. Still, indicators like intermarriage rates, interethnic cohabitation, and fertility have a significant link at immigrant groups' economic integration (Dribe & Lundh, 2008; Elwert & Tegunimataka, 2016; Dubuc, 2012). So, we can assume with some certainty that these results also indicate the economic assimilation of these immigrants.

The evidence in this chapter indicates that immigrants are affected by an increase in hostility. While the short-run, significant effects on employment and wages can be found in America. The effect on assimilation is only done more generally and shows differences in behavior between the Pearl Harbor and 9/11 cases. I am not aware of any research done on the election of Donald Trump, which also increased hostility against immigrants. This research will therefore add another new case study. In addition, like 9/11 and the election of Trump are not too far from each other in time, a comparison of these two events might. Another factor not covered by the literature is if cohorts are affected differently. The research of Åslund and Rooth (2007) stands to reason that lower job opportunities in the first period after arrival also affect the labor market assimilation in the long run. As the theory and literature predict that discrimination has this effect, a sudden shift in discrimination might also influence cohorts that came shortly before or during this period more heavily than more established cohorts. This research will try to investigate precisely this research gap.

2.5 Central American Immigation and the 2016 Election

The chapter will give a short summary of the facts of immigration from Central America. In addition, the 2016 presidential election and most importantly the rhetoric against immigration will be illustrated. This will help to adapt the theoretical concept onto this special case. It is also an important fact for developing the hypothesis.

The immigration from Central America is a special case. At first it is the closest main source region of immigration to the United States geographically. In addition, the land border with Mexico makes the United States much more accessible from this region than from anywhere else. As the costs (distance and overall accessibility play both an important role in this (Belot & Hatton, 2012)) of migration are an important determinant of the sorting of immigrants. As Belot & Hatton (2012) can show, the distance to the destination country does influence the skill distribution coming into OECD countries. This can also be seen in table 1, which shows the distribution of the education level of each ethnic group in the dataset for this paper. Immigrants from Central America have the lowest education of all immigrant groups.

Table 1: Educational distribution by ethnic group

	9/11 countries	Central American	South American	Asia without 9/11 countries	European	Africa without 9/11 countries
Elementary school or less	7.88	11.76	3.48	4.32	1.49	7.62
High school with not diploma	10.62	36.71	11	6.49	3.12	10.21
High school with diploma	21.47	26.7	29.54	12.76	15.49	25.44
College but no diploma	7.43	8.7	12.36	6.71	9.76	12.29
Bachelor’s degree	33.71	12.38	30.72	39.05	31.86	31.36
Master’s degree or above	18.88	3.76	12.89	30.67	38.28	13.09

Source: Own data set. See data descriptions

Another result of the geographical location of this region is that a significant share of illegal immigrants in the United States comes from Central America. As Rosenblum and Brick (2011) argue, the possibility of crossing the green border between the United States and Mexico makes it much easier to cross into the United States unnoticed than from other parts of the world.

Overall, the number of illegal immigrants from Central America remained relatively constant over the last decade. To reduce the number of illegal immigrants from 1990 onwards, diverse administrations significantly increased border protection and federal agencies' powers to detect and deport illegal immigrants (Rosenblum & Brick, 2011). Despite this effort, the estimated number of illegal immigrants remained relatively constant until 2017 (Passel & Cohn, 2019). One possible explanation might be that the push factors from this region compensate for the high barriers on the side of the United States (Rosenblum & Brick, 2011). In addition, the low-skilled workers from Central America are also badly needed in the United States Economy. As the native workforce does not engage in these low-skilled jobs anymore, and only a limited number of low-skilled green cards for legal immigration are provided, employers often must rely on illegal immigrants for low-skilled jobs (Ramanujan, 2009; Rosenblum & Brick, 2011).

In his election campaign, Donald Trump also said that the measures against illegal immigration are not enough. To lower illegal immigration, he proposed to extend the wall on the southern border and strengthen law enforcement to deport illegal immigrants (Mayda & Peri, 2017). He also signed executive orders to accomplish his goals (Mayda & Peri, 2017). These two policy instruments also impacted migration streams but with some delay. According to the numbers of border apprehensions, Martin (2020) estimates that the number of families crossing the border only rose drastically in relation to single men crossings from 2019 onwards. Before the year 2019, the changes were only marginally, with single men being the biggest group of illegal immigrants (Martin, 2020). As the analysis of this research is ending in 2019, the changes in migration patterns from this region most likely have no crucial impact on the estimates since it appears that the demographics are not changing significantly in the study period.

Apart from the actions to regulate illegal immigration, the rhetoric of Donald Trump on this topic is of great importance for this research. During his election campaign and in his presidency afterward, Trump called immigrants crossing the southern border of the United States rapists and murderers (Finley & Esposito, 2020). As this is only a brief example, the overall framework of his (and most of the right-wing media) wording creates a message that immigrants from Central America are an existential threat to American society (Finley & Esposito, 2020). Suggesting that most of them will do wrong in the United States, this dehumanizing rhetoric also creates an us-versus-them mentality among his followers (Finley & Esposito, 2020). In addition, he and other prominent right-wing figures helped the grand replacement theory enter the political mainstream (Zaru, 2022). All of this rhetoric suggests an existential threat to the status quo in the United States. Such theories are related to sparks of violence, as these concepts are often at the core of the manifestos of many brutal hate crimes against ethnic minorities in the last years (Zaru, 2022). As we saw in the theory part, this rhetoric is associated with increased resentment against the targeted group.

Summarizing can be said that immigrants from Central America are an essential part of the total immigration stream into the United States and are also filling a vital part of the economy. By regulating undocumented immigration, many administrations increased their capabilities to reduce the inflow of people. However, push factors in the sending countries are still too high that these determents reduce it significantly. In comparison, the administration of Donald Trump implemented even harder policies which only showed a lagged impact. This may also be because most of the measurements were executive orders which do not have the same impact as proper legislation (Mayda & Peri, 2017). This is also different from former rises in resentment against certain ethnic groups, for example, after the 9/11 terror attacks. There actual legislation discriminating against Muslim immigrants was passed, which might have influenced their labor market outcomes (Rabby & Rodgers, 2011). Due to this, it can be said that this incident is unique in many ways, as it appears that an internal force created the shift in resentments with the actual election results as an eruption point. Edwards and Rushin (2018) show that directly after the election, hate crimes increase. It will be interesting to see if this different event has the same impact.

For the time of the Donald Trump election and the following presidency, no research that I am aware of has tried to estimate the effect on Central American immigrants. So this study will try to investigate the impact of the harmful rhetoric against this ethnic group on their labor market assimilation. Another layer is that most research looking at a shift in public opinion look at a scenario where an external shock shift led to a rise in resentment against certain immigrant groups.

Research questions is:

How does the increase in discrimination against Central American Immigrants during and after the Trump presidency influence their labor market assimilation?

The hypotheses are:

1. Central American immigrants experience higher unemployment rates in areas with higher resentment against immigrants.
2. Central American immigrants in areas with higher resentments in their assimilation process have lower wages.

3 Data and Methods

In the following, the primary data sources will be introduced. It will be argued why the ACS is the best available source for this research design. Additionally, some limitations to the data will be discussed as well. Afterward, the two main approaches, OLS and probit, will be shown with an explanation of all included variables. Afterward, a descriptive summary of the investigated population will give the reader an overview of trends in composition and labor market performance.

3.1 Source Material

The primary data source is the annual ACS from the American Census Bureau (2021b). As the vote for Trump was at the end of 2016, the dataset was created using the survey waves from 2014 to 2019 to have a pre-election and a post-election phase. The year 2019 is the newest available wave in this study. In addition, the dataset allows for the identification of the most important demographic and socio-economic indicators from an individual. A summary of these factors will be shown in the descriptive part. As the American Census Bureau provides the raw data set and is used in various publications studying immigration (Rabby & Rodgers, 2011; Gould & Klor, 2016), the dataset is arguably the best publicly available source for cross-sectional analysis.

