Taste-based discrimination: In-group bias on peer-to-peer lending platforms? Evidence from Lending Club

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Date of submission: 27-07-2020

Abstract

This study examines whether in-group bias affects the funding likelihood, interest rate, and loan amount received by peer-to-peer borrowers. It exploits a difference-in-difference approach on Lending Club loan data over the years 2008 to 2015. Within this timeframe, the Boston Marathon Bombing is used as an exogenous shock. This study investigates whether borrowers, living in a top decile Metropolitan Statistical Area in terms of the Middle Eastern and Southeast Asian immigrant ratio, are being discriminated against. The key findings of this study show that borrowers living in these areas are less likely to receive a loan, pay higher interest, but appear to perform better than the control group. This evidence fits best with the taste-based model of discrimination, implying that peer-to-peer lenders are willing to leave money on the table to avoid interaction with the discriminated group.

Keywords: Discrimination, Ethnicity, Peer-to-peer Lending

Contents

I. Introduction

Peer-to-peer lending platforms are one of the most prominent innovations of the FinTech era (Varga, 2017). These platforms have emerged since 2005 and allow both individuals and small enterprises to borrow money without the need for a traditional financial intermediary. However, removing the financial intermediary poses larger behavioral challenges. Peer-to-peer lenders might engage in bidding on multiple loans resulting in more investment decisions. Therefore, any behavioral bias displayed by these lenders affect more investment decisions, and thus enlarges the impact of the bias.

Empirical evidence proves that stereotyping and the familiarity bias exist in peer-to-peer lending. Stereotyping, either positive or negative, could stop people from processing both new and unexpected information (McCarthy, 2002). This can lead to discrimination that impacts financial decision-making in various ways. Economic theory distinguishes between statistical discrimination (Phelps, 1972) and taste-based discrimination (Becker, 1957). Statistical discrimination is based on rational investors having imperfect information, whereas taste-based discrimination is based on animus towards a group.

Existing studies draw divergent conclusions on discrimination in peer-to-peer lending. Some find that peer-to-peer lenders discriminate against younger borrowers because lenders perceive younger borrowers to have a lower likelihood of repaying their loan (Komorova Loureiro & Gozalez, 2014). This indicates a form of statistical discrimination because there is a higher probability of default in this group. On the contrary, Pope & Syndor (2011) conclude that the probability of funding is higher for younger borrowers.

Several studies agree on the fact that the impact of demographic discrimination on the likelihood of funding and interest rates is relatively small. However, they highlight one exception, namely when it comes to race. Ravina (2008) concluded that black borrowers pay up to 146 basis points more for their loans compared to white borrowers with similar characteristics. Adding a picture lowers the probability of funding by up to 30 percent when being black (Pope & Syndor, 2011). This is evidence supporting the taste-based form of discrimination. Existing literature does not elaborate on discrimination against belief or religion that is associated with a borrower's ethnicity. This research aims to fill this gap by answering the following research question:

Do in-group stereotypes affect the funding likelihood, interest rate, and loan amount that peer-to-peer borrowers receive?

This study analyses whether in-group stereotypes associated with a person's origin and beliefs affect the investment decisions of peer-to-peer lending borrowers. More specifically, it examines whether peer-to-peer borrowers living in a Metropolitan Statistical Area with a top decile ratio of Middle Eastern and Southeast Asian immigrants are discriminated against in terms of obtaining a loan, the payable interest rate, and the loan amount received. To empirically test this, a difference-in-difference approach is applied using the Boston Marathon Bombing as an exogenous shock. Following Arnold, Dobbie, & Yang (2018), lenders are defined as racially biased against minority borrowers if they perceive higher benefits of funding a majority borrower, then of funding an observably identical minority borrower.

The results show that living in a top decile Metropolitan Statistical Area in terms of minority immigrant ratio after the Boston Marathon Bombing significantly decreases the likelihood of getting funded with 1.28%, while increasing the interest rate up to 11 basis points. Conditional on getting funded, the loan amount received decreases by up to $3,105. However, borrowers living in a top decile Metropolitan Statistical after the Boston Marathon Bombing decreases the default rate with 0.48%. In sum, the minority group is less likely to receive a loan, pay higher interest, but appear to perform better than the control group. This evidence fits best with the taste-based model of discrimination. It implies that peer-to-peer lenders are willing to leave money on the table to avoid interaction with the discriminated group.

The method and findings of this study contribute to the growing literature on in-group bias and discrimination in financial markets. Research on discrimination in the labor market (Becker, 1957), courtrooms (Arnold, Dobbie, & Yang, 2018), mutual funds (Kumar, Niessen-Ruenzi, & Spalt, 2015), FinTech mortgage providers (Barlett et al., 2018) and peer-to-peer lending (Ravina, 2008) has already been well-established. This study enriches existing literature by proving that a terrorist attack induces taste-based discrimination within the peer-to-peer lending market. Furthermore, most studies examine discrimination against black or Hispanic people. This study builds upon the method and findings of Kumar, Niessen-Ruenzi, & Spalt (2015) and confirms the existence of discrimination towards Middle Eastern and Southeast Asian immigrants as a minority group. The applied methodology of measuring discrimination could be applied to a wider variety of settings.

The remainder of this study is structured as follows. First, the reader is provided with a literature review, after which the hypotheses are introduced. Then, the data and methodology are explained. After, the results are displayed, followed by the discussion. Lastly, the main conclusions are drawn.

II. Literature review

This section elaborates on discrimination in a variety of settings. First, it explains two classes of discrimination theories between which existing literature distinguishes. Next, it elaborates on discrimination in equity markets. This highlights that group of interest for this study, Middle Eastern and Southeast Asian immigrants, are being discriminated against. Then, it elaborates on existing literature regarding discrimination in FinTech applications, followed by the definition of taste-based discrimination as it is referred to in this study.

A. Two classes of discrimination theory

The American Oxford Dictionary (2006) defines discrimination as 'the unjust or prejudicial treatment of different categories of people or things, especially on the grounds of race, age, or sex'. Many economic researchers have attempted to detect, measure and understand discrimination in economic markets. A large part of this interest is because these unjust or prejudicial treatments towards a distinct group of people can result in the exclusion of access to financial markets and the opportunities these markets bring along. This, in turn, has large implications for public policymakers who often aim to reduce these disparities. One of the most prominent theories that is still widely applied to economics is the taste-based discrimination theory developed by Becker (1957). Before delving into the models measuring discrimination, the more psychological origin of discrimination must be addressed. Tajfel (1982) stated that humans identify other individuals based on group membership and form opinions about one another accordingly. Psychological research has shown that people systematically form more favorable opinions about individuals within their group, compared to individuals outside their group. This opinion-forming behavior in favor of in-group members has severe social and financial implications and is the main driver for forming prejudices, stereotyping, and discrimination (Hewstone, Rubin, & Willis, 2002).

Becker (1957) started to explore whether individual tastes of employers, co-workers or customers, in the form of prejudices, might produce discriminating outcomes in the labor market. The most critical assumption he made was that economic agents behave as if they are rational, with agents having a taste for discrimination being the only behavioral factor. In other words, agents are willing to give up part of their income or pay something extra to prevent themselves from being associated with particular people. This is contradicting rational economic theory that assumes that agents aim to maximize their income. To measure discrimination empirically, Becker introduced the discrimination coefficients. Part of Becker's work explored the relationship between individual prejudice concerning race, black or white, and market discrimination. The market discrimination coefficient is defined as the "difference between the actual ratio of the incomes of W and N and this ratio without discrimination", where N is the negatively prejudiced group (Becker, 1976). Specifically, he found that discrimination harmed the income of African American people. This effect is stronger for monopolistic industries, implying that market competition influences the way individual tastes result in discriminatory outcomes.

The taste-based discrimination model of Becker received some criticism. For example, Becker assumes discriminatory tastes as given. Based on these criticisms, Phelps (1972) and Arrow (1972) designed the statistical discrimination model. In this model, agents are assumed to show rational optimizing behavior. However, due to imperfect information, agents might treat an individual as a member of a group. To illustrate, imagine an employer that tries to estimate an applicant's productivity. Next to the applicant's resumé, the employer knows the applicant's demographic characteristics, including race, gender and age. As there is imperfect information, the employer bases the hiring decision on a weighted average of the impression he or she got from the resumé and the average productivity of the group that the employer associates the applicant with.

The main difference between the two models is the underlying cause of discrimination. Becker's taste-based discrimination stems from an animus towards a certain group that make market participants willing to pay a price for not interacting with this group, while market participants in the statistical model discriminate by treating individuals as part of a group due to imperfect information (Altonji & Blank, 1999). In other words, statistical discriminators are aiming to optimize their behavior and thus not willing to pay a price for not interacting with a certain group. These two models are widely applied in the existing literature and aim to assess both the presence of market discrimination and the magnitude of the observed discrimination (Charles & Guryan, 2008). Understanding the roots of observed discrimination, which model explains the observed discriminatory behavior best, is highly relevant to interpret the results in this research. Also, it has broad policy-related implications. Policymakers might need different strategies to tackle discrimination based on animus compared to discrimination stemming from imperfect information.

