Do Algorithms Discriminate Against African Americans in Lending?

Jérémie Bertrand[+]
IESEG

Laurent Weill[*]
EM Strasbourg Business School, University of Strasbourg

Abstract

We investigate whether discrimination against African Americans occurs in peer-to-peer lending. We consider data from a large peer-to-peer lender that uses algorithms and no face-to-face interview to decide loan approval and conditions. Using data from 3.6 million loan applications and 817,000 granted loans for 2016 and 2017, we perform regressions of loan acceptance and loan conditions on the percentage of African Americans by 3-digit zip area. We observe evidence of discrimination in peer-to-peer lending. African Americans have a greater chance to have their loan applications rejected, pay higher loan rates, and obtain loans with shorter maturity. Discrimination is more pronounced after the election of Trump.

JEL Codes: G21, J15.
Keywords: discrimination, Fintech, peer-to-peer lending, loans.

Acknowledgements

We thank Iftekhar Hasan, Matthew Henriksson, Marianne Verdier, Lionel Potier, Rebel Cole, Mikael Juselius, Christa Hainz, Zuzana Fungacova, Gene Ambrocio, Esa Jokivuolle, Mikko Mäkinen, Eleonora Granziera, Patrick Roger, Anaïs Hamelin for valuable comments and suggestions, as well as participants from the Conference on Fintech and Digital Finance in Nice (May 2019), the Conference on Big Data and Artificial Intelligence in Banking in Paris (June 2019), the Symposium in Money, Banking and Finance in Besançon (June 2019), the Southern Finance Association Meeting in Orlando (November 2019) and from seminars in Bank of Finland and University of Strasbourg.

[+] Email : jeremie.bertrand@edhec.com
[*] Corresponding author. Institut d'Etudes Politiques, Université de Strasbourg, 47 avenue de la Forêt Noire, 67082 Strasbourg Cedex. Phone: 33-3-68-85-81-38. Email: laurent.weill@unistra.fr

1. Introduction

A large volume of literature has documented the existence of discrimination in lending markets in the United States (e.g., Black, Schweitzer and Mandell, 1978; Ladd, 1998; Ross and Yinger, 2002; Ghent, Hernandez-Murillo and Owyang, 2014; Hanson et al., 2016). Recent chronicles[1] and studies have put the concern associated with the persistence of such discrimination upfront in public debate.[2]

The emergence of peer-to-peer lenders can, however, alter the manner through which discrimination manifests in lending markets. Peer-to-peer lending marketplaces match individuals who need loans with individuals who want to invest. To this end, peer-to-peer lending marketplaces use different processes for matching.

On the one hand, companies like Prosper allow lenders to choose the borrowers to whom they want to lend their money. Pope and Sydnor (2010) explain how borrowers can include information in the form of picture and text descriptions that can signal their ethnicity on the Prosper marketplace. As a consequence, lenders can influence the use of their money, that is, the lenders' personal biases can lead to discrimination among borrowers.

On the other hand, peer-to-peer lenders include companies like Lending Club, who finance their activities with investors to grant loans by using algorithms based on applications completed on the web including individual information such as credit scoring. These lenders therefore benefit from lower costs and greater reactivity with clients than conventional banks. However, this business model also means the absence of face-to-face interviews between clients and loan officers, which should suppress discrimination based on loan officer biases.

The objective of this paper is to investigate whether Lending Club discriminates against African Americans attempting to obtain a loan. We test the hypothesis that the use of algorithms leads to the absence of discrimination in lending. This hypothesis is based on the total absence of information on the ethnicity of the borrower because no explicit information is included in the application and no face-to-face interview occurs. Then, we can examine whether peer-to-peer lending can end discrimination in lending.

[1] https://www.nytimes.com/2018/03/07/opinion/mortage-minority-income.html
[2] A study by the Center for Investigative Reporting's online publication Reveal shows that African-Americans are far more likely to be denied a mortgage loan than Whites. For instance, in Philadelphia, although there are similar populations of African-Americans and Whites, Whites received 10 times more mortgage loans than African-Americans in 2015 and 2016 (https://www.revealnews.org/article/for-people-of-color-banks-are-shutting-the-door-to-homeownership/).

Lending Club is the largest peer-to-peer lender in the US; thus, Lending Club is the ideal peer-to-peer lender for our investigation due to the large availability of data and its wide geographic coverage across the United States, except for Iowa because of regulatory reasons. Investors buy notes that correspond to fractions of loans, which are backed by payments made on loans. Investors do not explicitly choose the borrowers they finance. However, investors can choose their investment strategy, in the sense that they can adopt a pre-set strategy that accords with their risk profile or create an investment strategy. When investors create a strategy, they build a portfolio for which they "may consider information about the loan grade, purpose, term (36 or 60 months), the debt-to-income ratio and most recent credit score, as well as other factors."[3] Therefore, investors cannot select borrowers based on ethnicity in the absence of direct (race) or indirect (geographic location) information on this individual characteristic.

Borrowers can apply online to obtain a loan. Borrowers provide information on their individual characteristics, for example, income and credit score. To this end, borrowers must provide their name and location to enable Lending Club to perform a credit check. Lending Club proposes unsecured personal loans between US$1,000 and US$40,000. The loan period can be either 3 years or 5 years. These loans can be used for several purposes. Lending Club provides information on how borrowers are screened for quality: "Qualified loan applications are approved based on stringent credit criteria designed to focus on the most creditworthy borrowers. To evaluate the credit risk of borrowers and to assign an interest rate to approved loans, proprietary models examine a variety of inputs including borrower credit reports, loan applications, and behavioral data. The models also incorporate the historical performance of the billions of dollars in loans facilitated through our marketplace. The models are consistently refined and improved with the goal of minimizing risk while providing consistent returns for investors."[4] Thus, it appears that loan acceptance is based on individual characteristics of the loan application including borrower information and on big data use of the historical performance of former granted loans.

Lending Club explicitly explains how its interest rates are set. Lending Club assigns a credit grade for each approved loan based on the borrower criteria and the data for all loans. The interest rate increases for each loan grade. Notably, Lending Club sets the interest rate and the maturity of the loan in the sense that investors can influence only how much to fund to classes of borrowers but not the loan conditions.

[3] https://www.lendingclub.com/public/investing-faq.action
[4] https://www.lendingclub.com/public/investing-faq.action

Our investigation is performed as follows. We aim to investigate the existence of discrimination in peer-to-peer lending. To this end, we assess the presence of disparities for African Americans relative to other borrowers by detecting the existence of worse loan conditions. We perform regressions of loan acceptance, loan rate, and loan maturity on a large set of variables, including loan variables, borrower variables, and information about African Americans. Then, we can document the presence of greater rejection, adverse loan pricing, and lower loan maturity for African Americans.