The indicator of resentment against Central American immigrants will be the number of ethnical hate crimes against Latin American people. The official hate crime statistics are provided yearly by the Federal Bureau of Investigation (FBI) (2022b). The minor geographical level is the state level. An important caveat is that the total number of ethnically motivated hate crimes cannot be used for measuring the impact on a single group. As table 3 shows, it also contains anti-white, anti-black hate crimes. Together, these two groups combine more than 50 percent of the reported cases. Because of this, the treatment variable is created by using the reported number of hate crimes split into every single bias provided by the FBI (2022a) crime data explorer. This data makes it possible to develop resentment against people with Latin

American ethnic backgrounds. As the states have considerable differences in population size, the number of hate crimes also varies significantly. To make the number of hate crimes comparable between states, the number of hate crimes per capita is calculated, following Gould and Klor (2016), who had done the same with anti-Muslim hate crimes. The authors also used the number of Muslim populations in a state. Instead of using the number of Muslim people, the number of Latin American heritage per state is used here. For this number of Latin American people in each state, the ACS waves for each year are used to estimate the number of Latin American people living in each state and year. The 2010 census was not accessible, so this is the closest possible estimate. With this approach, I follow Grieco et al. (2012). They are doing the same by estimating the proportion of the foreign-born population using the 2010 ACS wave in an official governmental report. It seems appropriate to do this in this work as well.

The control variables are also calculated using the 2014 to 2019 ACS waves. Average native unemployment rates and wages are calculated by state and year. Individual control variables were mostly taken over unmodified. Only the education was reshaped to get more comparable categories.

3.2 Data Limiations

Using the ACS also brings limitations with it. One of the main limitations is the lack of information on the individual before immigration. The dataset makes it possible to observe the current education level of a person. It is, however, not clear where this education was acquired. Due to this, it cannot be said with certainty that the education was fully acquired in the sending country. The analysis is limited to individuals aged 16-64 who had not arrived in the US before 2014. Because of this, it is impossible to indicate if some individuals got parts of their education after they arrived in the United States. To minimize this risk, however, the dataset will be limited to the person at least 16 years old when they arrived in the United States and were eligible for work. In the sample used, 579 individuals met these criteria and got eliminated. Still, the education variable might lead to biased estimates. A high school diploma acquired in the United States has a higher impact on the salaries and chances of being employed, which means that the results will be biased upwards.

Another main way of studying assimilation is to use panel data, common when studying the economic assimilation of immigrants (see f.e.: Ålsund & Rooth, 2007; Rooth, 200; Chiswick, Lee & Miller, 2005; Abramitzky, Boustan & Eriksson, 2014). The main advantage of using this approach is that one can observe the same individual over time. Controlling individual heterogeneity leads to more reliable estimates because one can control for unobserved characteristics (Baltagi, 2011). This is not possible with the cross-sectional approach here, and we get a new random sample of individuals with each survey wave. Due to this, we have to assume that the sample is big enough that the same individual is observable over time. As a consequence, the characteristics are similar each year on average. As each cohort has at least over 10.000 observations, the law of the big number should hold. This law says that the distribution of each sample gets closer to a normal distribution with the increasing number of observations it contains (Wooldridge, 2015). The only publicly available longitudinal dataset I am aware of is the New Immigrant Survey. However, this survey was not done in this study's period (Princeton University, 2022). Therefore, the analysis cannot rely on longitudinal data, and ACS data is the best solution available.

3.3 The Model

Two distinct methods are used to measure the impact of hate crime on earnings and unemployment, respectively. The first will be ordinary least square (OLS) regression. Secondly, a probit model. The general design of the model, which is similar in both cases, leans on Gould and Klor's (2016) approach. They study the assimilation process of Muslim immigrants after the 9/11 attack. With this design, it will be possible to measure if gradual shifts in public opinion influence the assimilation of immigrants into the labor market. The overall model looks like the following:

$$outcome_{ist}^{e} = \alpha + Ethnic\ Hate\ Crime\ pc_{st}^{e} + \gamma' ind_{ist}^{e} + \delta' state_{s} + \theta' state_{st} + \vartheta' coh_{it}^{e} + \varepsilon_{ist}^{e}$$

$outcome_{ist}^{e}$ stands for the two outcome variables, the log yearly earnings of an individual in the last 12 months and the dummy variable if the person is unemployed from individual i, in state s, at time t, and the ethnicity e. The first one is a continuous variable. It will be estimated using the OLS regression. At the same time, the estimation of the effect on unemployment will be done by using a probit estimation as this is more suited to estimating a limited outcome variable with individual data (Baltagi, 2011). The main treatment variable here is

$Ethnic\ Hate\ Crime\ pc_{st}^{e}$. This is the number of reported hate crime incidences per capita in state s, in the year t, against an ethnic group e. As hate crimes against Muslims will be used as a sensitivity test, ethnicity also stands for religious motivation in this context. Per capita is here not the total number of residents in the state but the non-native population in a state. ind_{ist}^{e} stands for a vector of individual control variables which includes the gender, the education, the years the person already lives in the United States, the marital status, and if the household of individual *i* is multilingual. The vector coh_{it}^{e} is a set of cohort dummies, to include cohort fixed effects. This was leaned on the model of Åslund and Rooth (2007) who also want to observe the labor market performance of different cohorts over times, with varying conditions at the time of entry. Because of this including cohort fixed effects seems suitable for this approach as well.

When estimating the probit model, the interpretation must be made with some caution. The marginal effects of the probit model are changing with x and are not linear as with an OLS estimate (Baltagi, 2011). As a normal distribution is assumed, the marginal likelihood decreases on the distribution's tails. Due to this, the average marginal effect has to be computed to get a linear, interpretable result (Baltagi, 2011).

With this model, it will be possible to compare different cohorts' earnings and unemployment likelihoods at the same stage of their development. The model will also control for the years the individual is already in the United States. It will also measure the assimilation rates on a relative level. However, the overall assimilation process shown in Figures 2 and 3 is not the focus. The main goal of this research is if the development of resentments leads to a change in the assimilation rates of every single cohort. The change in the number of hate crimes against Latin Americans per capita can explain the different income levels of an immigrant. Everything also held constant. This also contains the year the immigrant is already in the country and which cohort he is in. Some descriptives by each group of interest are shown in the following chapter.

3.4 Descriptives

Before turning to the estimates of the model, this section shows the descriptive statistics of the observed cohorts and ethnic groups used in the analysis. The analysis uses a cross-sectional dataset built from the 2014 to 2019 waves of the Annual American Community Survey, which is described in detail in chapter 2.1. As Borjas (1985) shows, estimating assimilation rates of the cohort over time has the danger of bias due to unobserved differences in the quality of cohorts over time. Due to this, looking at the observable characteristics of the different cohorts is vital for later conclusions drawn from the estimates.

Observing the change in the educational level is crucial as education plays an essential role in assimilation since it is expected that immigrants increase their human capital stock in the host country as described by the assimilation theory. On the other hand, as it is not possible to observe an individual's other time with this dataset, remigration could also influence the average educational level. So, the optimal shift over time of the average education would be slow upwards, according to the assimilation theory. If the change is too sudden, the change is more likely due to remigration as this is most often selected for high or low-skilled individuals. Figure 2 shows the development of every single cohort over time. The 2019 cohort is not included as it only has one data point.