B. Discrimination in Financial Markets

Before delving into the financial markets, the legal system proved to play a key role in shaping the rights and responsibilities of investors, institutions, and other market participants (Pistor, 1999). Kennedy (1997) argued that if deemed reasonably related to prosecution, courts and its executors often believe race can be used as a determinant in predicting whether the defendant in the case committed the crime. Existing research proved that racial discrimination exists within police vehicle searches (Knowles, Persico, & Todd, 2001; Antonovics & Knight, 2009), pretrial release decisions (Arnold, Dobbie, & Yang, 2018), conviction verdicts (Anwar, Bayer, & Hjalmarsson, 2012), imprison verdicts (Abrams, 2012), and reversals of capital sentencing by first-degree courts (Alesina & La Ferrara, 2014). However, the above-mentioned researches provide contradicting evidence regarding the form of discrimination that mostly drives the racial bias.

Taking in mind that discrimination is present within the legal system, and the legal system plays a crucial role in shaping financial markets, existing literature on discrimination in financial markets is discussed for the remainder of this section. Even though researches have investigated discrimination based on a variety of demographic dimensions, this section solely highlight discrimination because of ethnicity. This is in line with the aim of this study, which examines whether peer-to-peer lenders are biased against an ethnic group based on the country of origin, associated beliefs and religion of this group.

One of the most examined behavioral biases in financial markets is the equity home bias. This bias implies that investors are under diversified, as a country disproportionally invests in domestic equity as opposed to the optimal diversified asset allocation (Tesar & Werner, 1995). Within country borders, investors also prefer investing in assets within their agglomerated cities as opposed to domestic equities outside of their city agglomerates (Goetzmann, Massa, & Simonov, 2004). Morse & Shive (2011) provide an additional explanation for this equity home bias. They measure patriotism and conclude that countries which scored ten percent lower on patriotism, have, on average, four percent more foreign equity holdings. By shedding light on specific company stock investments, Grinblatt & Keloharju (2001) investigate the equity home bias of Finnish institutional- and household investors. They find that both investor types invest and trade more heavily in firms that are headquartered close by; that have a CEO who speaks the same language; and that have a CEO with the same cultural beliefs. Additionally, their results are in line with the findings of

Goetzmann, Massa, & Simonov (2004), as the location effect weakens after the distance exceeds 100 kilometers.

One possible behavioral explanation for the above-mentioned results might stem from the in-group favoritism as described by Hewstone, Rubin, & Willis (2002). In other words, investors might use the firm's location, mother tongue, and cultural beliefs of its CEO as inputs to determine group membership. Therefore, the results by Grinblatt & Keloharju (2001) could be driven by this in-group bias, implying that investors believe they will earn excess returns by investing in these 'in-group' firms. These excess returns would then suggest that the statistical form of discrimination fits best. However, if the realized returns would turn out lower, investors paid a price to avoid interaction with a group, which is indicative of the taste-based form of discrimination.

Jannati et al. (2020) provide additional support for the in-group bias. The authors shift the root cause of the bias from investors to equity analysts. More specifically, they investigate whether equity analysts' earnings forecasts display in-group bias based on ethnicity. Using American analyst data, they find that when making forecasts, equity analysts have a higher probability of underestimating earnings of firms with a foreign CEO, compared to firms with a domestic CEO. This results in equity analysts making fewer buy recommendations for firms led by a foreign CEO. As individual- and institutional investors often base their investment decisions on these recommendations, these displayed ethnicity preferences of equity analysts enlarge the equity home bias.

Kumar, Niessen-Ruenzi, & Spalt (2015) examine whether mutual fund managers with foreign-sounding names affect the investment-decisions of mutual fund investors in the United States. They find that foreign-sounding managers have around ten percent fewer fund flows. To establish whether this is due to taste-based discrimination, the authors introduce the 9/11 attack as an exogenous shock that may have provoked negative stereotyping against mutual fund managers originating from Middle Eastern and Southeast Asian countries. The results confirm the presence of taste-based discrimination as the fund flows of mutual fund managers with a Middle Eastern and Southeast Asian sounding name declined abnormally after the 9/11 attack. Other mutual fund managers with a foreign-sounding name did not experience a significant abnormal decline in fund flows.

The above-mentioned literature proved the importance and presence of group membership within several dimensions of financial markets. This group membership can result in discrimination. Equity analysts recommending investors on their portfolios (Jannati et al., 2020), direct investments by individual and institutional investors (Grinblatt & Keloharju, 2001), and indirect investments are prone to forms of taste-based discrimination (Kumar, Niessen-Ruenzi, & Spalt, 2015). As the peer-to-peer lending market is an innovative application of a financial market that is less mature and less regulated than the stock and bond markets, this market might also be subject to discrimination. Additionally, Kumar, Niessen-Ruenzi, & Spalt (2015) show that market participants originating from Middle Eastern and Southeast Asian countries are discriminated against following a terrorist attack associated with Islamic beliefs. Using a similar identification strategy, this research investigates whether Middle Eastern and Southeast Asian immigrants in the United States are discriminated against following the Boston Marathon Bombing.

C. Discrimination in FinTech applications

This section elaborates on multiple forms of discrimination within FinTech applications. Even though the FinTech era is still relatively young, many researchers already devoted their attention to its behavioral implications. As most FinTech applications are running on an algorithm, one could expect that discrimination would vanish over time. However, existing literature agrees upon the existence of discrimination in FinTech applications but draws divergent conclusions on its underlying roots; taste-based discrimination or statistical discrimination.

Over the past two decades, as part of the FinTech era, a major shift from face-to-face originated consumer loans to algorithmic originated loans has occurred. Over 45% of U.S. mortgage lenders, including the well-known banks, act as FinTech operators offering their clients' complete online mortgage contracting (Barlett et al., 2018). As credibility assessments are being performed algorithmically, one would expect that the roots of discrimination would shift from in-group favoritism and racial bias to the statistical form of discrimination. Using the GSE pricing model, Barlett et al. (2018) aim to map out discrimination against minorities in the U.S. Their results show that where Latin American and African American minorities are discriminated against in terms of mortgage loan rejection rates by face-to-face mortgage providers, minorities are no longer discriminated against in rejection rates by FinTech mortgage providers. Nevertheless, amongst FinTech accepted mortgages, minorities pay 16.9 basis points higher interest. After controlling for income, loan-to-value ratios, loan characteristics, and country fixed effects, the authors show that 5.3 basis points purely exist due to discriminatory reasons. This evidence suggests that algorithms exhibit some form of taste-based discrimination.

Focusing solely on discrimination in peer-to-peer lending, it is important to keep in mind that lenders usually voluntarily choose in which borrower they invest. Regarding this choice, some argue that younger borrowers are perceived as riskier, as they have a lower likelihood of repaying their loan (Komorova Loureiro & Gozalez, 2014)**.** On the contrary, Pope & Syndor (2011) conclude that the probability of funding is significantly higher for younger borrowers.

Multiple pieces of research agree on the fact that the impact of demographic discrimination on the likelihood of funding and interest rates is relatively small. Nevertheless, they shed light on one exception, namely when the race is involved. While controlling for hard financial variables, personal borrowers' characteristics and listing characteristics, Ravina (2008) examines whether borrowers' race results in disparities of funding probability and interest paid by borrowers on Prosper. She finds that black borrowers pay up to 146 basis points more for their loans, or receive, on average, $2,483 less compared to white borrowers with similar characteristics. However, there is no statistical difference in delinquency rates between white and black borrowers. The author shows that this difference in interest rate is mostly explained by the proportion of black lenders to black borrowers as lenders might have a strong preference for funding borrowers of the same race. Black lenders prefer to fund black borrowers, and based on realized returns, black lenders seem to have an advantage when screening black borrowers compared to white borrowers. This is indicative of statistical discrimination.

Contradictory, adding a picture lowers the probability of funding up to 35 percent when being black (Pope & Syndor, 2011). Using similar Prosper data, these authors find that black borrowers with similar credit characteristics pay up to 80 basis points higher interest compared to white borrowers. Interestingly, peer-to-peer lenders are less likely to fund listings without a picture and base their investment decision on the perceived race from the picture above the credit characteristics. This is evidence suggests the presence of taste-based discrimination within peer-to-peer lending.

In summary, the established researches on behavioral biases in peer-to-peer lending agree that when controlling for personal characteristics and financial variables, racial discrimination is present. Yet, there is still contradicting evidence on whether the taste-based discrimination or statistical discrimination model explains the observed results best. Therefore, applying this new identification strategy to Lending Club data aims to gain insight into the correct model explaining discrimination, as well as it examines whether Middle Eastern and Southeast Asian immigrants are being discriminated against.

D. Defining taste-based discrimination in peer-to-peer lending

Based on the application of Becker's (1957) taste-based discrimination model developed by Arnold, Dobbie, & Yang (2018), taste-based discrimination within Lending Club is defined in this section. Borrower i has a listed loan on Lending Club, and possible lenders consider all borrower and loan characteristics denoted by V_i, except for the borrowers' ethnicity e_i. The expected costs for lender j, conditional on borrower and loan characteristics V_i and e_i, are corresponding to the expected probability of default. The perceived benefit of funding borrower i for lender j, is a function of borrower and loan characteristics, and is expressed by $t_e^j(V_i)$. These lender benefits are mainly in the form of interest earnings related to the funding. Essentially, the perceived benefit of funding can vary by ethnicity. For simplicity, ethnicity is split up into 'minority', Middle Eastern and Southeast Asian immigrants, and 'majority' borrowers. For the remainder of this study, Middle Eastern and Southeast Asian immigrants and minorities are used interchangeably.