We use the dataset from Lending Club, which provides all data on loan applications and loan conditions after acceptance. We employ data for 2016 and 2017 for approximately 3.6 million loan applications and 817,000 granted loans. Because information is not available for ethnicity in the dataset, we cannot use this information for our estimations. However, we link information from the zip code of the borrower with information on the ethnic breakdown by 3-digit zip area for 2017. We consider loan and borrower variables in the estimations, including the credit grade, the debt-to-income ratio, and the income of the borrower. Therefore, we investigate whether discrimination is observed even after controlling for differences in credit score, debt-to-income ratio, and several other factors.

This is a major point because banks have often claimed that they deny loans to minorities based on credit scores or debt-to-income ratios.[5] The basis of the banks' argumentation is that rejection would result from the lower quality of loan applications from minorities instead of explicit discrimination based on ethnicity. Thus, this phenomenon is irrelevant in our framework because we explicitly control for the factors associated with higher default rates.

We therefore test the presence of discrimination in peer-to-peer lending in which no explicit information on the ethnicity of the borrower is available. We are then able to observe whether the expansion of peer-to-peer lending can contribute to overcome discrimination in lending. The key hypothesis is that no discrimination occurs in such a framework in the absence of direct information on the ethnicity.

However, discrimination can occur in peer-to-peer lending through two mechanisms. First, the use of big data can preserve discrimination in the following manner. If loan performance varies across geographic areas, the use of big data by algorithms can lead to a higher proportion of loan applications being rejected in areas with lower loan performance. If

---

[5] https://www.nytimes.com/2018/03/07/opinion/mortage-minority-income.html

such areas are areas with a higher presence of African Americans, we would then observe discrimination in lending. In that case, rather than direct discrimination, statistical discrimination would occur based on the link between lower loan performance and the high presence of African Americans. Second, borrowers must provide information on their name. Such information can also be associated with greater chances to be African American and can then be used to exert discrimination. Bertrand and Mullainathan (2004) demonstrate that individuals with so-called African–American-sounding names are more discriminated against than individuals with so-called White-sounding names in the labor market. That case is an example of explicit discrimination.

Once we have examined the existence of discrimination against African Americans in peer-to-peer lending, we extend the investigation. First, we assess whether discrimination has been influenced by the election of Donald Trump in November 2016. Trump's election has been associated with a higher propensity of individuals to reveal racist attitudes (Bursztyn, Egorov and Fiorin, 2017). This association could therefore have contributed to enhance discrimination in lending. Second, we study whether discrimination in lending differs in states in the South relative to other US states. States in the South are commonly associated with greater negative stereotypes of African Americans than other states; however, according to our review of the literature, a counterargument is suggested: Southern states are not plagued by the highest levels of racism in the US (Chae et al., 2015). Third, we assess whether loan discrimination varies based on the loan purpose because some loans are less discriminated against than others because they are perceived as riskier based on the borrower's profile.

These additional estimations allow us to provide additional information on the reality of discrimination in lending and evidence of prime interest to understand the mechanisms in peer-to-peer lending. Namely, if loans are granted only on the basis of the criteria of the loan application, Trump becoming president would not have changed discrimination. Thus, we assert that this election result may have freed racist attitudes from society, but such attitudes do not influence algorithms.

Our results provide evidence of discrimination in peer-to-peer lending. We show that African Americans have a greater chance to have their loan applications rejected. We also observe adverse pricing for African Americans because the interest rate is significantly higher for minorities. Finally, we observe that loan maturity is lower for African Americans. In summary, we observe that peer-to-peer lending discriminates against African Americans' by accepting fewer loan applications from this group and by charging higher rates and accepting lower maturities for their loans conditional to acceptance. We do not observe greater discrimination for African Americans in the South. However, we clearly document that discrimination has increased following the election of Trump.

Our paper contributes to two key debates in the literature. First, we augment the vast literature on discrimination in lending by investigating the effect of peer-to-peer lending on this element. Second, we contribute to the nascent literature on lending by Fintech companies. We improve the understanding of how peer-to-peer lending changes loan markets. Although several studies have stressed how the major differences between Fintech and conventional banks will result in massive changes to lending markets (e.g., Morse, 2015, on how peer-to-peer lending diminishes information frictions; Butler, Cornaggia and Gurun, 2016, on the choice between conventional lenders and Fintech lenders), our work extends this literature by examining how discrimination in lending can persist in Fintech markets. The paper most similar to ours is by Pope and Sydnor (2010), who observe evidence of discrimination in peer-to-peer lending when a picture of the face of the borrower is revealed. However, we significantly depart from this work by considering a peer-to-peer lender with no explicit information on the race of the borrower in the loan decision.

Our evidence thus advances the understanding of discrimination in peer-to-peer lending. The presence of such discrimination has broad implications for the expansion of peer-to-peer lending. First, our evidence suggests that the expansion of peer-to-peer lending will not end to discrimination in lending. Even without face-to-face interviews or direct information on the ethnicity of the borrower, discrimination persists. Second, our evidence motivates further analysis of the functioning of peer-to-peer lenders to appraise the reasons for such discrimination and design peer-to-peer lending without loan discrimination.

The remainder of the paper is organized as follows. Section 2 describes the data and variables and provides empirical specifications. Section 3 reports the results. Section 4 concludes.

2. Data

Data on loan applications and loans funded by Lending Club are publicly available on their website.[6] The sample used in this study contains all loan applications and obtained loans for 2016 and 2017. We have a dataset of approximately 3.6 million loan applications and

[6] Lending Club data have been used in other studies including Jagtiani and Lemieux (2018a) on the use of alternative data sources by Fintech lenders and Jagtiani and Lemieux (2018b) on the ability of Fintech lenders to penetrate relatively underserved banking markets.

817,000 granted loans. Residents from all US states, except for Iowa, can borrow through Lending Club. We have information at the loan level and at the individual level for all loan applications.

We consider three loan-level variables as explained variables. First, we use loan acceptance. We create a dummy variable equal to one if the loan is obtained and zero otherwise (*Obtain*). Second, we consider the loan interest rate (*Int. Rate*). Third, we consider loan maturity. Lending Club grants loans for two possible terms: 36 months or 60 months. We therefore create a dummy variable equal to one if the loan is for 36 months, and zero otherwise (*Short Term*).