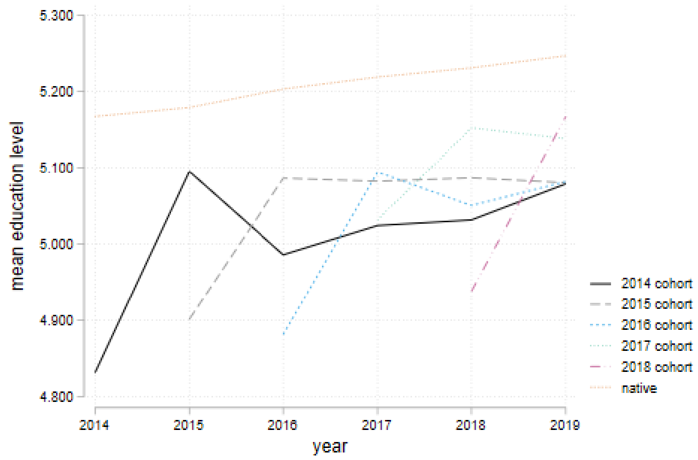

Figure 2: Average education by cohort and year

Note: Own calculations using ACS 2014-2019

Two common trends can be observed in all cohorts. From the first to the second year after arrival, each cohort's average educational level increases sharply. Afterward, it stays more constant. This is an interesting observation but not that important for this analysis as only a significant change between the cohorts would bias the estimates. The 2017cohort has a higher educational level in its first year in the United States. Compared to the other groups that lay around 4.9 on average, the 2017 cohort starts at 5.05. Because this is also the first year of the Trump presidency, it cannot be ruled out that this increase has something to do with the administration's action in its first month of office, which might make it harder for lower-educated immigrants to enter the country.

As the mean educational level from the 2018 cohort then dropped once again, one could also suggest that this might be a reaction to the rhetoric of Donald Trump. In the first year after the election, the administration also tried to impose immigration restrictions for specific countries but got dropped by high courts (Mayda & Peri, 2017). Therefore, the actual barriers are believed not to have become significantly higher for immigrating to the United States (Martin, 2020). However, the rhetoric might have discouraged certain groups from countries with a lower educational level like Africa or countries from Central America, as the rhetoric was mainly targeted at them (Finley & Esposito, 2020). As there is a spike in the educational level for the 2017 cohort, one could suggest that this might influence the estimates of the cross-sectional analysis.

Table 2 gives an overview of the characteristics of each cohort and the overall sample population. This is a good first test if the composition of the cohorts is changing significantly, which would lead to biased results. First, the age at migration is not significantly different between the cohorts. A certain upwards trend is occurring. An immigrant in the 2014 cohort was 34 years on average, while an immigrant from the 2018 cohort was a bit older than 36. This gradual increase in average age is, however, slight. The gender distribution, at 48 percent, and the marriage rates at around 66 to 67 percent are also very constant between the different cohorts.

Tabell 2: Descriptive Statistics

Cohort	2014	2015	2016	2017	2018	All
Age at migration	33.97	34.73	35.20	35.96	36.21	35
	(11.11)	(11.22)	(11.26)	(11.67)	(11.97)	(11.42)
Female	0.481	0.481	0.486	0.482	0.481	0.483
Married	0.672	0.673	0.669	0.665	0.634	0.664
Pre emigration education						
elementary school or less	5.56	5.46	5.61	5.63	5.58	5.6
high school but no diploma	13.4	13.24	13.56	11.69	13.13	13.25
high school with diploma	20.61	19.87	19.94	19.53	19.81	20.05
college but no diploma	9.43	9.25	9.09	9.19	8.53	9.15
Bachelor’s degree or equivalent	30.24	30.61	30.99	32.05	31.19	30.75
Master’s degree or above	20.77	21.58	20.85	21.91	21.76	21.2
Region of origin						
Arab and Muslim countries associated with 9/11	6.15	5.48	5.42	5.58	4.26	5.5
Central American	20.78	19.96	19.36	18.62	20.74	20.17
Latin American	16.07	18.43	19.03	17.16	16.3	17.36
Asian without 9/11 countries	37.2	35.97	35.59	36.32	37.42	36.38
European	11.14	11.54	11.25	12.52	11.62	11.49
African without 9/11 countries	5.1	5.03	5.65	5.76	5.12	5.3
Rest of North America	2.34	2.53	2.66	2.97	3.14	2.65
Oceania and Sea	1.2	1.07	1.05	1.07	1.34	1.14
Hate Crimes with ethnic motivation	197.9	201.0	207.93	224.4	223.6	207.1
	(181,5)	(185.3)	(190.61)	(195.6)	(189.7)	(187.1)
Hate Crimes with ethnic motivation per capita	0.0120	0.0126	0.0132	0.0138	0.0134	0.0128
	(0.173)	(0.185)	(0.0197)	(0.0198)	(0.0175)	(0.185)
Hate Crimes with ethnic motivation at the year of immigration	156.9	159.5	175.4	218.7	232.2	178.2
	(140.9)	(140.4)	(175.1)	(205.5)	(203.3)	(167.5)
Hate Crimes with ethnic motivation per capita at the year of immigration	0.0104	0.0109	0.0115	0.0143	0.0134	0.0116
	(0.158)	(0.156)	(0.0165)	(0.024)	(0.018)	(0.0175)
State unemployment rate in year of migration	6.343	5.408	4.934	4.436	3.966	5.254
	(0.965)	(0.748)	(0.61)	(0.537)	(0.466)	(1.101)

Table will continue the next page

State unemployment rate in year of survey	4.685 (1.036)	4.423 (0.82)	4.204 (0.693)	3.980 (0.585)	3.803 (0.518)	4.312 (0.862)
County unemployment rate in year of migration	6.199 (1.681)	5.285 (1.527)	4.837 (1.453)	4.322 (1.301)	3.899 (1.268)	5.139 (1.702)
County unemployment rate in year of survey	4.557 (1.561)	4.315 (1.43)	4.121 (1.363)	3.877 (1.28)	3.727 (1.313)	4.210 (1.455)
Number of Observations:	33,587	31,269	26,097	16,524	10.112	121,840

Notes: Standard deviation in parentheses. Calculations from the main dataset constructed by the ACS survey waves from 2014 to 2019. Values without additional parentheses in percentage.

Table 3: Nationwide hate crimes per ethnicity

	2014	2015	2016	2017	2018	2019
Motivation						
Anti-White	593	613	720	741	762	666
Anti-Black or African American	1,621	1,745	1,739	2,013	1,943	1,930
Anti-American Indian or Alaska Native	130	131	154	251	194	119
Anti-Asian	140	111	113	131	148	158
Anti-Native Hawaiian or Other Pacific Islander	3	4	9	16	20	21
Anti-Multiple Races, Group	81	113	136	180	137	134
Anti-Arab		37	51	102	82	95
Anti-Hispanic or Latino	299	299	344	427	485	527
Anti-Other Race/Ethnicity/Ancestry	349	257	223	270	276	313
Total	3,216	3,310	3,489	4,131	4,047	3,963

Source: Also from the FBI (2022b)- reports; Anti-Arab is not reported individually in 2014 and included in the "other" category.

The human capital is also very constant. A sure caveat is that more than 50 percent of the individuals have a bachelor's degree or higher in all cohorts. Let us look at the education in table 2 in each region. Huge differences can be observed where the immigrants from Central America appear to be the least educated while immigrants from Europe have, in the mean, the highest education. Table 2 also shows that in all ethnic groups, the skill level between cohorts does not change significantly. It shows that this analysis avoids the mistake of analyzing the assimilation of different cohorts in a single cross-sectional dataset. As Borjas (1985) points out, if the skill level between the different cohorts is too far apart, the results can be biased significantly. If older cohorts are more educated than newer ones, they already start with better labor market prospects. Therefore, the assumption that the newer, less educated cohorts started with the same income and employment level as their predecessors could be misleading. The same would also be true in the other direction, of course. By having somewhat similar cohorts, this bias will not occur in this analysis.