Lender j is defined as biased against minority borrowers if $t_{maj}^j(V_i) > t_{min}^j(V_i)$. In other words, lenders are racially biased against minority borrowers if they perceive higher benefits of funding a majority borrower, then of funding an observably identical minority borrower.

III. Hypotheses development

This research aims to provide evidence on whether discrimination in the form of in-group bias, towards Middle Eastern and Southeast Asian immigrants in the U.S., affects the funding likelihood, interest rate, and loan amount for peer-to-peer lending borrowers. In this section, the hypotheses that contribute to answering the above-stated research question are developed.

Following basic rational economic theory, rational investors want to be compensated for the investment with the risk-free rate plus an additional risk premium depending on investment-specific risk. However, following behavioral theory of taste-based discrimination developed by Becker (1957), economic agents are willing to pay a price to avoid interacting with a certain group of people. These agents would be willing to sacrifice part of their compensation to avoid interaction with this group. If Middle Eastern and Southeast Asian immigrants are associated with Islamic beliefs, animus towards this group is presumable. Applying this to peer-to-peer lending, lenders would avoid interaction with areas that have a high Middle Eastern and Southeast Asian immigrant ratio. This would result in a lower funding likelihood for these high minority ratio areas. To empirically test this, the following hypothesis is developed:

H1: The Middle Eastern and Southeast Asian immigrant ratio decreases the funding likelihood

Aside from the willingness to pay to avoid interaction with a group, if lenders discriminate based on taste, they might perceive members of the discriminated group as riskier. These higher perceived risks result in lenders demanding higher returns. If these excess perceived risks are compensated via the interest rate, lenders might be willing to interact with this group. Therefore, it is expected that an area with a high ratio of Middle Eastern and Southeast Asian immigrant ratio is perceived by lenders with higher risk, resulting in higher interest rates. This is in line with the findings of Barlett et al. (2018) and Ravina (2008).

H2: The Middle Eastern and Southeast Asian immigrant ratio increases the interest rate

Shifting away from interest rate to the loan amount, lenders might perceive a higher risk of interacting with a high Middle Eastern and Southeast Asian immigrant ratio area for relatively large loans compared to small loans. Put differently, a higher requested loan amount can be funded by either a larger number of lenders or by larger investments of lenders. Both options are likely to result in more screening by lenders. Combining this increase in screening with the higher perceived risk of interaction with high Middle Eastern and Southeast Asian immigrant ratio areas results in a negative relationship between the minority ratio and the funded loan amount. This is examined by testing the following hypothesis:

H3: The Middle Eastern and Southeast Asian immigrant ratio decreases the funded loan amount

Taste-based discrimination is based on animus towards Middle Eastern and Southeast Asian immigrants, rather than a rational form of discrimination based on risk. Therefore, the ability to repay the loan for observable identical borrowers should not differ between the discriminated group and other borrowers. This is in line with the findings of Ravina (2008). However, as the first hypothesis already examines, the default rate does not only depend on ethnicity, but also on the screening skills of the lenders at the first stage. Following the first hypothesis, it is expected that the perceived risk of high Middle Eastern and Southeast Asian immigrant ratio areas is already adjusted for. Logically, if loans in these high minority ratio areas are still getting funded after the screening, lenders perceive these loans as less risky, expecting that these loans default less compared to low minority ratio areas. This corresponds with the definition of taste-based discrimination, described in section D of the literature review. To examine whether peer-to-peer lenders exhibit a form of taste-based discrimination, the following hypothesis is formulated:

H4: The Middle Eastern and Southeast Asian immigrant ratio decreases the default rate

IV. Data & Methodology

This section describes the construction of the data set. In addition, it elaborates on the empirical identification strategy, including the variables, regressions and exogenous shock that are used to test the hypotheses. The methodology is mostly derived from Arnold, Dobbie, & Yang (2018), Ravina (2008), and Kumar, Niessen-Ruenzi, & Spalt (2015).

A. Data

This subsection starts with shortly describing Lending Club and its processes. After, it elaborates on the data collection and dataset construction. An overview of the used variables, including descriptions, can be found in Appendix A. This section concludes with the descriptive statistics of the data.

1. Lending Club

Lending Club is the largest online peer-to-peer lending platform in the United States. Their core business is to match borrowers to lenders for both personal and business loans. When applying for a loan, Lending Club decides to either reject or accept your application. Based on both personal and financial characteristics, Lending Club assigns each borrower with a loan grade that should reflect the creditworthiness of the borrower. Lending Club uses the FICO score, loan application information, debt-to-income ratio, and the applicants' credit history to determine this loan grade (Lending Club, 2020). Once accepted by Lending Club, the borrower is offered a range of products differing in the interest and the loan term. The loan term can either be 36 months or 60 months. After the borrower chooses its preferred option, the loan is listed on Lending Club's platform where lenders can decide to fund your requested amount. Therefore, the range of products that are offered to lenders should already reflect the risk of funding that specific borrower.

Lenders active on Lending Club can divide their total investment up to small investments with a minimum of $25. Investing multiple small amounts into different borrowers delivers a diversified portfolio. Lenders have two primary mechanisms to allocate their investment to borrowers. First, lenders can cherry-pick individual borrowers, and based on individual screening, decide whether they are willing to fund this borrower. This way, lenders must go through every borrower they invest in manually. Second, Lending Club offers an automated investment tool. This tool allows lenders to set their desired investment criteria and after, the tool automatically allocates funding based upon these criteria. With the criteria, an investor can decide to filter on its desired interest rate or loan grade. This method might be convenient for lenders with limited time or knowledge. Lending Club offers this tool to all its investors for free.

There are three main reasons why Lending club data is used in this study. First, it is one of the few peer-to-peer lending platforms of which their data is publicly available. Second, it provides the first three digits of the borrower's zip code, which is needed for the identification strategy. With these three digits, borrowers can be located up until their Metropolitan Statistical Area. Lastly, Lending Club is the largest peer-to-peer lender in the U.S., and thus the results are likely to apply more generally.

2. Data collection

Lending Club loan data for both accepted and rejected loans, starting from January 2008 up until December 2015, is retrieved from the Lending Club website. To empirically test whether Lending Club lenders are biased against minority borrowers, a distinction based on minority and majority borrowers needs to be made. Since the ethnicity of borrowers cannot be observed directly, this study distinguishes borrowers from one another based on the minority immigrant ratio per Metropolitan Statistical Area. Data regarding Middle Eastern and Southeast Asian immigrants and their location within the United States is retrieved from the Migration Policy Institute. The Migration Policy Institute is nonpartisan and aims to improve immigration and integration policies by doing authoritative analyses (Migration Policy Institute, 2020). Their website provides access to a database including the U.S. immigrant population, originating from Middle Eastern and Southeast Asian countries, by Metropolitan Statistical Area.

The average immigrant ratio over the pre-shock period is calculated and based on this average, the Metropolitan Statistical areas are ranked. Appendix B provides an overview of the Metropolitan Statistical Areas, including the corresponding minority immigrant ratio. The data set is divided into a treated group and a control group. Metropolitan Statistical Areas in the highest decile in terms of Middle Eastern and Southeast Asian immigrant ratio are defined as treated. At the same time, the remaining Metropolitan Statistical Areas function as the control group.

To be able to calculate the interest rate spread, the Federal Fed Funds rates are retrieved from Bloomberg. Furthermore, to test the last hypothesis, all current loans that cannot yet be classified as defaulted or paid back are dropped out of the data set. Lastly, outliers are deleted, and the loan amount, annual income, and total revolving balance variables are transformed into logarithmic variables.

3. Descriptive statistics

Existing studies often argue that black people and Hispanics, as two of major minority groups in the United States, are discriminated based on their race. If these minorities are highly correlated with the Middle Eastern and Southeast Asian immigrant ratio, this might be problematic. To ensure the examined minority ratio drives the results, the correlation coefficients between the five major racial categories, as recognized by the United States Census Bureau (United States Census Bureau, 2020) are displayed in Table 1. As the first column shows, the African American, Hispanic, and Native American ratios per Metropolitan Statistical Area are weakly correlated with the Middle Eastern and Southeast Asian immigrant ratio. The Asian American ratio is weak to moderately correlated with the Middle Eastern and Southeast Asian ratio. This might be explained as Asian Americans have interfaces with Southeast Asians and are therefore more likely to gather in particular Metropolitan Statistical Areas. However, based on the correlation coefficients, it can be assumed that the results found in this study are driven by the Middle Eastern and Southeast Asian immigrant ratio.

Table 1: Descriptive Statistics Major Racial Categories

Panel A: Correlation Matrix					
	(1)	(2)	(3)	(4)	(5)
(1) MENA &SEA	1.000				
(2) African American	-0.048	1.000			
(3) Hispanic	0.157	-0.167	1.000		
(4) Asian American	0.224	-0.021	-0.004	1.000	
(5) Native American	0.195	-0.181	0.185	0.026	1.000
Panel B: Descriptive Statistics					
	N	Mean	St.Dev.	Min	Max
MENA &SEA	72	0.018	0.015	0.004	0.092
African American	72	0.121	0.083	0.013	0.447
Hispanic	72	0.171	0.145	0.016	0.549
Asian American	72	0.069	0.072	0.010	0.498
Native American	72	0.016	0.007	0.009	0.058

This table shows the correlation coefficients and descriptive statistics of the major racial categories as recognized by the United States Census Bureau. Panel A provides the correlation matrix for these five categories. The correlations coefficients are based on the ratio of this racial group compared to the total number of inhabitants in this Metropolitan Statistical Area. These ratios are averaged over the period 2008-2013 and compared for the 72 Metropolitan Statistical Areas included in this study. Panel B shows the descriptive statistics for the racial categories. Column 1 reports the number of observations for each category (equals the number of Metropolitan Statistical Areas). Respectively, columns 2 and 3 denote the mean and stand deviation. Columns 4 and 5 comprise the range per racial category.