We also control for several loan characteristics that potentially affect loan acceptance and loan conditions. We use the natural logarithm of the loan amount (*Log(Amount)*) and a series of dummies denoting loan purpose: *Business, Car financing, Credit card refinancing, Debt consolidation, Home buying, Home improvement,* and *Other.*

A key variable is the grade assigned by Lending Club to each loan application. Lending Club uses the borrower’s FICO credit score and additional information (e.g., the requested loan amount, the length of credit history, the number of recent inquiries) to assign a credit grade. The grades range alphabetically from A to G, and A is the highest grade. We recode this information to create the variable *Grade* from 1 (A, the best) to 7 (G, the worst). Each grade is divided into five subgrades; thus, there are 35 subgrades from A1 to G5, and one is the highest subgrade. We recode this information to create the variable *Sub-Grade* from 1 (A1, the best) to 35 (G5, the worst). We also test the inclusion of information on the subgrade in the estimations. Information on subgrade is not available for loan applications but is available for obtained loans; thus, we include only this information in estimations explaining interest rate and maturity. Lending Club mentions that the grade is the key variable used to set interest rates. We confirm this element with a correlation between *Int. rate* and *Grade* of 0.965 for our full sample.

We also control for several borrower characteristics that can influence loan acceptance and loan conditions. We use the ratio of monthly debt payments divided by monthly income (*Debt-to-Income Ratio*), the number of past-due incidences of delinquency in the borrower’s credit file for the past 2 years (*Past Delinquency*), the employment length in years (*Employment length*), the natural logarithm of the annual income (*Log(Annual Income*)), and two dummy variables describing whether the borrower owns her/his house (*House Owner*) or rents her/his house (*Home Rent*).

We control for the Lending Club *Historical Default Rate* in the 3-digit area where the borrower lives (taking into account data from Lending Club in 2014 and 2015). This variable controls for a potential "learning effect" from the algorithm. Indeed, Lending Club can take into account its previous results to define credit characteristics.

Finally, we control for macroeconomic variables for two reasons. On the one hand, Lending Club explains that it uses big data to grant and price their credit. On the other hand, Bostic and Lampani (1999) show that geographic characteristics are correlated with ethnicity and credit conditions, meaning that their absence could lead to a potential bias. So we complete our sample with variables from the Bureau of Labor Statistics adding *Poverty Rate*, *Unemployment Rate*, *Median Income* and *High School Rate* (i.e., the average high school graduation rate) at the state level. We also add *Internet Rate* (i.e., the average internet coverage rate) at the state level.

The dataset on loan applications does not include the same amount of information as the dataset on obtained loans. As a consequence, the set of control variables is smaller for estimations explaining *Obtain* relative to those explaining *Interest Rate* and *Short Term*. It does not include four borrower characteristics: *Past Delinquency, Log(Annual Income), House Owner,* and *House Rent.*

Information on the ethnicity of the borrower is not included in the Lending Club dataset. This absence of information is a major point in our investigation because we thus assume that Lending Club is not explicitly aware of the ethnicity of the borrower, especially in the absence of the face-to-face interviews with loan officers performed by traditional lenders.

As a consequence, the investigation of the impact of the ethnic identity on loan acceptance and loan conditions should rely on an alternative means to measure this identity. To this end, we consider the information included in the loan applications in the Lending Club dataset on the zip codes of the borrowers. Next, we match loan applications with information on minorities for 2017 from the United States Zip Codes database. This dataset provides a wide range of variables for each location based on the zip code, including the percentage of the different ethnic groups.

We have information on the proportion of Whites, African Americans, Native Americans, Asian, Islander, and others for each zip code. We use this information to define our key variable of interest: the percentage of African Americans (*AFAM*) in the 3-digit area where the borrower lives.

Table 1 reports the summary statistics for the full sample of loans and for the subsamples of obtained and rejected loans. Obtained loans represent only 22.3% of all loans, showing the high rejection rate of loan applications. For obtained loans, we observe a mean interest rate of 13.14% with a large range from 5.32% to 30.99%. Loans with a short maturity represent 72.8% of all funded loans.

The classification by loan purpose shows that the majority of loans are requested for debt consolidation (51.3% of requested loans, 56.4% of obtained loans). “Credit card refinancing” is the second purpose (20.9% of obtained loans). The third purpose is “Home improvement,” with 7.4% of obtained loans. The other purposes represent very small shares of the obtained loans: “Business”: 1.2%, Car financing: 1.2%, Home buying: 0.6%, and “Other”: 6.9%. These figures confirm that loans provided by Lending Club are consumer loans. Table 2 summarizes the definitions of all the variables used and their sources.

Our objective is to investigate how the proportion of minorities can exert an impact on loan approval and conditions. Our baseline estimation is as follows:

$$Loan\ Outcome_i = \alpha + \beta\, AFAM_j + \chi\, X_i + \delta\, Z_j + \mu\, M_s + \varepsilon_i \qquad (1)$$

where *i* is the application; *j* the 3-digit zip code; *s* the state; *Loan Outcome* stands for one of the three dependent variables (*Obtain*, *Interest Rate*, *Short Term*); *AFAM* is our African-American variable; *X* is a set of loan-level control variables; *Z* is a set of borrower-level control variables; *M* is a set of State-level control variables; and ε is a random error term. We include month dummies and year dummies to control for seasonal and yearly effects. We use logit models to explain *Obtain* and *Short Term* and use an ordinary least squares (OLS) model to explain *Interest Rate*. Standard errors are clustered by three-digit zip code.

3. Results

3.1 Main estimations

We perform regressions explaining loan acceptance, loan interest rate, and loan maturity. Then, we can provide a broad analysis of the discrimination in peer-to-peer lending. Table 5 reports the estimations.

First, we analyze how the percentage of African Americans can influence loan acceptance with the regression in column (1). We observe that the coefficient of *AFAM* is significantly negative. Therefore, we observe that African Americans are discriminated against when attempting to obtain a loan with Lending Club.

We can question the economic significance of this discrimination. To do so, we calculate the marginal effect of the coefficient. We observe that an increase of one percentage point in African-Americans in the area leads to a decrease of 0.0129 percentage points in the ability of obtaining a loan.

The analysis of the control variables is in accordance with the expectations: lower debt-to-income ratio, better grade, higher employment length and lower poverty rate all contribute to enhance the probability to obtain a loan. Notably, we observe a significantly positive coefficient for loan amount.

Thus, the investigation of the relation between the percentage of African Americans and loan acceptance leads to the conclusion that Lending Club discriminates against African Americans applying for a loan. The loan applications from African Americans have a higher rate of rejection than the applications from other applicants.

Second, we investigate how the percentage of African Americans affects the interest rate. We test several specifications to assess how the credit rating of Lending Club influences the results. As aforementioned, Lending Club explicitly sets interest rates based on the credit grade, which is supported by the very high correlation between credit grade and interest rate. We start by using the credit grade in the estimations. Next, we test the inclusion of the credit subgrade instead because we also have this information in the dataset. Finally, we perform estimations without information on the credit rating of the borrower. The very high correlation questions that factors other than the grade including the percentage of African Americans would influence the interest rate. The inclusion of information on credit rating can then contribute to reduce the significance of any other explaining variable when explaining the interest rate. We display the results of the OLS regressions in columns 2 to 4 in Table 5.