Another fact can be observed when comparing the development of the unemployment rate and the number of annual statewide hate crimes. While there is a gradual decrease in the unemployment rates, a rise in hate crimes is accruing (the unemployment rate in the year of immigration can also be seen as a yearly development). That this trend is quite universal across all ethnic motivations can be shown in table 3. So, from a mean of 4,685 percent in 2014, it gradually decreased to 3,803 in 2018. When comparing this with the development of the number of hate crimes in the year of immigration, we see that hate crime increases simultaneously. This is interesting because typically, resentments against immigrants are positively correlated with unemployment rates, as shown by poling results from Hatton (2016) for the European Union. The average unemployment rates of natives decrease over time, as seen in figure 3. However, from 2016 to 2017, we see an uptake from 0,115 hate crimes per immigrant to 0,143 hate crimes per immigrant. This is an increase of almost 25 percent. It also shows that after the 2017 spike, the trend afterward leveled off slightly but did not reach the pre-election level again. This may indicate that Donald Trump's rhetoric was affecting the number of hate crimes against immigrants, as the development of the unemployment numbers would suggest the opposite pattern for the number of hate crimes.

Next, the development of the dependent variables will be shown. The mean unemployment rate and the mean log earnings of each cohort are displayed in Figures 3 and 4. The overall trend is as the assimilation theory predicts for each cohort and both variables. The earnings of each cohort start well below the earnings of natives but then catch up over the years the cohorts are in the host countries' labor market. However, by far, it does not reach the level of native earnings. This is not surprising given the insights from Borjas (1985), who predicts that the assimilation process is not finished after ten years in the host country. The same is true for the unemployment rate. Here all cohorts tend to come to native unemployment rates other times. The cohorts from 2014 to 2016 have nearly reached native employment levels. This shows that the overall assimilation pattern holds in the sample used in this analysis.

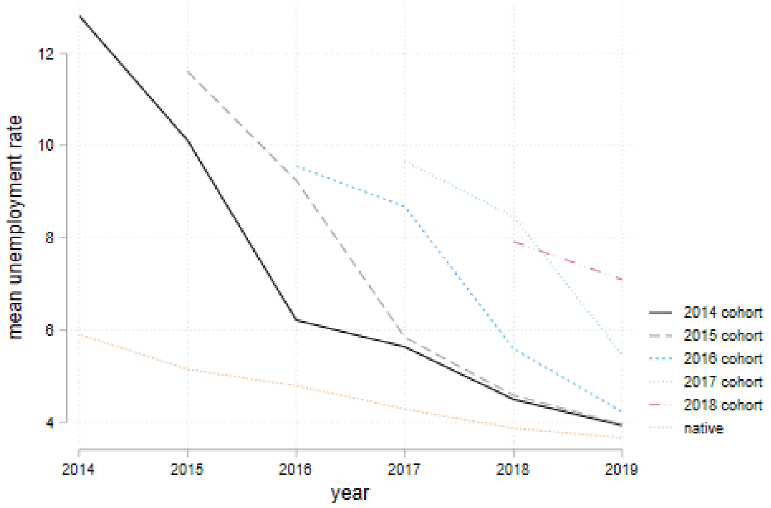

Figure 3: Mean unemployment rate by cohort

Note: Own calculations using ACS 2014-2019

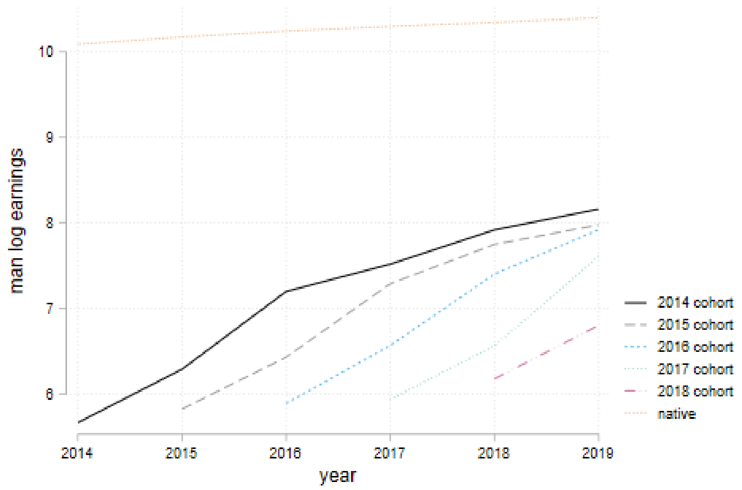

Figure 4: Mean log earnings by cohort

Note: Own calculations using ACS 2014-2019

Another aspect worth mentioning is that in Figures 3 and 4, no declines are seen in the trends from 2017 onwards. The leveling off in some trends instead seems to be a general pattern in the data and seems to come from the actual year the cohort is currently in (the assimilation rates level off in the third year after arrival). Nevertheless, this is still in line with the assumption that the increase in hate crime, with a simultaneous increase in discrimination, will cause a slowing in the labor market assimilation of immigrants. As the rhetoric of Donald Trump and his campaign were mainly focused on specific ethnic groups of immigrants, a pooled average over all ethnic groups might hide some effect in single ethnic groups. His rhetoric was mainly against immigrants from Central America Figures. So, Figures 5 and 6, which display earning and unemployment rates for this subsample, may have better indications. Here the pattern is different. For the cohorts 2015 to 2017, a rise in unemployment rates from the first to the second year can be seen. This is not seen in the 2014 and 2018 cohorts. The 2016 cohort also has the most considerable increase from 6 to 9 percent unemployment in one year. Some caveats are that all three cohorts are recovering quickly after the initial increase to similar levels. In Figure 5, only the earnings of the 2016 cohort show a deviation from the anticipated increase in earnings over time. From the first to the second year, a slight decrease appears. At the same time, it has to be said that this cohort also has the highest first-year earnings. Overall, it can be said that the deviation from the expected pattern only occurs in that ethnic group that was explicitly targeted by racist rhetoric and only at the time around the 2016 election.

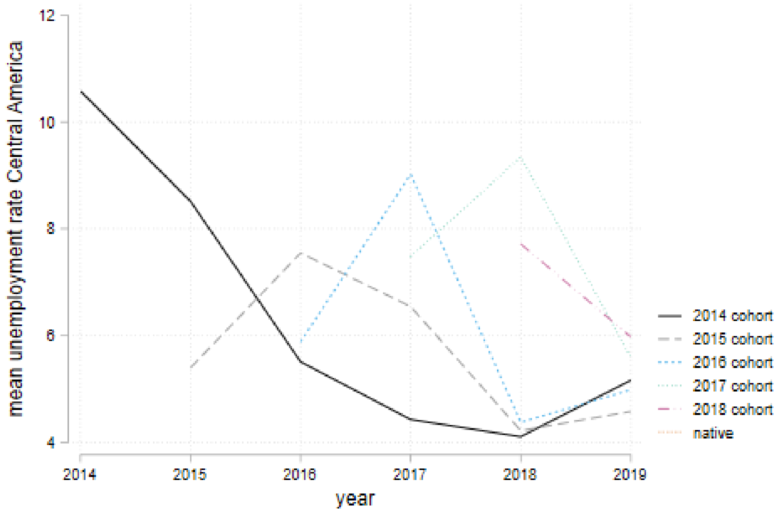

Figure 5: Mean unemployment for Central American immigrants

Note: Own calculations using ACS 2014-2019

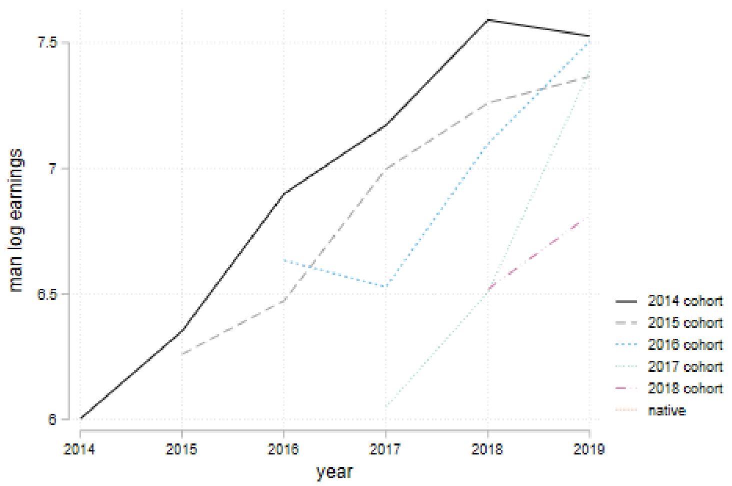

Figure 6: Mean log earning for Central American immigrants

Note: Own calculations using ACS 2014-2019

That this effect is only observable for Central American immigrants can be assured by observing the development of every single ethnic group in appendix A. Overall, it can be said that the descriptive statistic gives the first hint that the data itself is of good quality and no biases from changes in cohort quality are likely to occur. The development of the dependent variables is also the first evidence that Donald Trump's rhetoric against immigrants from Central America and their labor market outcomes might have a correlation expected by the theory. In the next chapter, the methods used to estimate this effect further will be presented.