Table 2 provides the descriptive statistics of the included variables over the full sample period (Jan 2008-Dec 2015). Variable definitions can be found in Appendix A. Panel B shows that the average funded loan has a size of $14,928, paying an annualized interest rate of 13.14%.

The average borrower has an annual pre-tax income of $79,653, resulting in an average loan-to-income ratio of 18.74% of the borrower's annual income. Amongst the funded borrowers, 16.02% default on their Lending Club loans. Furthermore, 17.04% of the funded borrowers are living in a top decile Metropolitan Statistical Area in terms of the Middle Eastern and Southeast Asian immigrant ratio. The Middle Eastern and Southeast Asian immigrant ratio in the top decile ranges from 4.13% to 9.25% with an average of 5.91%.

Table 2: Descriptive Statistics Full Sample

	N	Mean	Std.Dev.	Min	Max
Panel A: Rejected loan applications					
	N	Mean	Std.Dev.	Min	Max
Loan Amount	1,876,429	12,766	10,576	1,000	35,000
FICO	1,876,429	634.12	64.31	491	794
EmpLength	1,876,429	1.65	1.96	1	10
Debt-to-income	1,876,429	26.60	38.07	0	270.24
Panel B: Accepted loan applications					
	N	Mean	Std.Dev.	Min	Max
Imm90	123,308	.06	.02	0.04	0.09
Loan Amount	723,738	14,928	8,658	500	40,000
Interest rate	723,738	13.14	4.57	5.32	30.99
Default rate	723,738	.16	.37	0	1
EmpLength	723,738	5.98	3.56	1	10
AnnualIncome	723,738	79,653	70,914	2,000	9,550,000
Debt-to-income	723,738	17.75	8.44	0	202.73
NrDelinq2yrs	723,738	.33	.89	0	10
FICO	723,738	698.05	30.17	614	850
NrCreditLines	723,738	11.82	5.55	1	56
NrPublicRecord	723,738	.21	.60	0	18
TotRevolvBal	723,738	17,476	24,518	1	2,904,836

This table shows the summary statistics for the full sample period; 2008-2015. Column 1 reports the total observations for each variable. Respectively, columns 2 and 3 denote the mean and stand deviation. Columns 4 and 5 comprise the range per variable. Variable definitions can be found in Appendix A.

B. Methodology

This section specifies the conducted regression analyses, including the dependent and independent variables that are tested. Also, it elaborates on the identification strategy, followed by a robustness check in the form of placebo tests.

1. Baseline regressions

To start with, baseline regressions are conducted to estimate the relationship between the funding likelihood, interest rate spread, and funded loan amount, and the minority immigrant ratio. Following Ravina (2008), these baseline regressions control for hard financial variables. Appendix A provides an overview of all variables, including descriptions. Afterward, an identification strategy for taste-based discrimination like the one of Kumar, Niessen-Ruenzi, & Spalt (2015) is applied.

The first regression examines the relationship between the funding likelihood and the minority immigrant ratio. To empirically test this, the *SuccesDum* variable is computed. This is a dummy variable that equals 1 for funded loans and 0 for rejected loans. By regressing the minority immigrant ratio plus control variables on this success dummy, the relationship and magnitude of the top decile Metropolitan Statistical Areas in terms of minority immigrant ratio on the funding likelihood is estimated. This is expressed by the following equation:

$$SuccesDum_{i,t} = \beta_0 + \beta_1 * Immigrant90_i + \beta_2 * HardFinVar_{i.t} + \varphi_t + \Upsilon_i + \Phi_{i.t} + \varepsilon_{i,t} \qquad (1)$$

The dataset is split up into a treated and control group based on the average minority immigrant ratio over the years 2008 to 2015. The variable *Immigrant90* resembles a dummy variable that equals 1 for the top decile Metropolitan Statistical Areas in terms of the average minority immigrant ratio and 0 for all other Metropolitan Statistical Areas. More specifically, the β_1 coefficient measures the effect of living in a top decile Metropolitan Statistical Area in terms of minority immigrant ratio on the funding likelihood. *HardFinVar* denotes the financial information about the borrower that Lending Club retrieved from the credit bureaus. This includes the FICO score, debt-to-income ratio, and employment status. As Lending Club does not release more variables for rejected loan applications publicly, the next regressions control for more dimensions and variables. Furthermore, φ_t and Υ_i respectively control for Yearly fixed effects and Metropolitan Statistical Area fixed effects. $\Phi_{i,t}$ controls for State × Year fixed effects and thus allows to control for credit supply effects at the state-level. As equation (1) resembles an OLS regression, the error term $\varepsilon_{i,t}$ must be independently distributed. In order to estimate the beta's correctly, the standard errors are clustered per Metropolitan Statistical Area. This because borrowers' traits might be very similar within the same city, and thus observations might be clustered per Metropolitan Statistical Area.

The second regression investigates the relationship between the minority immigrant ratio and the interest rate. To empirically test this, the *IntSpread* variable is generated by deducting the United States FED funds rate from the interest rate paid by borrowers. Next, the minority immigrant ratio plus control variables are regressed on this interest spread. This is described by the following equation:

$$IntSpread_{i,t} = \beta_0 + \beta_1 * Immigrant90_i + \beta_2 * HardFinVar_{i,t} + \varphi_t + \square_i + \Phi_{i,t} + \varepsilon_{i,t} \quad (2)$$

Hard financial variables control for the credit grade assigned by Lending Club and the FICO score. Other included hard financial variables are annual income, homeownership, employment length, debt-to-income ratio, delinquencies in the past two years, number of public records, total revolving credit balance, and the number of open credit lines. Again, the standard errors are clustered.

The third regression examines the relationship between the minority immigrant ratio and the loan amount that borrowers receive. This is done by running a panel regression, including Borrower (δ_i), Yearly (φ_t), State × Year ($\Phi_{i,t}$), and Metropolitan Statistical Area fixed effects (Υ_i). Furthermore, the amount variable is transformed into a logarithmic variable. This transformation results in a normal distribution. The regression again controls for the same variables as equation (2). Also, standard errors are clustered.

$$Log\_Amount_{i,t} = \beta_0 + \beta_1 * Immigrant90_i + \beta_2 * HardFinVar_{i,t} + \delta_i + \varphi_t + \Upsilon_i + \Phi_{i,t} + \varepsilon_{it} \quad (3)$$

This research aims at providing evidence regarding which discrimination model fits best with possible discrimination on Lending Club. In order to conclude on the underlying model, the repayment performance of the minority group needs to be investigated. The fourth baseline regression examines the relationship between the minority immigrant ratio on the default rate.

$$Default_{i,t} = \beta_0 + \beta_1 * Immigrant90_i + \beta_2 * HardFinVar_{i,t} + \varphi_t + \Upsilon_i + \Phi_{i,t} + \varepsilon_{i,t} \quad (4)$$

Default resembles a dummy variable that equals 0 for loans that are fully paid back and 1 for loans that are more than four months delinquent and are thus charged off to a collection agency. The control variables are identical to those of equation (2), and standard errors are clustered.

2. Identification strategy

Following a similar strategy as Kumar et al. (2015), a terrorist attack associated with Islamic beliefs is plausible to affect stereotyping towards the minority lenders negatively. Before delving into this strategy, the relationship of terrorist attacks and anti-Islam sentiment must be established. Using Gallup Poll survey data, Margulies (2013) shows that U.S. citizens have an unfavorable perspective of the Islam and its beliefs starting from 2001 onwards. The survey provides evidence that following the 9/11 attack, this 'negative' perspective towards the Islam enlarged. Confirmative, Kumar et al. (2015) find that the 9/11 attack amplifies negative stereotyping to the detriment of mutual fund managers with Middle Eastern and Southeast Asian sounding names. More specifically, the fund flows for these mutual fund managers declined abnormally after the attack. This is in line with the taste-based form of discrimination.

This research uses the Boston Marathon Bombing as an exogenous shock. The attack occurred on April 15, 2013 and was motivated by extreme Islamic beliefs. The Bombing caused nearly 300 injured casualties and three actual fatalities. Since Middle Eastern and Southeast Asian immigrants are associated with the Islam, this event might negatively affect stereotyping against these minorities. To provide evidence of whether this negative stereotyping results in discrimination, a difference-in-difference strategy is exploited. More specifically, this study compares the top decile Metropolitan Statistical Areas with the remaining Metropolitan Statistical Areas around the Boston Marathon Bombing. The *Post* dummy variable is created for both accepted and rejected loans. This dummy is equal to 0 for pre-shock loans and 1 for post-shock loans. The following set of difference-in-difference regressions are tested.

$$SuccesDum_{i,t} = \beta_0 + \beta_1 * Immigrant90_i + \beta_2 * Post_t + \beta_3 * Immigrant90 \times Post_{i,t} + \beta_4 * HardFinVar_{i,t} + \varphi_t + \Upsilon_i + \Phi_{i,t} + \varepsilon_{i,t} \tag{5}$$

The interaction term β_3 measures the change in funding likelihood for borrowers living in one of the top decile Metropolitan Statistical Areas after the Boston Marathon Bombing. Similar control variables compared to equation (1) are included. Equation (6) and (7) are capturing a similar effect on the interest rate and loan amount, and again control for similar variables as equation (2) and (3), respectively.

$$IntSpread_{i,t} = \beta_0 + \beta_1 * Immigrant90_i + \beta_2 * Post_t + \beta_3 * Immigrant90 \times Post_{i,t} + \beta_4 * HardFinVar_{i,t} + \varphi_t + \Upsilon_i + \Phi_{i,t} + \varepsilon_{i,t} \tag{6}$$

$$Log\_Amount_{i,t} = \beta_0 + \beta_1 * Immigrant90_i + \beta_2 * Post_t + \beta_3 * Immigrant90 \times Post_{i,t} + \beta_4 * HardFinVar_{i,t} + \varphi_t + \Upsilon_i + \Phi_{it} + \varepsilon_{it} \tag{7}$$

Again, as this research is testing the form of discrimination, the relationship between the minority immigrant ratio and the default rate is measured by equation (8).