The main finding is evidence of adverse loan pricing against African Americans. The coefficient of *AFAM* is significantly positive in all estimations, suggesting that African Americans pay higher loan rates. An increase of one percentage point of African Americans in an area leads to an increase of 0.079% points in the interest rate. Thus, the interest rate increases by 5.293% points in Jackson-Main, where the proportion of African Americans is equal to 67%.

Notably, *AFAM* is also significantly positive when *Grade* or *Sub-Grade* are included. This finding means that even if credit grade explains a large proportion of the variance in the interest rate, the percentage of African Americans still contributes to exert an influence on loan pricing.

We turn to the analysis of control variables. When no grade variable is included (because this variable incorporates a large set of information), we observe the expected findings: a higher loan rate is associated with a lower income (for individual and at a state level), lower employment length, lower unemployment rate, and a higher debt-to-income ratio.

Third, we consider the relation between the percentage of African Americans and loan maturity. Borrowers can be rationed through loans with lower maturity. As a consequence, borrowers would not have access to the same opportunities associated with loans. We investigate this question with logit regressions in columns 5 and 6 in Table 5. We test, alternatively, the inclusion of *Grade* and *Sub-Grade* in the estimations.

We again observe clear evidence of discrimination. The coefficient of *AFAM* is significantly positive, supporting the perspective that African Americans have shorter loan maturity than other borrowers. In terms of economic significance, we observe that, at means, the probability of having a shorter loan maturity increases by 0.0429% point when the proportion of African Americans increases by one percentage point.

The observation of the control variables shows—as expected—that short maturity is associated with higher debt-to-income ratio and past delinquency. We can also see that the lower the high school rate, the longer the loan. However, we also observe that longer employment length and better credit grade are associated with shorter maturity for the requested loan.

In summary, our results provide strong support for discrimination in peer-to-peer lending. The percentage of African Americans is significantly associated with lower loan acceptance, higher loan rate, and lower loan maturity. Thus, Lending Club discriminates against African Americans by using all three forms of discrimination: higher loan rejection, adverse loan pricing, and shorter loans. Therefore, our key conclusion is that discrimination exists in peer-to-peer lending. Next, we attempt to explain our conclusion.

A first explanation regards statistical discrimination based on geography. Namely, Lending Club considers data on the historical performance of former granted loans. As a consequence, differences in past loan performance across geographic areas can influence differences in loan conditions in the present. For instance, if loan performance is on average higher in Tampa than in Saint Petersburg, Florida, based on data from former loans, the algorithm can provide a better valuation for locations in Tampa. Thus, if lower past loan performance is associated with a higher presence of African Americans, we could then observe discrimination based on geography.

Thus, the explanation would be statistical discrimination based on geography, which would not be illegal in the sense that geography would not be used to proxy for ethnicity but to inform regarding past performance of loans. Notably, as aforementioned, our estimations consider a large set of individual characteristics of the borrowers, including their income and credit grade. Thus, the explanation based on statistical discrimination means that location would continue to have a significant influence on loan conditions after controlling major individual characteristics.

A second explanation is that the Lending Club policy explicitly considers factors associated with the probability that the borrower belongs to the African American minority group. Lending Club is transparent about its lending policy: The company explains how the loan rate is conditional on the credit grade. What can occur, however, is that non-disclosed factors are used that also influence loan conditions, for instance, the name of the borrower. Bertrand and Mullainathan (2004) perform an investigation of the influence of the name on labor discrimination by focusing on the association between name and race. They use name frequency data calculated from birth certificates of babies born during a certain period of time in Massachusetts and observe large differences between so-called White names and so-called African American names, with some names being distinctively White and others being distinctively African American (e.g., Allison and Brad are distinctively White names and Keisha and Darnell are distinctively African American names). They observe that individuals with so-called African–American-sounding names are more discriminated against than individuals with so-called White-sounding names in the labor market.

3.2 Influence of Trump being elected president

Our main estimations indicate the existence of discrimination in peer-to-peer lending. We can therefore question whether discrimination has increased following the election of Donald Trump as president in November 2016. Trump’s campaign has been associated with an increase in racist attitudes in the public debate (Bobo, 2017). The election of Trump was observed to have favored racist attitudes. In addition to increased reports of hate incidents after the election of Trump, Bursztyn, Egorov and Fiorin (2017) investigated the influence of the election of Trump on attitudes. Using a survey, they show that the propensity of individuals to express xenophobic attitudes increased after Trump was elected president. No study has ever investigated the effect of the election of Trump on discrimination in lending to the best of our knowledge. Thus, we provide a novel analysis of this question.

We conduct an investigation to assess if discrimination in peer-to-peer lending has increased during the election of Trump. Loan acceptance and conditions in peer-to-peer lending are presented not as the outcome of human decisions but of algorithms based on the characteristics of the loan application and the borrower, which are not affected by the election. However, our first results show discrimination in peer-to-peer lending even in the absence of any information on the ethnicity of the borrower. Thus, we question whether peer-to-peer lending is really not sensitive to the same elements that can affect traditional lenders, including an increase in the number of individuals espousing negative stereotypes against minorities in the public sphere.

To investigate the effect of the election of Trump, we create three dummy variables: the first one, *Trump M-3*, is equal to one if the loan is dated during the three months prior to Trump election (from August to October 2016); the second one, *Trump Election*, is equal to one if the loan is dated during Trump election (in November and December 2016); and the last one, *Trump M+3*, is equal to one if the loan is dated during the three months following Trump election (from January to March 2017). If Trump election leads to an increase of the discrimination, we should observe a peak of discrimination during this period and not before, nor after.

We redo the estimations by adding one of the three dummies, and the interaction term between the dummy and the percentage of African Americans. We can then check whether the election of Trump influenced discrimination against African Americans. We report the results in Tables 6-1, 6-2 and 6-3 respectively for *Obtain*, *Interest Rate* and *Short Term*. As explained by Norton *et al.* (2004), it is not possible to directly analyze the significance and the value of the interaction term in a non-linear model; thus we use the methodology developed by Karaca-Mandic *et al.* (2012) to compute the correct marginal effect of the interaction term (displayed in the last row of each table).

First, we observe for *Obtain* that discrimination is higher during Trump Election, the interaction term *AFAM* × *Trump Election* being negative and significant, and not before. Discrimination seems to decrease just after Trump Election: the interaction term *AFAM* × *Trump M+3* is positive and significant. These results are confirmed by the marginal effect in the last row of the table.

Second, Trump Election also leads to greater discrimination for *Interest Rate*. The only significant interaction term is *AFAM* × *Trump Election* (confirmed by the marginal effect) which is positive, while none of the other two is significant. So discrimination increases during Trump Election, with this trend observed neither before, nor after. Finally, we can see that there is no evidence concerning *Short Term* of a higher discrimination during the Trump Election.