4 Emperical Analysis

The first step in this chapter will present the main results. It will show the estimated effect of hate crime on earnings and unemployment assimilation of Central American immigrants. Here the focus will lay only on the description of the results and their implication for the hypothesis built in the theory part. After a sensitivity test where the same models are used to estimate the effect on South American immigrants, the discussion will interpret the results. It will build a hypothesis why the main estimates lead to a negation of the hypothesis.

4.1 Results

Table 4: Effect of Latin American hate crime on log earnings of Central American Immigrants

	(1)	(2)	(3)	(4)	(5)	(6)
Latin American hate crime pc	8.502***	7.797***	8.338***	10.81**	10.52**	6.246
	(2.224)	(2.030)	(2.007)	(4.500)	(4.627)	(6.072)
Age		-0.0959***	-0.0951***	-0.0942***	-0.100***	-0.0981***
		(0.00927)	(0.00925)	(0.00926)	(0.00946)	(0.00963)
Age squared		1.309***	1.301***	1.292***	1.354***	1.331***
		(0.111)	(0.111)	(0.111)	(0.113)	(0.115)
Female		-0.405***	-0.417***	-0.419***	-0.415***	-0.414***
		(0.0244)	(0.0244)	(0.0244)	(0.0245)	(0.0248)
Married		0.0897***	0.0957***	0.100***	0.0977***	0.0978***
		(0.0195)	(0.0194)	(0.0195)	(0.0196)	(0.0201)
Female & married		-0.223***	-0.222***	-0.225***	-0.241***	-0.244***
		(0.0361)	(0.0360)	(0.0359)	(0.0361)	(0.0368)
Years after immigration		0.146***	0.144***	0.140***	0.125***	0.125***
		(0.00639)	(0.00636)	(0.00641)	(0.00862)	(0.00877)
Bilingual household		0.0856**	0.0930**	0.0901**	0.0727*	0.0703*
		(0.0370)	(0.0370)	(0.0371)	(0.0375)	(0.0381)
Year fixed effects	x	x	x	x	x	x
Basic individual controls		x	x	x	x	x
State control variables			x	x	x	x
State fixed effects				x	x	x
Cohort fixed effects					x	x
States with less than 500 Latin American Inhabitants excluded						x
Observations	16,304	16,304	16,304	16,304	15,630	15,121

Robust Standard errors in parathesis. Statistical significance is marked by stars. *** at 1 percent statistical significance ** at 5 percent statistical significance * at 10 percent statistical significance. The individual controls, from column two onwards, are in addition to the displayed variables the education of the individual. State control variables are the mean earnings and unemployment rates of natives in a state s at time t.

Table 4 shows the results of the OLS regressions of the number of hate crimes against Latin Americans on the log wages of Central American immigrants. The first row shows the estimates where only the year-fixed effects are included. Column 2 includes control variables on the individual level, while column 3 adds time-varying state control variables. In columns 4 and 5, state and cohort fixed effects are added to the model. Overall, the estimated coefficient shows a statistically significant increase in average wages with increased hate crime per capita. The statistical significance decreases from 1 to 5 percent when including state-fixed effects. The general implication does not change over the modifications. For example, column 5 estimates indicate that an increase of one hate crime per capita increases, ceteris paribus, the wages of 10.52 percent on average. We also control for years after immigration and cohort. This also suggests that a higher hate crime rate does help the assimilation process because it compares immigrants at the same stage of development. The results are contrary to the theory's predictions, which indicates that the effect would be the opposite.

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Table 5: Effect of Latin American hate crime on unemployment of Central American Immigrants

	(1)	(2)	(3)	(4)	(5)	(6)
Latin American hate crime pc	-6.939*	-7.638*	-5.728	-9.899	-9.580	-7.487
	(3.940)	(3.989)	(4.148)	(9.190)	(9.401)	(12.57)
Age		0.0917***	0.0908***	0.0874***	0.0926***	0.0948***
		(0.0172)	(0.0173)	(0.0174)	(0.0178)	(0.0180)
Age squared		-1.126***	-1.116***	-1.082***	-1.149***	-1.177***
		(0.206)	(0.207)	(0.208)	(0.213)	(0.216)
Female		0.513***	0.501***	0.503***	0.481***	0.472***
		(0.0442)	(0.0444)	(0.0446)	(0.0460)	(0.0465)
Married		-0.0759	-0.0655	-0.0657	-0.0598	-0.0609
		(0.0462)	(0.0464)	(0.0463)	(0.0474)	(0.0481)
Female & married		0.185***	0.187***	0.184***	0.186***	0.192***
		(0.0634)	(0.0636)	(0.0639)	(0.0654)	(0.0663)
Years after immigration		-0.0870***	-0.0872***	-0.0879***	-0.0651***	-0.0615***
		(0.0129)	(0.0129)	(0.0131)	(0.0171)	(0.0174)
Bilingual household		-0.0755	-0.0708	-0.0665	-0.0494	-0.0306
		(0.0756)	(0.0759)	(0.0765)	(0.0775)	(0.0777)
Year fixed effects	x	x	x	x	x	x
Basic individual controls		x	x	x	x	x
State control variables			x	x	x	x
State fixed effects				x	x	x
Cohort fixed effects					x	x
States with less than 500 Latin American Inhabitants excluded						x
Observations	16,756	16,756	16,756	16,732	16,072	15,581

Robust Standard errors in parathesis. Statistical significance is marked by stars. *** at 1 percent statistical significance ** at 5 percent statistical significance * at 10 percent statistical significance. The individual controls, from column two onwards, are in addition to the displayed variables the education of the individual. State control variables are the mean earnings and unemployment rates of natives in a state s at time t.

In table 5, the probit model on unemployment has the same variations as described in table 3. The results also indicate the opposite direction as predicted by the theory. Here the estimates of hate crime per capita are all statistically insignificant at the 5 percent level. As all estimates are based on over sixteen thousand observations, a 10 percent statistical significance level in columns 1 and 2 is insufficient. So, no result for unemployment is statistically significant. Overall, the mean likelihood of being unemployed decreases with a higher rate of hate crime.

The same estimates were done in column 6 of tables 4 and 5 as in column 5, but the sample was limited. States with lower than 500 Latin American immigrants in the ACS were excluded. This represents around 3.2 percent of the total observations in the used sample. It is primarily a part of the sensitivity tests as it tries to spot the possibility of reverse causality. In both cases, this limitation does make the estimates less significant. Both coefficients are smaller than column 5, and the standard deviation increases drastically, causing the earnings estimates to lose their statistical significance.

The results point in the exact opposite direction as the theory predicts. They suggest that a higher rate of hate crimes per capita leads to quicker assimilation of Central American immigrants. Both hypotheses do not hold in light of these results.