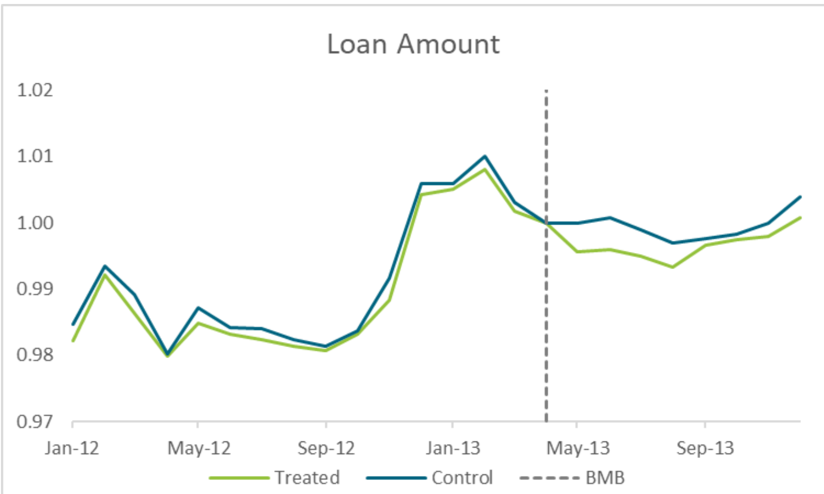
$$Default_{i,t} = \beta_0 + \beta_1 * Immigrant90_i + \beta_2 * Post_t + \beta_3 * Immigrant90 \times Post_{\,i,t} + \beta_4 * HardFinVar_{i,t} + \varphi_{\,t} + \Upsilon_i + \Phi_{i,t} + \varepsilon_{i,t} \tag{8}$$

To examine the robustness of the results, two placebo tests are conducted. These tests are performed by almost repeating the above-mentioned regressions, except for the dummy variable *Post.* One placebo test randomly assigns the exogenous shock before the actual Boston Marathon Bombing, while the second placebo test date randomly sets the date after the actual event. Based on this variable, the data set is divided randomly. This is expected to result in insignificant results.

3. Treatment and control group prior to April 2013

As this study exploits a difference-in-difference approach, the parallel trend assumption is critical for getting unbiased estimates. This assumption demands that without treatment, both the treated and the control group follow similar trends (Lechner, 2011). To test this assumption, the trends are visualized. More specifically, these trends are plotted for treated and control Metropolitan Statistical Areas around the Boston Marathon Bombing. Figure 1 shows that for the loan amount received by borrowers, the trends run parallel for the two groups in the period prior to the Boston Marathon Bombings. This graph validates the parallel trend assumption and thus justify the difference-in-difference approach used in this study.

Figure 1: Loan amount around the Boston Marathon Bombing



The graph plots the logarithmic transformation of the loan amount on Lending Club, for treated and control Metropolitan Statistical Areas, around the Boston Marathon Bombing. The vertical axis shows the log transformation of the loan amount which is averaged over all treated and control Metropolitan Statistical Areas. The graph is normalized to 1 at the date of the Boston Marathon Bombing (15th of April 2013). The graph reports that following the Boston marathon bombing borrowers in treated Metropolitan Statistical Areas receive loans with a lower face value than borrowers in control Metropolitan Statistical Areas.

V. Results

This section presents the results of the empirical analysis. First, the relationship between living in a top decile Metropolitan Statistical Area in terms of the minority immigrant ratio and the likelihood of receiving a loan on Lending Club is discussed. Second, it elaborates on the effect on the interest rate spread. Third, the findings on the loan amount received by borrowers are presented. Finally, the results on the default rate are described, followed by a short discussion of the placebo tests.

A. Funding likelihood

To test the first hypothesis, the results on the relationship between living in a top decile area in terms of the Middle Eastern and Southeast Asian immigrant ratio and the funding likelihood are presented in Table 3. Model 1 suggests that living in a top decile Metropolitan Statistical Area in terms of minority immigrant ratio increases the likelihood of getting your loan funded on Lending Club. However, the coefficient is insignificant, also after controlling for hard financial variables and listing characteristics in model 3.

Model 2 and 4 add an interaction term of living in a top decile Metropolitan Statistical Area in terms of minority immigrant ratio after the Boston Marathon Bombing. This interaction term tests whether negative stereotyping, that is likely to occur following a terroristic attack, affects the results found in the baseline regressions displayed by model 1 and 3. Model 2 suggests that living in a top decile area after the Boston Marathon Bombing decreases a lenders' likelihood of getting funded with 0.10%. However, model 4 shows that after controlling for hard financial variables, living in a top decile Metropolitan Statistical Area after the Boston Marathon Bombing decreases the funding likelihood with 1.28%. This result is significant at the 1%-level. Considering the average pre-shock funding likelihood is 23.53%, this effect resembles a 5.44% decrease.

Based on the r-squared, model 4 is considered most reliable. Therefore, the first hypothesis, that argues that the Middle Eastern and Southeast Asian immigrant ratio decreases the funding likelihood, is accepted.

Table 3: Funding likelihood

	(1) SuccesDum	(2) SuccesDum	(3) SuccesDum	(4) SuccesDum
Immigrant90	0.002		0.027	
	(0.008)		(0.020)	
Immigrant90 x Post		-0.001***		-0.013***
		(0.003)		(0.003)
FICO			0.001***	0.001***
			(0.000)	(0.000)
EmploymentLength			0.056***	0.056***
			(0.001)	(0.001)
Debt-to-income			-0.001***	-0.001***
			(0.000)	(0.000)
Constant	0.999***	0.999***	-0.225***	-0.058***
	(0.003)	(0.002)	(0.019)	(0.021)
Observations	2,600,167	2,600,167	2,600,167	2,600,167
Yearly fixed effects	Yes	Yes	Yes	Yes
MSA fixed effects	No	Yes	No	Yes
State × Year fixed effects	Yes	Yes	Yes	Yes
R-squared	0.342	0.344	0.565	0.566

This table shows the results of four Ordinary Least Squares (OLS) regressions. The dependent variable is SuccesDum, and the main independent variables are Immigrant90 and the interaction variable Immigrant90 x post. The regressions control for Yearly, Metropolitan Statistical Area and State × Year fixed effects. Full variable definitions can be found appendix A. Robust standard errors are clustered per Metropolitan Statistical Area, and standard errors are reported in parentheses. *, **, *** indicate significance at the 10%-, 5%-, and 1%-level.

B. Interest rate spread

The results to test the second hypothesis, regarding the interest rate spread, are presented in Table 4. Model 1 and 3 represent the baseline analysis and show that after controlling for hard financial variables and listing characteristics, there is no significant effect. This suggests that living in a top decile Metropolitan Statistical Area, in terms of the minority immigrant ratio, does not influence the interest rate spread paid by borrowers.

Adding the interaction term of living in a top decile area after the Boston Marathon Bombings does deliver significant results. Model 2 suggests living a top decile Metropolitan Statistical Area after the Boston Marathon Bombing increases the interest rate borrowers pay by 11 basis points. However, once controlling for hard financial variables and listing characteristics in model 4, this effect decreases down to a 9 basis points increase. This result is significant at the 5%-level. The average pre-shock interest rate Lending Club borrowers pay is 12.09%. Taking this into consideration, the decreasing effect size of 9 basis points account for a 0.77% increase, meaning it has relatively small economic significance. Based on these results, the second hypothesis that argues that the Middle Eastern and Southeast Asian immigrant ratio increases the interest rate paid by borrowers is accepted. However, the effect size does not have large economic significance.