These results suggest discrimination has increased during the election of Trump; however, loan decisions and conditions are supposed to be decided by algorithms. We propose the argument that algorithms can change the loan outcomes because the variables they use have been influenced by the election of Trump. However, we observe no reason why the credit rating or the key characteristics, for example, past delinquency or income of borrowers, would have been influenced by such an event.

These results are therefore puzzling. Our first interpretation of discrimination in peer-to-peer lending, statistical discrimination based on geography, is not satisfactory here, at least in its naïve version—the location of the borrower would be used based on past performance of loans in a specific area—because this element results in the same information before, during and after the election of Trump. However one possibility is that the algorithm has been modified to provide a different weight to the location after this event. Our second interpretation of discrimination was the possibility of explicit discrimination through the use of factors associated with the probability that the borrower belongs to a minority in the algorithms. The increased discrimination following the election of Trump can also result from changes in the algorithms. In both interpretations, we tend to suggest that individuals' decisions exert an effect on loan decisions and conditions for Lending Club through changes in algorithms.

In any case, our conclusion is that the election of Trump has contributed to an increase in discrimination in peer-to-peer lending. Hence, this finding provides an additional argument that peer-to-peer lending does not end discrimination in lending.

3.3 Is the South associated with greater discrimination?

We observe evidence of discrimination in peer-to-peer lending. Thus, we can question whether discrimination varies by region among the US states. In particular, states in the South may differ in the level of discrimination against African Americans because the area has a documented history of this behavior, which includes their enslavement of African Americans, their Confederate stance in the Civil War, and—more recently—voter suppression.

States in the South may differ in discrimination in lending from the rest of the country in opposite ways. On the one hand, discrimination could be higher for African Americans because of persistent discrimination in aspects of everyday life including lending. The perspective accords with the view of persistent negative stereotypes and racism against African Americans and lower empowerment of African Americans in states in the South. On the other hand, discrimination could be lower for African Americans because of the specific history of these states in the last decades associated with affirmative action policies, efforts to promote the fight against discrimination, and greater electoral participation of African Americans.[7]

Several empirical works have supported that discrimination would not be higher in the states in the South. Maryl and Saperstein (2013) examine the determinants of discrimination for White Americans. They observe evidence that Whites have higher chances to be victims of racial discrimination in the South, with 11% of Southern Whites reporting that incidence compared with 6% of Whites outside the South. When assessing racism with an internet-based measure, Chae et al. (2015) do not observe the greatest levels of racism in the states in the South, but instead along the spine of the Appalachian Mountains from North Carolina to Vermont.

Thus, we explore the existence of geographic differences in discrimination in lending. We investigate this question by creating the dummy variable *South* equal to one if the borrower lives in a state in the South and zero otherwise. For our purpose, the South includes the South Atlantic, East South Central, and West South Central census divisions, which comprise the following states: Delaware, Maryland, Florida, Georgia, North Carolina, South Carolina, Virginia, West Virginia, Alabama, Mississippi, Arkansas, Louisiana, Texas, Oklahoma, Kentucky, and Tennessee.

We perform new estimations by adding *South* and its interaction term with, alternately, the percentage of all minorities and the percentage of African Americans. Table 7 displays these estimations, the last raw display the marginal effect of the interaction term. Several conclusions emerge.

When considering loan acceptance, the interaction term of *South* is only positive and significant with *AFAM* in the logistic regression. Therefore, loans to African Americans are more often accepted in the South. The analysis of the interest rate shows that the interaction term of *South* is significantly negative with *AFAM*. These results suggest lower rates for African Americans in states in the South, that is, lower adverse loan pricing in this region of the US. Finally, the examination of loan maturity reveals significantly negative coefficients

[7] According to the US census, the percentage of African-Americans voting in the 2016 election has been higher in the South states (59.2 percent) than countrywide (55.9 percent).

for the interaction terms *South* × *AFAM*. This result means that African-Americans have longer loan maturities in the South than in the rest of the country.

In summary, our results document lower loan discrimination in the South than in the rest of the US. The conclusion of spatial differences in loan discrimination is important and again tends to show that algorithms do not provide the same results in a manner as automatic and standardized as expected.

3.4 Estimations by purpose

The results provided thus far strongly indicate that minorities are treated differently in peer-to-peer lending. However, until now, we have only considered all loans without distinguishing their purpose, although discrimination can vary across loan purposes. Consequently, we complete our analysis of discrimination in peer-to-peer lending by investigating differences across loan purposes.

We consider the five main loan purposes observed in the sample: debt consolidation, credit card refinancing, business, car financing, and home improvement. We redo the estimations by focusing on each purpose, one at a time. Table 8 reports the estimations. We obtain several notable results.

First, we observe strong evidence of discrimination in lending for "debt consolidation," "credit card refinancing"—both major purposes for loans, and "home improvement" for African Americans. For each, we observe discrimination in all three considered loan characteristics (loan approval, interest rate, maturity), with significant coefficients for *AFAM*, which are, respectively, negative when explaining *Obtain* and positive when explaining *Int. Rate* and *Short Term*.

Second, some evidence of discrimination is observed for the loan purpose "car financing." We highlight that there was lower loan approval and adverse loan pricing but no shorter maturity for African Americans. Third, we observe no evidence of discrimination for loans motivated by "business." *AFAM* is not significant when explaining each of the three considered loan characteristics.

Therefore, the analysis by purpose shows limited differences across loan purposes in loan discrimination. With the exception of loans requested for "business," African Americans are discriminated whatever the loan purpose. African Americans are subjected to higher rates of rejected loan applications and adverse loan pricing for all loan purposes and for shorter loan maturities, except for "car financing" loans.

4. Conclusion

This paper investigates discrimination in peer-to-peer lending. We use data from Lending Club, a major peer-to-peer lender providing loans on the basis of algorithms using loan applications completed on the web. Loans are therefore granted without face-to-face interviews and information on the ethnicity of the borrower. We can therefore question the persistence of loan discrimination with such companies to analyze whether this lending process can end discrimination in lending. To this end, we investigate how the percentage of African Americans in one geographic area influences the probability to obtain a loan, the loan rate, and the loan maturity conditional to the loan acceptance.

We observe strong evidence of discrimination against African Americans in peer-to-peer lending. African Americans have greater chances to have their loan applications rejected, are charged higher rates, and obtain loans with shorter maturity. We observe that discrimination is overall and not conditional to loan purpose: African Americans are discriminated against for all types of loans, except for loans requested for business. We observe that the election of Trump has been followed by an increase in discrimination. Finally, we do not observe greater discrimination in the states in the South.