4.2 Sensitivity Test

The main results show that the treatment does affect immigrants from Central America, but not in an expected way. Some more tests on the same model with other immigrants groups might shed some light on the mechanisms behind these findings. As the anti-immigrant rhetoric around the 2016 presidential election was mainly targeted at Mexicans and other immigrants from Central America (caravans), it would be interesting to see if the effect does differ for South American immigrants. Therefore, a first try is to do the same analysis for immigrants from South America. As the United States Census Bureau (2021a) makes no distinction between Central America and South America and defines both as Latin American, it stands to reason that these two groups should be pretty similar. In addition, the two groups are relatively similar in size in this sample, as can be seen when comparing tables 4 and 5 with 6 and 7. As Tables 6 and 7 show that the estimates of Latin American hate crime per capita of immigrants from South America are quite different. In table 6, the effect on earnings is negative but not statistically significant in most cases. An increase in hate crime decreases the average earnings of an immigrant from South America. No estimate is significant at the 5 percent level. Interestingly the coefficient is negative, contrary to the results in table 3.

Table 6: Effect of Latin American hate crime on earnings of South American immigrants

	(1)	(2)	(3)	(4)	(5)	(6)
Latin American hate crime pc	-0.588	1.055	-1.881	-2.971	-2.506	-0.766
	(2.829)	(2.638)	(2.503)	(3.160)	(3.281)	(8.884)
Age		-0.169***	-0.169***	-0.167***	-0.164***	-0.165***
		(0.0111)	(0.0111)	(0.0112)	(0.0112)	(0.0113)
Age squared		2.175***	2.185***	2.160***	2.123***	2.135***
		(0.137)	(0.136)	(0.137)	(0.138)	(0.138)
Female		-0.340***	-0.343***	-0.343***	-0.337***	-0.346***
		(0.0276)	(0.0276)	(0.0277)	(0.0276)	(0.0278)
Married		0.125***	0.127***	0.126***	0.127***	0.127***
		(0.0258)	(0.0258)	(0.0258)	(0.0258)	(0.0259)
Female & married		-0.301***	-0.301***	-0.303***	-0.312***	-0.303***
		(0.0368)	(0.0367)	(0.0368)	(0.0368)	(0.0371)
Years after immigration		0.151***	0.154***	0.153***	0.166***	0.165***
		(0.00839)	(0.00837)	(0.00838)	(0.0121)	(0.0123)
Bilingual household		0.162***	0.153***	0.147***	0.153***	0.148***
		(0.0250)	(0.0250)	(0.0255)	(0.0254)	(0.0256)
Year fixed effects	x	x	x	x	x	x
Basic individual controls		x	x	x	x	x
State control variables			x	x	x	x
State fixed effects				x	x	x
Cohort fixed effects					x	x
States with less than 500 Latin American Inhabitants excluded						x
Observations	14,250	14,250	14,250	14,250	13,990	13,676

Robust Standard errors in parathesis. Statistical significance is marked by stars. *** at 1 percent statistical significance ** at 5 percent statistical significance * at 10 percent statistical significance. The individual controls, from column two onwards, are in addition to the displayed variables the education of the individual. State control variables are the mean earnings and unemployment rates of natives in a state s at time t.

The estimates of Latin American hate crimes on South American immigrants' unemployment rates in table 7 compared with the results in table 6 point in the same direction. This is different from estimates on earnings. The estimates are also negative but approximately double the size. And also get statistically insignificant when introducing more control variables.

Table 7: Effect of Latin American hate crime on unemployment of South American Immigrants

	(1)	(2)	(3)	(4)	(5)	(6)
Latin American hate crime pc	-16.46***	-18.13***	-19.29***	-17.94	-17.19	-17.17
Age	(4.835)	(5.115)	(5.382)	(13.48)	(15.67)	(17.13)
		0.0831***	0.0827***	0.0818***	0.0779***	0.0764***
Age squared		(0.0169)	(0.0169)	(0.0169)	(0.0172)	(0.0172)
		-0.991***	-0.984***	-0.972***	-0.921***	-0.904***
Female		(0.208)	(0.208)	(0.209)	(0.212)	(0.212)
		0.0898**	0.0888*	0.0940**	0.113**	0.112**
Married		(0.0456)	(0.0456)	(0.0459)	(0.0467)	(0.0471)
		-0.141***	-0.140***	-0.142***	-0.127***	-0.132***
Female & married		(0.0462)	(0.0462)	(0.0465)	(0.0473)	(0.0478)
		0.344***	0.344***	0.342***	0.322***	0.326***
Years after immigration		(0.0602)	(0.0602)	(0.0606)	(0.0614)	(0.0619)
		-0.144***	-0.143***	-0.145***	-0.150***	-0.149***
Bilingual household		(0.0141)	(0.0141)	(0.0142)	(0.0172)	(0.0174)
		0.146***	0.140***	0.136***	0.129***	0.121***
Year fixed effects		(0.0390)	(0.0391)	(0.0405)	(0.0411)	(0.0416)
Basic individual controls	x	x	x	x	x	x
State control variables		x	x	x	x	x
State fixed effects			x	x	x	x
Cohort fixed effects				x	x	x
States with less than 500 Latin American Inhabitants excluded					x	x
Observations	15,102	15,102	15,102	15,066	14,799	14,519

Robust Standard errors in parathesis. Statistical significance is marked by stars. *** at 1 percent statistical significance ** at 5 percent statistical significance * at 10 percent statistical significance. The individual controls, from column two onwards, are in addition to the displayed variables the education of the individual. State control variables are the mean earnings and unemployment rates of natives in a state s at time t.

In additon, another sensitivity test was done in all tables from 4 to 9 and can be seen in column 6. Here, the states with the lowest immigrant population were excluded. The decision on which states got excluded was made by investigating possible outliers. Around 3% percent of the states got excluded, which seem to be the most significant outliers. The coefficients got closer to zero in all cases and lost their statistical significance. A discussion on the implications of these estimates will be done in the next chapter.

4.3 Discussion

The results suggest that the exact opposite of the stated hypotheses is true. In states with higher hate crimes per capita, Central American Immigrants have statistically higher wages. The question is if this means that discrimination could still be an explanation for these estimates.

One possible explanation is that the increase in hostility led to the sorting of immigrants. As already described, many immigrants from Central America are in the United States illegally and work mostly in low-skill jobs. As illegal immigrants are the main target of rhetoric and policy from the Trump administration, one can assume that hate crimes are also mainly against this group and may cause them to remigrate. Illegal immigrants are present in the ACS survey, which can be detected (Warren, 2018; Warren, 2019). As this is beyond the scope of this research, this possibility has to be left aside for future work. However, Warren (2019) also estimates that the number of illegal immigrants shrank from 2010 to 2017. Each subsequent year's survey might consist of more legal immigrants, with just higher wages on average. As Borjas and Cassidy (2019) can show, illegal immigrants earn significantly less than legal immigrants because legal immigrants have better labor protections. These differences, however, mostly disappear if correctly controlled for differences in education (Borjas & Cassidy, 2019). This may also point to the fact that the variable to control for the immigrant's education is not accurate enough. It is impossible to measure the years of education, and if the education was in the host or the source country, it might fail to accurately measure the skill level. If so, an increase in legal immigrants in the sample may have led to the effect that more hate crimes lead to a higher wage on average.

Another factor speaking for this theory is that unemployment is not changing as significantly as the earnings estimates, as can be seen when comparing the main results with the sensitivity tests. If the wages are influenced by hate crime but unemployment rates do not change significantly, this may explain that illegal immigrants remigrate more than legal immigrants. As diverse research points out, there is an urgent need in the United States economy for positions filled out by the primarily lower-skilled, Central American immigrants (Rosenblum & Brick, 2011; Borjas & Cassidy, 2019). If there is a high demand for lower-skilled workers, an open position will also be filled out by a legal immigrant instead, which has to be paid more. This would explain why the wages are influenced so much more significantly.