Table 4: Interest rate spread

	(1) IntSpread	(2) IntSpread	(3) IntSpread	(4) IntSpread
Immigrant90	-0.169		-0.004	
	(0.613)		(0.028)	
Immigrant90 x Post		0.110**		0.094**
		(0.052)		(0.047)
FICO			-0.005***	-0.005***
			(0.000)	(0.000)
Log_AnnualIncome			-0.035***	-0.035***
			(0.005)	(0.005)
Home Ownership				
Rent			0.031***	0.025***
			(0.004)	(0.004)
Own			0.033***	0.029***
			(0.006)	(0.005)
Other			-0.229	-0.224
			(0.162)	(0.157)
EmploymentLength			0.002***	0.002***
			(0.000)	(0.000)
Debt-to-income			0.085***	0.077***
			(0.002)	(0.003)
NrDelinquencies2yrs			0.156***	0.136***
			(0.019)	(0.018)
NrOpenCreditLines			-0.028***	-0.023***
			(0.002)	(0.003)
NrPublicRecords			-0.007**	-0.005**
			(0.003)	(0.002)
Log_TotalRevolvBal			-0.341***	-0.272***
			(0.022)	(0.016)
Constant	10.593***	10.360***	6.506***	6.372***
	(0.760)	(0.764)	(0.301)	(0.276)
Observations	723,738	723,738	723,738	723,738
Yearly fixed effects	Yes	Yes	Yes	Yes
MSA fixed effects	No	Yes	No	Yes
State × Year fixed effects	Yes	Yes	Yes	Yes
R-squared	0.023	0.023	0.928	0.928

This table shows the results of four Ordinary Least Squares (OLS) regressions. The dependent variable is IntSpread, and the main independent variables are Immigrant90 and the interaction variable Immigrant90 x post. The regressions control for Yearly, Metropolitan Statistical Area and State × Year fixed effects. Full variable definitions can be found appendix A. Robust standard errors are clustered per Metropolitan Statistical Area, and standard errors are reported in parentheses. *, **, *** indicate significance at the 10%-, 5%-, and 1%-level.

C. Loan Amount

To test the third hypothesis, the results on the relationship between the Middle Eastern and Southeast Asian immigrant ratio and loan amount funded are presented in Table 5. Again, model 1 and 3 show the results of the baseline regressions and prove that after controlling for hard financial variables and listing characteristics, living a top decile area in terms of the minority immigrant ratio does not significantly affect the loan amount received by borrowers.

Following models 2, 4 and 5, living in a top decile Metropolitan Statistical area after the Boston Marathon Bombing significantly decreases the funded loan amount by 20.08% $((\exp(0.183) - 1) * 100)$ up to 20.80%, depending on the added control variables and fixed effects. These results are significant at the 1%-level. Considering an average loan amount of $14,928, this represents a higher loan amount by up to $3,105. Therefore, it can be argued that the effect size is both econometrically and economically significant. This result supports the graphical animation represented in Figure 1. Based on the above-mentioned results, the third hypothesis, arguing that the Middle Eastern and Southeast Asian immigrant ratio decreases the loan amount received by borrowers, is accepted.

Table 5: Loan amount

	(1) Log_Amount	(2) Log_Amount	(3) Log_Amount	(4) Log_Amount	(5) Log_Amount
Immigrant90	0.003		-0.001		
	(0.003)		(0.005)		
Immigrant90 x Post		-0.183***		-0.189***	-0.185***
		(0.010)		(0.010)	(0.017)
FICO			0.001***		0.001***
			(0.000)		(0.000)
Log_AnnualIncome			0.048***		0.049***
			(0.001)		(0.001)
Home Ownership					
Rent			-0.003***		-0.003***
			(0.001)		(0.001)
Own			-0.001***		-0.001***
			(0.000)		(0.000)
Other			-0.020***		-0.017***
			(0.005)		(0.005)
EmploymentLength			0.001**		0.001*
			(0.000)		(0.000)
Debt-to-income			0.001***		-0.001***
			(0.000)		(0.000)
NrDelinquencies2yrs			-0.001**		-0.002**
			(0.000)		(0.000)
NrOpenCreditLines			-0.001***		-0.001***
			(0.000)		(0.000)
NrPublicRecords			-0.001		-0.001*
			(0.001)		(0.001)
Log_TotalRevolvBal			0.017***		0.017***
			(0.001)		(0.001)
Constant	0.004***	-0.008*	-0.828***	-0.008*	-0.859***
	(0.001)	(0.006)	(0.015)	(0.005)	(0.024)
Observations	5,790,240	5,790,240	5,790,240	5,790,240	5,790,240
Yearly fixed effects	Yes	Yes	Yes	Yes	Yes
MSA fixed effects	No	Yes	No	No	Yes
State × Year fixed effects	Yes	Yes	Yes	Yes	Yes
Borrower fixed effects	No	No	No	Yes	No
R-squared	0.122	0.122	0.167	0.168	0.168

This table shows the results of five panel regressions. The dependent variable is Log_Amount, and the main independent variables are Immigrant90 and the interaction variable Immigrant90 x post. The regressions control for Yearly, Metropolitan Statistical Area, Borrower and State × Year fixed effects. Full variable definitions can be found appendix A. Robust standard errors are clustered per Metropolitan Statistical Area, and standard errors are reported in parentheses. *, **, *** indicate significance at the 10%-, 5%-, and 1%-level.

D. Default

To test the last hypothesis, the results regarding the effect of living in a top decile Middle Eastern and Southeast Asian immigrant ratio on the probability of default are presented in Table 6. The baseline results are compromised by models 1 and 3 and show that the minority immigrant ratio does not have a significant effect on the probability of default. However, living in a top decile Metropolitan Statistical after the Boston Marathon Bombing decreases the probability of default by 0.34% up to 0.48%. After controlling for hard financial variables, this result is significant at the 5%-level. Considering that the average pre-shock probability of default is 14.69%, this is an economically substantial decrease of 3.27%. Based on the above-mentioned results, the fourth and last hypothesis arguing that that the Middle Eastern and Southeast Asian immigrant ratio decreases the probability of a borrower defaulting is accepted.

To sum up, living in a top decile Metropolitan Statistical Area in terms of minority immigrant ratio after the Boston Marathon Bombing significantly decreases the funding likelihood, increases the interest rate spread, and decreases the loan amount received by the borrower. Combining this with the finding that borrowers living in such a top decile area after the Boston Marathon Bombing default significantly less, suggests that taste-based discrimination is present within the Lending Club process. In other words, the Lending Club process seems to contain a form of in-group bias to the detriment of borrowers living in a top decile Metropolitan Statistical Area in terms of the Middle Eastern and Southeast Asian immigrant ratio.

E. Placebo tests

To ensure the findings, as mentioned above, are robust and driven by the Boston Marathon Bombing instead of being induced by another factor or event, two placebo tests are conducted. The placebo tests run the same regressions; however, the event date is randomly assigned. Placebo 1 denotes a randomly assigned event date before the actual Boston Marathon Bombing, while Placebo 2 represents a random event date after the Boston Marathon Bombing. The results of these regressions can be found in Appendix D. Most importantly, living in a top decile Metropolitan Statistical Area in terms of the Middle Eastern and Southeast Asian immigrant ratio after one of these placebo tests does not significantly impact the funding likelihood, interest rate spread, loan amount, and the probability of default of Lending Club. These insignificant results, combined with the parallel trend graphs, support that the earlier findings are indeed a result of the Boston Marathon Bombing.

Table 6: Default

	(1) Default	(2) Default	(3) Default	(4) Default
Immigrant90	0.021		0.023	
	(0.053)		(0.051)	
Immigrant90 x Post		-0.003*		0.005**
		(0.002)		(0.002)
FICO			-0.001***	-0.001***
			(0.000)	(0.000)
Log_AnnualIncome			-0.010***	-0.010***
			(0.002)	(0.002)
Home Ownership				
Rent			0.035***	0.035***
			(0.003)	(0.003)
Own			0.017***	0.017***
			(0.003)	(0.003)
Other			0.003	0.003
			(0.024)	(0.024)
EmploymentLength			0.001**	0.001**
			(0.000)	(0.000)
Debt-to-income			0.004***	0.004***
			(0.001)	(0.000)
NrDelinquencies2yrs			0.002***	0.002***
			(0.001)	(0.001)
NrOpenCreditLines			0.002***	0.002***
			(0.000)	(0.000)
NrPublicRecords			0.002*	0.002*
			(0.001)	(0.001)
Log_TotalRevolvBal			-0.016***	-0.016***
			(0.001)	(0.001)
Constant	0.032***	0.052***	1.150***	1.179***
	(0.010)	(0.009)	(0.028)	(0.101)
Observations	723,738	723,738	723,738	723,737
Yearly fixed effects	Yes	Yes	Yes	Yes
MSA fixed effects	No	Yes	No	Yes
State × Year fixed effects	Yes	Yes	Yes	Yes
R-squared	0.004	0.004	0.294	0.297

This table shows the results of four Ordinary Least Squares (OLS) regressions. The dependent variable is Default, and the main independent variables are Immigrant90 and the interaction variable Immigrant90 x post. The regressions control for Yearly, Metropolitan Statistical Area and State × Year fixed effects. Full variable definitions can be found appendix A. Robust standard errors are clustered per Metropolitan Statistical Area, and standard errors are reported in parentheses. *, **, *** indicate significance at the 10%-, 5%-, and 1%-level.

VI. Discussion

This section discusses the implications that can be drawn from the key findings. The most significant implications concern the ethical and legal side of the story. From an ethical perspective, the results of this study are likely to harm the trust that lenders, borrowers, and other stakeholders have in the product offered by Lending Club. Over the past years, social and ethical responsibility has become a central point of discussion. This translates into a fictive 'social license to operate', which refers to the approval of operational procedures and practices by a company's direct stakeholders and the general public. Once a form of discrimination by the Lending Club algorithm becomes known to the general public, this can severely damage the trust and credibility of its product. This might result in Lending Club losing users, in the form of both borrowers and lenders, as well as a substantial decrease in goodwill the company currently possesses.

From a legal perspective, peer-to-peer lending platforms are currently regulated based on their services. These platforms must comply with the same laws as other institutions that provide credit to their consumers. Therefore, peer-to-peer borrowers are protected according to the same existing laws as traditional borrowers, including the Equal Credit Opportunity Act. This Federal Act restrains credit providers from discriminating against loan applicants based on race, sex, age, religion, skin color, national origin, and marital status (15 U.S.C. § 1691).