These results are notable and contribute to the literature because they demonstrate persistence of discrimination in a peer-to-peer lending company that requests no explicit information on the ethnicity of the borrower. Because we control for individual characteristics, the results cannot be interpreted based on differences in income or in credit rating that would lead to differences in loan conditions. These factors can be explained either by statistical discrimination based on geography or by explicit discrimination. Evidence of greater discrimination following the election of Trump tends to suggest that statistical discrimination in a naïve form (the use of information on past performance of loans in geographic areas) cannot explain all the results.

Our study therefore shows evidence of discrimination in lending in peer-to-peer lenders. The results consequently indicate a pessimistic view is appropriate regarding the consequences of the expansion of such lenders by showing these novel practices are insufficient to end discrimination in lending. This conclusion should, however, not be interpreted overbroadly. The rates of discrimination against minority groups could be lower for peer-to-peer lenders than for conventional lenders; thus, peer-to-peer lenders may provide some advantages compared with conventional lenders despite the aforementioned discriminatory practices against African Americans. Further work is required to understand the origin of discrimination in peer-to-peer lending and document whether peer-to-peer lending contributes to reducing discrimination against various minority groups in lending.

References

Bertrand, M., Mullainathan, S., 2004. “Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination.” American Economic Review 94, 4, 991-1013.

Black, H., Schweitzer, R., Mandell, L., 1978. “Discrimination in Mortgage Lending.” American Economic Review 68, 2, 186-191.

Bobo, L., 2017. “Racism in Trump’s America: Reflections on Culture, Sociology, and the 2016 Presidential Election.” British Journal of Sociology 68, S1, S85-S104.

Bostic, R., Lampini, K., 1999. “Racial Differences in Patterns of Small-Business Finance: the Importance of Local Geography”. N775, Proceedings, Federal Reserve Bank of Chicago, 149-179.

Bursztyn, L., Egorov, G., Fiorin, S., 2017. “From eEtreme to Mainstream: How Social Norms Unravel.” NBER Working Paper n°23415.

Butler, A., Cornaggia, J., Gurun, U., 2016. “Do Local Capital Market Conditions Affect Consumers’ Borrowing Decisions?” Management Science 63, 12, 4175-4187.

Chae, D., Clouston, S., Hatzenbuehler, M., Kramer, M., Cooper, H., Wilson, S., Stephens-Davidowitz, S., Gold, R., Link, B., 2015. “Association between an Internet-Based Measure of Area Racism and Black Mortality.” Plos One 10, 4, e0122963. doi:10.1371/journal.pone.0122963.

Ghent, A., Hernandez-Murillo, R., Owyang, M., 2014. “Differences in Subprime Loan Pricing Across Races and Neighborhoods.” Regional Science and Urban Economics 48, 199-215.

Hanson, A., Hawley, Z., Martin, H., Liu, B., 2016. “Discrimination in Mortgage Lending: Evidence from a Correspondence Experiment.” Journal of Urban Economics 92, 48-65.

Jagtiani, J., Lemieux, C., 2018a. “The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the Lending Club Consumer Platform.” Federal Reserve Bank of Philadelphia Working Paper 18-15, April 2018.

Jagtiani, J., Lemieux, C., 2018b. “Do Fintech Lenders Penetrate Areas That Are Underserved by Traditional Banks?” Journal of Economics and Business 100, 43-54.

Karaca-Mandic P., Norton E.C., Dowd B. 2012. “Interaction Terms in Nonlinear Models.” Health Services Research. 47, 255–274.

Ladd, H., 1998. “Evidence on Discrimination in Mortgage Lending.” Journal of Economic Perspectives 12, 2, 41-62.

Maryl, D., Saperstein, A., 2013. “When White People Report Racial Discrimination: The Role of Region, Religion, and Politics.” Social Science Research 42, 742-754.

Morse, A., 2015. “Peer-To-Peer Crowdfunding: Information And The Potential For Disruption In Consumer Lending.” NBER Working Paper n°20899.

Norton, E.C., Wang, H., Ai, C. 2004. “Computing Interaction Effects and Standard Errors in Logit and Probit Models.” Stata Journal 4, 2, 154–167.

Pope, D., Sydnor, J., 2010. “What’s in a Picture? Evidence on Discrimination from Prosper.com.” Journal of Human Resources 46, 1, 53-91.

Ross, S., Yinger, J., 2002. The Color of Credit: Mortgage Discrimination, Research Methodology, and Fair-Lending Enforcement. MIT Press Books.

Table 1
Summary Statistics for full sample and sub-samples.

	Full sample				Obtain = 0				Obtain = 1			
Variable Name	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Dependent variables												
Obtain	0.223	0.416	0	1								
Int. Rate									13.136	5.066	5.320	30.990
Log(Amount)	9.115	0.992	5.303	11.781	9.036	1.043	5.303	11.781	9.392	0.723	6.909	10.597
Short Term									0.728	0.445	0	1
Independent variables												
Key variable												
AFAM	0.138	0.132	0.001	0.875	0.141	0.134	0.001	0.875	0.128	0.124	0.001	0.875
Borrower characteristics												
Debt to Income Ratio	23.574	17.753	0.700	67.620	24.983	19.317	0.700	67.620	18.674	9.086	0.700	67.620
Past Delinquency									0.349	0.940	0	42
Employment length	1.609	3.261	0	10	0.368	1.654	0	10	5.926	3.755	0	10
Log(Annual Income)									11.151	0.540	3.258	18.516
House Owner									0.113	0.317	0	1
House Rent									0.395	0.489	0	1
Grade	4.116	1.275	1	7	4.531	0.944	1	7	2.669	1.221	1	7
Sub-Grade									11.302	6.156	1	35
Loan characteristics												
Purpose												
Business	0.019	0.135			0.021	0.142			0.012	0.107		
Car financing	0.047	0.211			0.057	0.232			0.012	0.107		
Credit card refinancing	0.147	0.354			0.129	0.335			0.209	0.406		
Debt consolidation	0.513	0.500			0.499	0.500			0.564	0.496		
Home buying	0.016	0.125			0.019	0.136			0.006	0.075		
Home improvement	0.053	0.224			0.047	0.211			0.074	0.262		
Other	0.119	0.323			0.133	0.339			0.069	0.254		
Macroeconomic variables												
Poverty Rate	12.925	2.271			12.98	2.278			12.736	2.234		
Unemployment Rate	4.888	0.631			4.89	0.627			4.882	0.645		
Internet Rate	79.283	4.566			79.165	4.592			79.695	4.450		
High School Rate	86.436	3.986			86.42	3.959			86.489	4.078		
Median Income	29028.89	3940.738			28914.85	3922.687			29425.59	3977.512		
Other												
Historical Default Rate	0.186	0.064			0.188	0.064			0.181	0.066		
South	0.398	0.490			0.41	0.492			0.356	0.479		
Trump M-3	0.088	0.283			0.081	0.273			0.112	0.315		
Trump Election	0.088	0.283			0.089	0.286			0.081	0.272		
Trump M+3	0.137	0.344			0.145	0.353			0.110	0.313		
Number of observations	**3,661,310**				**2,843,818**				**817,492**			