The sensitivity tests with the immigrants of South America shown in Tables 6 and 7 might also point in this direction. The wage increase cannot be observed; instead, the expected decrease from the theory part. Most illegal immigrants come from Central America, and the group from South America is a small minority (Warren, 2019). Due to this, it is not possible sorting out illegal immigrants in this group, which may also reduce the bias of the results. As they may appear very similar, they experience the same level of resentment. So one could argue that the estimates in this group are closer to the actual value of anti-Latin American hate crime on labor market assimilation. Because here, the bias is not as high if we cannot control for an individual's immigrant status.

Another explanation is a sorting pattern between states. A hint that this might be the case is column 6 in Tables 4 and 5. It was conducted by excluding the states with the lowest population estimated. Because immigrants are most commonly drawn to places where an established community of their home country is already established (Gurak & Fee, 1992). Therefore, for immigrants to go to places with no or just a small community has to have a different incentive, like a job offer. The immigrants in this state might not be representative of the average population. In addition, sentiments in regions with low numbers of immigrants usually are higher than in regions where the native population is confronted with other ethnic groups more regularly (Rees et al., 2019).

To conclude, immigrants who migrate to places with low numbers of immigrants may have concrete job opportunities there. Nevertheless, as the population in these regions is expected to have the highest resentments against immigration, discrimination, and hate crime, it might also be higher on a per capita basis. So, these individuals might do even better with lower discrimination in their state. As they have a better position in the labor market than the average, this difference cannot be observed in a cross-sectional analysis.

The results that occurred in this way might also be because of the general approach taken. Because the estimates were based on a cross-section dataset, it was impossible to observe the same individual over time. This even allowed the possibility of sorting in the first place. It might be interesting to conduct similar research for further research but with a longitudinal dataset. In summary, that the estimates for Central American Immigrants suffer from omitted variable bias, is one of the most likely explanations for the deviating results for Central American Immigrants. As the information if the individuals are legal- or illegal immigrants cannot be included. As this pattern is not observed in the estimates for Muslim immigrants in Appendix B. In addition, the sensitivity test, excluding low-population states has revealed the possible explanation of sorting. It shed a light at possible biases when including territories with very heterogeneous immigrant populations with respect to size and composition into the same model. However, it is unlikely that one of these explanations is responsible for the deviation from the main results from the theoretical estimates on its own.

5 Conclusion

This research aimed to investigate if the rise in resentment against Central American immigrants made it harder for them to assimilate into the American labor market. In addition, it focused on the time of the 2016 presidential election and the rise in hate crimes during this period. This period was not investigated before in this context. By combining the theories of immigrant assimilation, discrimination, and hate crime, the assumption was that later cohorts, which phase more discrimination, have a more challenging time integrating into the labor market. The number of hate crimes was used to measure resentment against immigrants.

Using an OLS and a probit model, the influence of the increase in hate crimes on earnings and unemployment rates was measured, respectively. However, the estimates point in the opposite direction as the theory predicts. When hate crime rates increase, Central American immigrants are less likely to be unemployed and have higher earnings. Especially the rise in earnings is quite significant. Engaging in this respect is that for South American and Muslim immigrants, this pattern does not occur. As hate crimes also increased against these groups, there is possibly another factor behind this deviation of results. Some possible explanations are the unique composition of the group of Central American immigrants. As the proportion of illegal immigrants is the highest in this group, the rising pressure might lead to a lower proportion of illegal immigrants in the population and, therefore, the ACS surveys.

In addition, the exclusion of low populated states shows a lowering of the effects overall analyzed ethnic groups. This may highlight the problems of measuring discrimination in a country with such heterogeneous community compositions as the United States. This also may question other research results looking at pushback against immigrants in the United States after other events like 9/11. It would be maybe valuable to conduct this research once again with a bigger focus on the possible difference between the different states.

As this is the first study that looks specifically at the impact of the Trump presidency on the economic situation of Central American immigrants, this paper still contributes valuable insight into the topic. It can clearly show that this group does react differently and that cross-sectional approaches are unlikely to find reliable estimates without information about the legal status of immigrants. In the next step, a new investigation should use a longitudinal dataset. Both described problems could be better managed when observing the same individual over time and should try to focus. Furthermore, this research showed that discrimination could influence immigrant groups differently. The explanation that the high share of illegal immigrants might drive some of the shown effects for Central American immigrants shows that further research should investigate the link between discrimination and an immigrant's legal status in more detail. This thesis, therefore, brought the first insights into this topic.