The discrimination found in this study can be driven by two actors, namely Lending Club and its automated investment tool or individual lenders directly picking their investments. Which of these two actors drives the key findings raises different legal questions. First, it might be primarily driven by the automated investment allocation tool offered by Lending Club. This means that Lending Club, acting on behalf of the lenders as credit providers, might be held responsible for violating the Equal Credit Opportunity Act. This disadvantages both borrowers living in top decile Metropolitan Statistical Areas in terms of the Middle Eastern and Southeast Asian immigrant ratio, and lenders using the automated investment allocation tool provided by Lending Club. The first group is disadvantaged due to lower funding likelihood and loan amount while paying higher interest rates. They might hold Lending Club liable for this discrimination and thus violating the Equal Credit Opportunity Act. By using the automated investment tool, the latter group forgoes investment opportunities that pay higher interest while defaulting less. Looking at precedents, the KleinBank is previously accused of redlining minority neighborhoods in Minnesota (The United States Department of Justice, 2018). In other words, this bank was intentionally trying to avoid providing loans to borrowers from these neighborhoods. The case ended in a settlement that led to the bank committing over half a million dollars into providing banking services to these discriminated neighborhoods. Therefore, discrimination driven by the automated investment tool has serious legal implications for Lending Club. Second, the effect could also be primarily driven by lenders operating as credit providers. If lenders are deemed to engage in credit decisions frequently, they are also subordinate to the Equal Credit Opportunity Act.

On the other hand, it could be argued that lenders, operating as investors, have the freedom to invest in projects of their choice. This contradiction raises serious policy implications for public policymakers. In my personal opinion, these policymakers should balance two major goals. First, ensuring a fair and equal process for borrowers to receive a loan at peer-to-peer lending platforms without being discriminated based on race, ethnicity and religion. Second, peer-to-peer lenders should maintain a level of freedom to choose to invest in products of their choice. Even though the best method to achieve these objectives goes beyond the scope of this study, I recommend algorithm auditing as a step in the right direction. Neutral third-party auditing can focus on validating whether algorithms exhibit internal social and psychological biases. This algorithm auditing should help public policymakers authenticate the ethical and social responsibility, as well as legal compliance of the algorithm.

VII. Conclusion

This study aims at providing evidence on whether in-group stereotypes affect the funding likelihood, interest rate, and loan amount received by peer-to-peer lenders. More specifically, it examines whether peer-to-peer borrowers living in a top decile area in terms of Middle Eastern and Southeast Asian immigrant ratios are discriminated against following a terrorist attack associated with the Islam. This study exploits a difference-in-difference approach, using the Boston Marathon Bombing as an exogenous shock, on Lending Club loan data stemming from 2008 up to 2015.

The results show that living in a top decile Metropolitan Statistical Area in terms of minority immigrant ratio after the Boston Marathon Bombing significantly decreases the likelihood of getting funded and, conditional on getting funded, the loan amount received. However, it slightly increases the interest rate paid by the borrowers. Looking at borrower quality and loan performance, this study finds that borrowers living in a top decile Metropolitan Statistical after the Boston Marathon Bombing default significantly less. In sum, the minority group is less likely to receive a loan, pay higher interest, but appear to perform better than the control group. This evidence fits best with the taste-based model of discrimination. It implies that peer-to-peer lenders display in-group bias to the detriment of borrowers living in a top decile Metropolitan Statistical Area in terms of the Middle Eastern and Southeast Asian immigrants. Investors are willing to leave money on the table to avoid interaction with the discriminated group. This raises serious public policy questions on how to ensure equality while ensuring investor autonomy.

The key methods and findings of this study contribute to the growing literature on in-group bias and discrimination in financial markets. Discrimination in the labor market (Becker, 1957), courtrooms (Arnold, Dobbie, & Yang, 2018), mutual funds (Kumar, Niessen-Ruenzi, & Spalt, 2015), FinTech mortgage providers (Barlett et al., 2018) and peer-to-peer lending (Ravina, 2008) was already established. However, this study enriches existing literature by proving that a terrorist attack induces taste-based discrimination within the peer-to-peer lending market. Furthermore, most studies examine discrimination against black or Hispanic people. This study builds upon the method and findings of Kumar, Niessen-Ruenzi, & Spalt (2015). It confirms the existence of discrimination towards Middle Eastern and Southeast Asian immigrants as a minority group. The applied methodology of measuring discrimination could be applied to a wider variety of settings.

Besides the abovementioned contributions, this study does have its limitations that need to be acknowledged. First, studies on racial and ethnic discrimination are notably sensible to omitted-variable bias. Racial differences are often tightly correlated with economic and cultural differences. Therefore, the omission of these economic and cultural differences might lead to biased estimations. Second, the data only allowed to locate borrowers up until Metropolitan Statistical Area. Hence, any differences in discrimination within these Metropolitan Statistical Areas cannot be observed. Third, this study cannot observe which investment allocation mechanism drives the results.

For future research, it is interesting to test the generality of the results by widening the scope towards other peer-to-peer platforms, possibly outside the United States. Additionally, investigating the persistence and duration of discrimination. It might vanish as time without extreme events passes. Furthermore, it is very interesting to benchmark the level of discrimination found in this study against traditional credit providers. Do traditional credit providers exhibit a larger level of discrimination, resulting in more minority borrowers applying for a loan trough peer-to-peer lending platforms? Last, it is extremely interesting and relevant to examine whether the current Black Lives Matter protests induce the exact opposite effect.

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IX. Appendix

A. Appendix A: Variables and descriptions

Table 7: Variables including descriptions

Variable	Definition
SuccesDum	Equals 1 for funded loans and 0 for rejected loans
IntSpread	Equals is the interest rate minus the average FED rate of the corresponding year
Log_Amount	Logarithmic transformation of the loan amount
Immigrant90	Equals 1 for top decile Metropolitan Statistical Areas in terms of Middle Eastern and Southeast Asian immigrant ratio and 0 for other Metropolitan Statistical Areas
Default	Equals 1 for loans that are defaulted, charged off or late (31-120 days) and equals 0 for loans that are fully paid or late (16-30 days)
Post	Equals 1 for loans originated after 15th of April 2013 and 0 for other loans
Placebo	Equals 1 for loans originated after randomly assigned event date and 0 for others
FICO	Specifies borrower's FICO score. Calculated as average of the highest and lowest FICO score range
Grade	Credit grade assigned by Lending Club. Values can contain A, B, C, D, E, F, and G.
Log_AnnualIncome	Logarithmic transformation of the borrower's annual income
Home Ownership	Equals 1 for rented homes, 2 for own homes (mortgage or private), and 3 for other.
EmploymentLength	Employment length in years. Values >10 are denoted with the value 10.
Debt-to-income	Debt to income ratio calculated as the total monthly debt payments (excl. mortgage) divided by the self-reported monthly income.
NrDelinquencies2yrs	The number of delinquencies in the borrower's credit file over the last 2 years.
NrOpenCreditLines	The number of open credit lines as reported in the borrower's credit file
NrPublicRecords	The number of derogatory public records in the borrower's credit file
Log_TotalRevolvBal	Logarithmic transformation of the total revolving credit balance.
LoanTerm	The repay period, 36 or 60 months.

This table shows the variables included in this study. The first column denotes the variable name and the second column provides the variable descriptions.

B. Appendix B: Metropolitan Statistical Areas and minority immigrant ratios

Table 8: Metropolitan Statistical Areas

Metropolitan Statistical Area	N Imm	Total metro pop	Tot % Imm
San Jose-Sunnyvale-Santa Clara	183,243	1,981,616	9.25%
San Francisco-Oakland-Hayward	286,076	4,673,221	6.12%
San Diego-Carlsbad	186,850	3,302,833	5.66%
Los Angeles-Long Beach-Anaheim	729,547	13,262,234	5.50%
Las Vegas-Henderson-Paradise	100,294	2,141,574	4.68%
Sacramento--Roseville--Arden-Arcade	94,709	2,291,738	4.13%
Seattle-Tacoma-Bellevue	145,001	3,809,717	3.81%
Fresno	33,295	978,130	3.40%
Detroit-Warren-Dearborn	125,430	4,317,000	2.91%
Washington-Arlington-Alexandria	170,144	6,138,382	2.77%
Riverside-San Bernardino-Ontario	124,907	4,518,699	2.76%
Houston-The Woodlands-Sugar Land	182,251	6,779,104	2.69%
Oxnard-Thousand Oaks-Ventura	21,808	848,112	2.57%
Lincoln	8,313	327,221	2.54%
Modesto	13,371	539,301	2.48%
Minneapolis-St. Paul-Bloomington	83,441	3,557,528	2.35%
Portland-Vancouver-Hillsboro	54,337	2,417,931	2.25%
Des Moines-West Des Moines	13,030	634,000	2.06%
Bakersfield	17,755	883,053	2.01%
Boston-Cambridge-Newton	92,123	4,811,732	1.91%
Dallas-Fort Worth-Arlington	137,756	7,255,028	1.90%
New York-Newark-Jersey City	365,148	19,990,592	1.83%
Virginia Beach-Norfolk-Newport News	31,256	1,722,001	1.82%
Chicago-Naperville-Elgin	170,503	9,536,428	1.79%
Nashville-Davidson-Murfreesboro-Franklin	31,285	1,864,138	1.68%
Phoenix-Mesa-Scottsdale	73,907	4,673,634	1.58%
Orlando-Kissimmee-Sanford	37,392	2,450,261	1.53%
Worcester	14,231	938,818	1.52%
Greensboro-High Point	11,150	757,810	1.47%
Denver-Aurora-Lakewood	40,007	2,850,000	1.40%
Tampa-St. Petersburg-Clearwater	42,275	3,030,047	1.40%
Salt Lake City	16,509	1,185,990	1.39%
Jacksonville	28,831	2,106,632	1.37%
New Orleans-Metairie	17,102	1,263,635	1.35%
Philadelphia-Camden-Wilmington	79,793	6,069,448	1.31%
Oklahoma City	17,962	1,369,759	1.31%
Austin-Round Rock	26,945	2,058,351	1.31%
Atlanta-Sandy Springs-Roswell	74,615	5,779,463	1.29%
Buffalo-Cheektowaga-Niagara Falls	14,390	1,131,570	1.27%
Raleigh	15,786	1,302,632	1.21%
Lansing-East Lansing	5,657	476,615	1.19%