Table 2
Definition of variables

Variable Name	Description
Dependent variables	
Obtain	1 if the borrower obtains the credit, 0 otherwise (Source: Lending Club)
Int. Rate	Interest Rate on the loan (Source: Lending Club)
Short Term	1 if the maturity of the loan if equal to 36 months, 0 otherwise (60 months) (Source: Lending Club)
Independent variables	
Key variable	
AFAM	Percentage of African-Americans in the 3-digit area where the borrower lives (Source: UnitedStatesZipCodes)
Borrower characteristics	
Debt to Income Ratio	A ratio calculated using the borrower’s total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower’s self-reported monthly income. (Source: Lending Club)
Past Delinquency	The number of 30+ days past-due incidences of delinquency in the borrower's credit file for the past 2 years. (Source: Lending Club)
Employment length	Employment length in years. (Source: Lending Club)
Log(Annual Income)	Log of the self-reported annual income provided by the borrower during registration. (Source: Lending Club)
House Owner	1 of the borrower owns his house, 0 otherwise. (Source: Lending Club)
House Rent	1 if the borrower rents his house, 0 otherwise. (Source: Lending Club)
Grade	Loan grade from A - the best - to G - the worst, encoded from 1 – the best – to 7 – the worst. (Source: Lending Club)
Sub-Grade	Subdivision of loan grade, each grade is divided in 5 categories, from 1 – the best – to 5 – the worst. The sub-grade goes from A1 – the best – to G5 – the worst, encoded from 1 – the best – to 35 – the worst. (Source: Lending Club)
Loan characteristics	
Log(Amount)	The total amount committed to that loan at that point in time. (Source: Lending Club)
Purpose	A category provided by the borrower for the loan request (Source: Lending Club)
Business	1 if the category is Business, 0 otherwise
Car financing	1 if the category is Car financing, 0 otherwise
Credit card refinancing	1 if the category is Credit card refinancing, 0 otherwise
Debt consolidation	1 if the category is Debt consolidation, 0 otherwise
Home buying	1 if the category is Home buying, 0 otherwise
Home improvement	1 if the category is Home improvement, 0 otherwise
Other	1 if the category is Other, 0 otherwise
Macroeconomic variables	
Poverty Rate	Average poverty rate between 2016 and 2017 by state. (Source: Bureau of Labor Statistics)
Unemployment Rate	Average unemployment rate between 2016 and 2017 by state. (Source: Bureau of Labor Statistics)
Internet Rate	Average internet coverage rate between 2016 and 2017 by state. (Source: Bureau of Labor Statistics)
High School Rate	Average high school graduation rate between 2016 and 2017 by state. (Source: Bureau of Labor Statistics)
Median Income	Average median income between 2016 and 2017 by state. (Source: Bureau of Labor Statistics)
Other variables	
Historical Default Rate	Lending Club historical default rate during the previous 2 years (2014 and 2015) in the 3-digit area where the borrower lives. (Source: Lending Club)
South	1 if the borrower lives in a South State (Delaware, Maryland, Florida, Georgia, North Carolina, South Carolina, Virginia, West Virginia, Alabama, Mississippi, Arkansas, Louisiana, Texas, Oklahoma, Kentucky, Tennessee) (Source: Census)
Trump M-3	1 if the loan is dated during the three months prior to Trump election (so from August to October 2016), 0 otherwise. (Source: Lending Club)
Trump Election	1 if the loan is dated during Trump election (so in November and December 2016), 0 otherwise (source: Lending Club)
Trump M+3	1 if the loan is dated during the three months following Trump election (so from January to March 2017), 0 otherwise (Source: Lending Club).

Table 3
Correlation matrix for the full sample

This table shows the pairwise correlation coefficients for the full sample (including borrowers who obtained and who did not obtain a loan). * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

	Int. Rate	Short Term	AFAM	Log(Amount)	Sub-Grade	Grade	Debt to Income Ratio	Past Delinquency	Employment length	Log(Annual Income)	House Owner	House Rent	Historical Default Rate
Int. Rate	1.000												
Short Term	-0.367***	1.000											
AFAM	0.022***	0.010***	1.000										
Log(Amount)	0.121***	-0.406***	-0.018***	1.000									
Sub-Grade	0.988***	-0.373***	0.022***	0.121***	1.000								
Grade	0.965***	-0.365***	0.021***	0.119***	0.972***	1.000							
Debt to Income Ratio	0.198***	-0.073***	-0.027***	0.058***	0.206***	0.198***	1.000						
Past Delinquency	0.038***	0.012***	0.014***	-0.010***	0.043***	0.042***	-0.017***	1.000					
Employment length	-0.025***	-0.040***	-0.004***	0.068***	-0.026***	-0.023***	0.013***	0.018***	1.000				
Log(Annual Income)	-0.132***	-0.124***	-0.008***	0.441***	-0.139***	-0.130***	-0.234***	0.060***	0.155***	1.000			
House Owner	0.005***	0.024***	0.010***	-0.025***	0.004***	0.005***	-0.000	0.009***	0.030***	-0.033***	1.000		
House Rent	0.076***	0.093***	0.033***	-0.153***	0.081***	0.075***	-0.038***	-0.046***	-0.185***	-0.222***	-0.289***	1.000	
Historical Default Rate	0.026***	0.000	0.172***	-0.031***	0.027***	0.026***	0.050***	-0.015***	0.012***	-0.069***	0.027***	-0.048***	1.000

Table 4
Correlation matrix for the sub-sample of borrowers who obtained their loan.

This table shows the pairwise correlation coefficients for the sample of borrowers who obtained their loan. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	Obtain	AFAM	Log(Amount)	Grade	Debt to Income Ratio	Employment length	Historical Default Rate
Obtain	1.000						
AFAM	-0.041***	1.000					
Log(Amount)	0.149***	-0.065***	1.000				
Grade	-0.608***	0.062***	-0.251***	1.000			
Debt to Income Ratio	-0.148***	-0.035***	0.152***	0.043***	1.000		
Employment length	0.710***	-0.034***	0.150***	-0.484***	-0.144***	1.000	
Historical Default Rate	-0.045***	0.174***	-0.039***	0.044***	-0.015***	-0.033***	1.000

Table 5
Main estimations

This table reports coefficients and p-values (in brackets). The dependent variable is *Obtain* in column (1); *Interest rate* in columns (2) to (4) and *Short Term* in columns (5) and (6); all variables are defined in Table 2. Estimation method is OLS regression in columns (2) to (4) and logistic regression in columns (1), (4) and (5). The regression is robust to heteroscedasticity and we use 3-digit clusters. *, **, *** denote statistical significance at the 10%, 5%, 1% level respectively.