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Appendix A

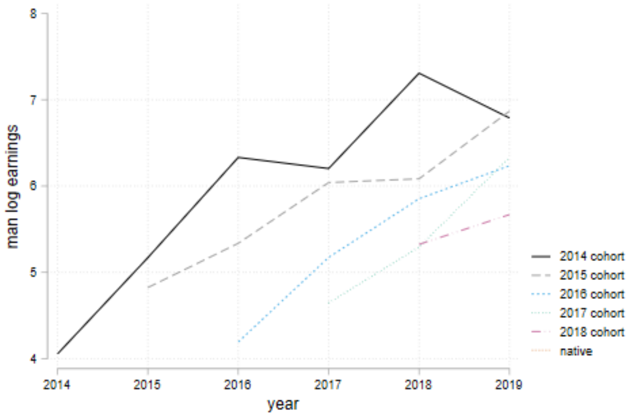

Figure 8: log earnings of 9/11 countries

Note: Own calculations using ACS 2014-2019

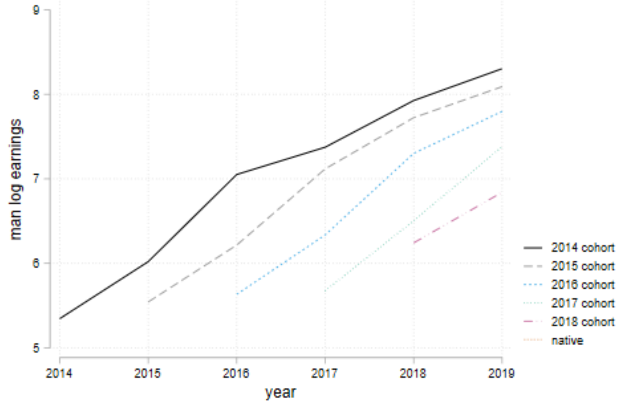

Figure 7: log earnings Asian without 9/11 countries

Note: Own calculations using ACS 2014-2019

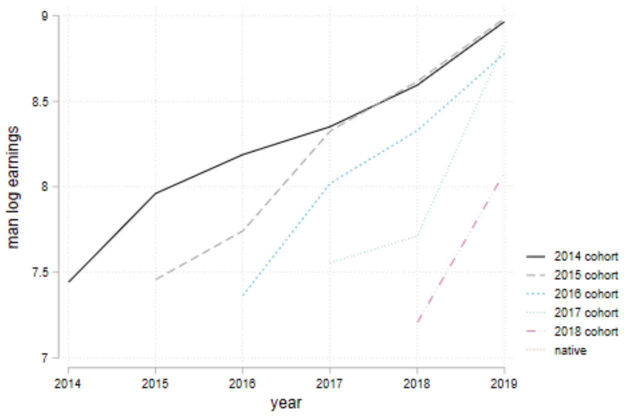

Figure 10: log earnings European immigrants

Note: Own calculations using ACS 2014-2019

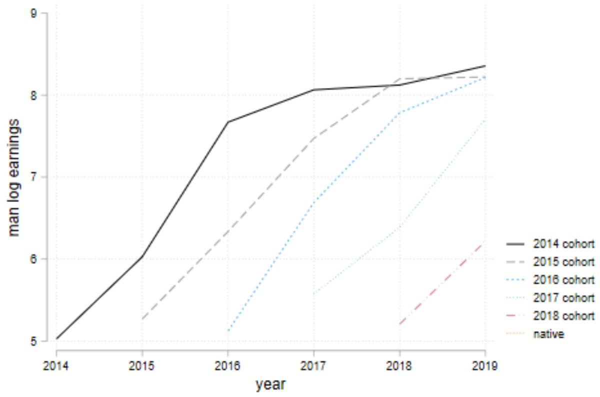

Figure 9: log earnings of South American immigrants

Note: Own calculations using ACS 2014-2019

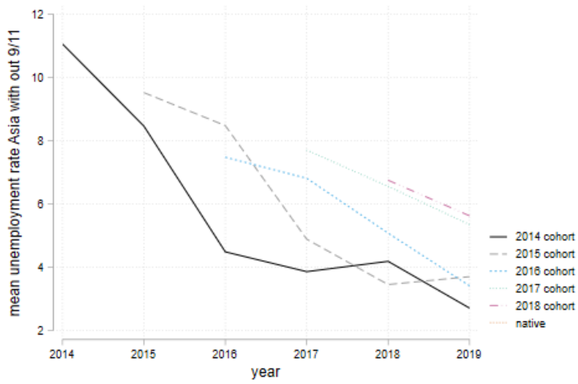

Figure 12: mean unemployment rate Asia without 9/11

Note: Own calculations using ACS 2014-2019

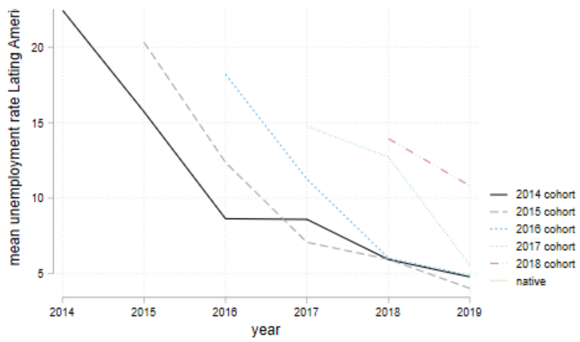

Figure 14: mean unemployment rate Laten American immigrants

Note: Own calculations using ACS 2014-2019

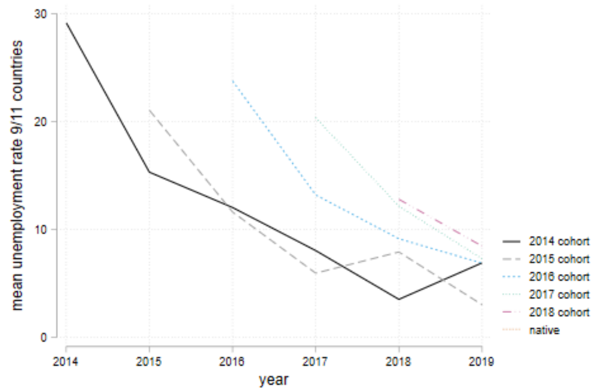

Figure 11: mean unemployment 9/11 countries

Note: Own calculations using ACS 2014-2019

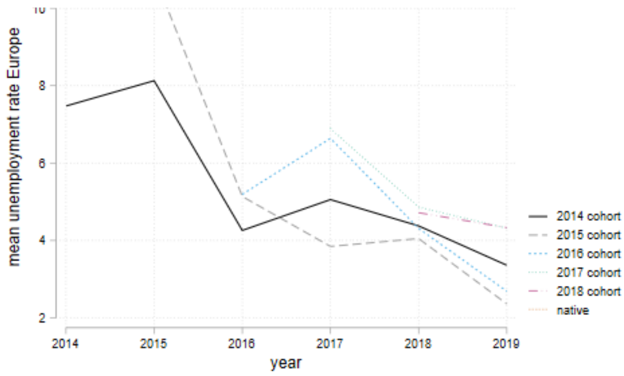

Figure 13: mean unemployment rate European immigrants

Note: Own calculations using ACS 2014-2019

Appendix B

Table 8: Effect of Muslim hate crime on log earnings of 9/11 country immigrants

	(1)	(2)	(3)	(4)	(5)	(6)
Muslim hate crime pc	-1.755*	-1.531*	-1.294	-1.696	-1.262	-2.297
	(0.963)	(0.862)	(0.865)	(1.959)	(2.131)	(2.405)
Age		-0.214***	-0.215***	-0.209***	-0.215***	-0.215***
		(0.0302)	(0.0302)	(0.0307)	(0.0308)	(0.0311)
Age squared		2.735***	2.743***	2.670***	2.742***	2.750***
		(0.373)	(0.373)	(0.379)	(0.381)	(0.384)
Female		-0.228***	-0.231***	-0.238***	-0.256***	-0.256***
		(0.0786)	(0.0783)	(0.0788)	(0.0797)	(0.0806)
Married		0.0586	0.0587	0.0651	0.0446	0.0468
		(0.0552)	(0.0550)	(0.0555)	(0.0561)	(0.0568)
Female & married		-0.386***	-0.383***	-0.379***	-0.354***	-0.365***
		(0.0951)	(0.0947)	(0.0954)	(0.0962)	(0.0975)
Years after immigration		0.125***	0.126***	0.128***	0.127***	0.124***
		(0.0170)	(0.0170)	(0.0172)	(0.0254)	(0.0257)
Bilingual household		0.138*	0.140*	0.123	0.123	0.129*
		(0.0775)	(0.0776)	(0.0770)	(0.0780)	(0.0785)
Year fixed effects	x	x	x	x	x	x
Basic individual controls		x	x	x	x	x
State control variables			x	x	x	x
State fixed effects				x	x	x
Cohort fixed effects					x	x
States with less than 500 Latin American Inhabitants excluded						x
Observations	3,720	3,720	3,720	3,720	3,639	3,554

Robust Standard errors in parathesis. Statistical significance is marked by stars. *** at 1 percent statistical significance ** at 5 percent statistical significance * at 10 percent statistical significance. The individual controls, from column two onwards, are in addition to the displayed variables the education of the individual. State control variables are the mean earnings and unemployment rates of natives in a state s at time t.

Table 9:Effect of Muslim hate crime on unemployment of 9/11 country immigrants

	(1)	(2)	(3)	(4)	(5)	(6)
Muslim hate crime pc	0.671	0.636	0.750	-1.813	-1.999	0.520
	(1.235)	(1.300)	(1.306)	(3.111)	(3.362)	(3.617)
Age		0.0890**	0.0888**	0.0914**	0.0933**	0.0827**
		(0.0354)	(0.0354)	(0.0358)	(0.0366)	(0.0371)
Age squared		-1.067**	-1.065**	-1.099**	-1.114**	-0.993**
		(0.443)	(0.443)	(0.447)	(0.457)	(0.463)
Female		-0.0426	-0.0434	-0.0400	-0.0432	-0.0701
		(0.117)	(0.117)	(0.119)	(0.120)	(0.121)
Married		-0.0107	-0.00963	-0.00425	-0.00409	-0.0262
		(0.0867)	(0.0866)	(0.0872)	(0.0886)	(0.0887)
Female & married		0.489***	0.490***	0.502***	0.487***	0.519***
		(0.135)	(0.135)	(0.137)	(0.138)	(0.139)
Years after immigration		-0.144***	-0.145***	-0.147***	-0.132***	-0.128***
		(0.0256)	(0.0256)	(0.0256)	(0.0351)	(0.0358)
Bilingual household		-0.201*	-0.201*	-0.211*	-0.205*	-0.203
		(0.119)	(0.120)	(0.122)	(0.123)	(0.124)
Year fixed effects	x	x	x	x	x	x
Basic individual controls		x	x	x	x	x
State control variables			x	x	x	x
State fixed effects				x	x	x
Cohort fixed effects					x	x
States with less than 500 Latin American Inhabitants excluded						x
Observations	3,895	3,895	3,895	3,838	3,756	3,680

Robust Standard errors in parathesis. Statistical significance is marked by stars. *** at 1 percent statistical significance ** at 5 percent statistical significance * at 10 percent statistical significance. The individual controls, from column two onwards, are in addition to the displayed variables the education of the individual. State control variables are the mean earnings and unemployment rates of natives in a state s at time t.