Milwaukee-Waukesha-West Allis	18,700	1,575,907	1.19%
Baltimore-Columbia-Towson	32,466	2,793,250	1.16%
Allentown-Bethlehem-Easton	9,678	834,615	1.16%
Omaha-Council Bluffs	10,616	922,891	1.15%
Palm Bay-Melbourne-Titusville	6,595	576,808	1.14%
Bridgeport-Stamford-Norwalk	10,666	944,348	1.13%
Harrisburg-Carlisle	6,331	567,872	1.11%
Syracuse	7,119	654,705	1.09%
Indianapolis-Carmel-Anderson	21,654	2,007,497	1.08%
Tucson	10,943	1,019,722	1.07%
Richmond	13,712	1,281,530	1.07%
New Haven-Milford	9,120	859,339	1.06%
Providence-Warwick	16,326	1,615,516	1.01%
Charlotte-Concord-Gastonia	24,882	2,473,125	1.01%
Portland-South Portland	5,206	529,323	0.98%
San Antonio-New Braunfels	23,768	2,426,204	0.98%
Columbus	20,073	2,054,062	0.98%
Kansas City	20,536	2,106,632	0.97%
Toledo	5,686	604,620	0.94%
Hartford-West Hartford-East Hartford	10,930	1,209,367	0.90%
Dayton	7,218	802,645	0.90%
Akron	6,330	704,454	0.90%
Miami-Fort Lauderdale-West Palm Beach	51,762	6,070,944	0.85%
Rochester	8,651	1,074,667	0.80%
Albany-Schenectady-Troy	7,072	880,481	0.80%
Cleveland-Elyria	16,007	2,061,766	0.78%
St. Louis	20,864	2,805,551	0.74%
Memphis	9,689	1,345,991	0.72%
Louisville/Jefferson County	8,813	1,285,270	0.69%
Cincinnati	11,786	2,168,825	0.54%
Pittsburgh	10,048	2,339,941	0.43%

This table shows the Middle Eastern and Southeast Asian immigrant ratio per Metropolitan Statistical Area. Column 1 shows the Metropolitan Statistical Area. Column 2 and 3 show the number of minority immigrants and the total Metropolitan Statistical Area population respectively. Column 4 comprises the minority immigrant ratio, ranked form high to low.

C. Appendix D: Placebo tests

Table 9: Funding likelihood

	(1) Placebo 1	(2) Placebo 2
Immigrant90 x Placebo	-0.001	-0.002
	(0.005)	(0.002)
FICO	0.001***	0.001***
	(0.000)	(0.000)
Debt-to-income	-0.001***	-0.001***
	(0.000)	(0.000)
Employment Length	0.056***	0.056***
	(0.001)	(0.001)
Constant	-0.058***	-0.058***
	(0.021)	(0.021)
Observations	2,600,167	2,600,167
Yearly fixed effects	Yes	Yes
MSA fixed effects	Yes	Yes
State × Year fixed effects	Yes	Yes
R-squared	0.566	0.566

This table shows the results of two Ordinary Least Squares (OLS) regressions. The dependent variable is SuccesDum, and the main independent variable is the interaction variable Immigrant90 x Placebo. Placebo 1 comprises the exogenous shock date on the 1st of April 2011 and placebo 2 on 1st of December 2015. The regressions control for Yearly, Metropolitan Statistical Area and State × Year fixed effects. Full variable definitions can be found appendix A. Robust standard errors are clustered per Metropolitan Statistical Area, and standard errors are reported in parentheses. *, **, *** indicate significance at the 10%-, 5%-, and 1%-level.

Table 10: Interest rate spread

	(1) Placebo 1	(2) Placebo 2
Immigrant90 x Placebo	-0.020	-0.024
	(0.029)	(0.026)
FICO	-0.047***	-0.047***
	(0.005)	(0.005)
Log_AnnualIncome	-0.035***	-0.035***
	(0.005)	(0.005)
Home Ownership		
Rent	0.024***	0.025***
	(0.004)	(0.004)
Own	0.028***	0.028***
	(0.006)	(0.006)
Other	-0.231	-0.237
	(0.163)	(0.161)
EmploymentLength	0.002***	0.002***
	(0.000)	(0.000)
Debt-to-income	0.008***	0.008***
	(0.001)	(0.001)
NrDelinquencies2yrs	0.014***	0.014***
	(0.002)	(0.002)
NrOpenCreditLines	-0.002***	-0.002***
	(0.000)	(0.000)
NrPublicRecords	-0.005	-0.005
	(0.003)	(0.003)
Log_TotalRevolvBal	-0.027***	-0.027***
	(0.002)	(0.002)
Constant	7.541***	6.991***
	(0.312)	(0.304)
Observations	723,738	723,738
Yearly fixed effects	Yes	Yes
MSA fixed effects	Yes	Yes
State × Year fixed effects	Yes	Yes
R-squared	0.928	0.928

This table shows the results of four Ordinary Least Squares (OLS) regressions. The dependent variable is IntSpread, and the main independent variable is the interaction variable Immigrant90 x Placebo. Placebo 1 comprises the exogenous shock date on the 1st of April 2011 and placebo 2 on 1st of December 2015. The regressions control for Yearly, Metropolitan Statistical Area and State × Year fixed effects. Full variable definitions can be found appendix A. Robust standard errors are clustered per Metropolitan Statistical Area, and standard errors are reported in parentheses. *, **, *** indicate significance at the 10%-, 5%-, and 1%-level.

Table 11: Loan amount

	(1) Placebo 1	(2) Placebo 2
Immigrant90 x Placebo	-0.037	-0.027
	(0.105)	(0.155)
Constant	0.008*	0.008*
	(0.006)	(0.006)
Observations	5,790,240	5,790,240
Yearly fixed effects	Yes	Yes
MSA fixed effects	No	No
State × Year fixed effects	Yes	Yes
Borrower fixed effects	Yes	Yes
R-squared	0.163	0.163

This table shows the results of four panel regressions. The dependent variable is Log_Amount, and the main independent variable is the interaction variable Immigrant90 x Placebo. Placebo 1 comprises the exogenous shock date on the 1st of April 2011 and placebo 2 on 1st of December 2015. The regressions control for Yearly, Metropolitan Statistical Area, Borrower and State × Year fixed effects. Full variable definitions can be found appendix A. Robust standard errors are clustered per Metropolitan Statistical Area, and standard are reported in parentheses. *, **, *** indicate significance at the 10%-, 5%-, and 1%-level.

Table 12: Default

	(1) Placebo 1	(2) Placebo 2
Immigrant90 x Placebo	-0.003	-0.002
	(0.011)	(0.003)
FICO	-0.001***	-0.001***
	(0.000)	(0.000)
Log_AnnualIncome	-0.010***	-0.010***
	(0.002)	(0.002)
Home Ownership		
Rent	0.035***	0.035***
	(0.003)	(0.003)
Own	0.017***	0.017***
	(0.003)	(0.003)
Other	0.003	0.003
	(0.023)	(0.023)
EmploymentLength	0.001	0.001
	(0.001)	(0.001)
Debt-to-income	0.004***	0.003***
	(0.001)	(0.000)
NrDelinquencies2yrs	0.002***	0.002***
	(0.001)	(0.001)
NrOpenCreditLines	0.002***	0.002***
	(0.000)	(0.000)
NrPublicRecords	0.002*	0.002*
	(0.001)	(0.001)
Log_TotalRevolvBal	-0.016***	-0.016***
	(0.001)	(0.001)
Constant	1.183***	1.185***
	(0.099)	(0.101)
Observations	723,738	723,738
Yearly fixed effects	Yes	Yes
MSA fixed effects	Yes	Yes
State × Year fixed effects	Yes	Yes
R-squared	0.064	0.064

This table shows the results of four Ordinary Least Squares (OLS) regressions. The dependent variable is default, and the main independent variable is the interaction variable Immigrant90 x Placebo. Placebo 1 comprises the exogenous shock date on the 1st of April 2011 and placebo 2 on 1st of December 2015. The regressions control for Yearly, Metropolitan Statistical Area and State × Year fixed effects. Full variable definitions can be found appendix A. Robust standard errors are clustered per Metropolitan Statistical Area, and standard errors are reported in parentheses. *, **, *** indicate significance at the 10%-, 5%-, and 1%-level.