	(1) Obtain	(2) Int. Rate	(3) Int. Rate	(4) Int. Rate	(5) Short Term	(6) Short Term
AFAM	-0.233***	0.079***	0.024***	0.745***	0.315***	0.330***
	[0.002]	[0.000]	[0.004]	[0.000]	[0.000]	[0.000]
Log(Amount)	0.027***	0.102***	0.007***	1.564***	-1.913***	-1.901***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Grade	-1.197***	3.984***			-0.766***	
	[0.000]	[0.000]			[0.000]	
Sub-Grade			0.815***			-0.158***
			[0.000]			[0.000]
Business	-0.627***	0.042***	-0.023***	1.370***	0.808***	0.828***
	[0.000]	[0.006]	[0.010]	[0.000]	[0.000]	[0.000]
Car financing	-1.321***	-0.036**	0.042***	-0.962***	-0.231***	-0.241***
	[0.000]	[0.018]	[0.000]	[0.000]	[0.000]	[0.000]
Credit card refinancing	0.695***	-0.101***	-0.001	-2.067***	-0.116***	-0.133***
	[0.000]	[0.000]	[0.790]	[0.000]	[0.000]	[0.000]
Debt consolidation	0.646***	-0.023***	-0.022***	-0.457***	0.016	0.017
	[0.000]	[0.000]	[0.000]	[0.000]	[0.340]	[0.298]
Home buying	-0.495***	0.021	-0.016	1.191***	0.336***	0.347***
	[0.000]	[0.387]	[0.288]	[0.000]	[0.000]	[0.000]
Home improvement	0.264***	-0.039***	0.003	-0.660***	-0.084***	-0.089***
	[0.000]	[0.000]	[0.483]	[0.000]	[0.000]	[0.000]
Other	0.157***	0.050***	-0.001	0.792***	0.294***	0.304***
	[0.000]	[0.000]	[0.800]	[0.000]	[0.000]	[0.000]
Debt to Income Ratio	-0.024***	0.004***	-0.002***	0.088***	0.012***	0.013***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Employment length	0.437***	0.001	0.002***	-0.003*	-0.013***	-0.013***
	[0.000]	[0.128]	[0.000]	[0.069]	[0.000]	[0.000]
Historical Default Rate	-0.457***	0.034	-0.038**	1.362***	0.018	0.026
	[0.002]	[0.151]	[0.029]	[0.000]	[0.884]	[0.838]
Poverty Rate	-0.033***	0.002	0.001	0.013	0.011	0.012
	[0.000]	[0.129]	[0.350]	[0.267]	[0.155]	[0.140]
Unemployment Rate	0.009	-0.007**	-0.004**	0.010	-0.012	-0.012
	[0.689]	[0.013]	[0.023]	[0.647]	[0.484]	[0.473]
Internet Rate	-0.009**	0.001	0.000	0.002	0.015***	0.015***
	[0.020]	[0.376]	[0.667]	[0.531]	[0.000]	[0.000]
High School Rate	0.005	-0.000	-0.000	0.008*	-0.024***	-0.024***
	[0.170]	[0.977]	[0.796]	[0.090]	[0.000]	[0.000]
Median Income	-0.000	0.000***	0.000***	0.000**	0.000	0.000
	[0.124]	[0.006]	[0.001]	[0.040]	[0.159]	[0.150]
Past Delinquency		-0.000	-0.019***	0.281***	0.067***	0.071***
		[0.809]	[0.000]	[0.000]	[0.000]	[0.000]
Log(Annual Income)		-0.096***	0.039***	-1.614***	0.269***	0.245***
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
House Owner		0.022***	-0.009***	0.436***	0.364***	0.372***
		[0.000]	[0.002]	[0.000]	[0.000]	[0.000]
House Rent		0.038***	-0.038***	0.860***	0.404***	0.419***
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.131***	1.880***	2.954***	12.893***	18.970***	18.805***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	3,661,310	817,492	817,492	817,492	817,492	817,492
R^2		0.935	0.979	0.117		
Adjusted R^2		0.935	0.979	0.117		
Pseudo R^2	0.634				0.281	0.286
Marginal effect of AFAM	-0.0129				0.0429	0.0445

Table 6-1
Trump election analysis - Obtain

This table reports coefficients and p-values (in brackets). The dependent variable is at the top of the column and all variables are defined in Table 2. Estimation method is logistic regression and marginal effects for interaction are displayed at the end of the table. The regression is robust to heteroscedasticity and we use 3-digit clusters. *, **, *** denote statistical significance at the 10%, 5%, 1% level respectively.

	(1) Obtain	(2) Obtain	(3) Obtain
AFAM	-0.236***	-0.113	-0.244***
	[0.002]	[0.146]	[0.001]
Trump M-3	0.451***		
	[0.000]		
AFAM × Trump M-3	0.039		
	[0.577]		
Trump		1.277***	
		[0.000]	
AFAM × Trump Election		-1.330***	
		[0.000]	
Trump M+3			-0.129***
			[0.000]
AFAM × Trump M+3			0.133*
			[0.060]
Log(Amount)	0.026***	0.022***	0.027***
	[0.000]	[0.000]	[0.000]
Grade	-1.196***	-1.195***	-1.197***
	[0.000]	[0.000]	[0.000]
Business	-0.624***	-0.625***	-0.626***
	[0.000]	[0.000]	[0.000]
Car financing	-1.312***	-1.330***	-1.323***
	[0.000]	[0.000]	[0.000]
Credit card refinancing	0.701***	0.679***	0.694***
	[0.000]	[0.000]	[0.000]
Debt consolidation	0.647***	0.645***	0.646***
	[0.000]	[0.000]	[0.000]
Home buying	-0.487***	-0.534***	-0.497***
	[0.000]	[0.000]	[0.000]
Home improvement	0.264***	0.273***	0.264***
	[0.000]	[0.000]	[0.000]
Other	0.165***	0.134***	0.156***
	[0.000]	[0.000]	[0.000]
Debt to Income Ratio	-0.024***	-0.024***	-0.024***
	[0.000]	[0.000]	[0.000]
Employment length	0.437***	0.436***	0.437***
	[0.000]	[0.000]	[0.000]
Historical Default Rate	-0.459***	-0.456***	-0.457***
	[0.002]	[0.002]	[0.002]
Poverty Rate	-0.033***	-0.033***	-0.033***
	[0.000]	[0.000]	[0.000]
Unemployment Rate	0.009	0.007	0.008
	[0.690]	[0.734]	[0.693]
Internet Rate	-0.009**	-0.009**	-0.009**
	[0.019]	[0.020]	[0.020]
High School Rate	0.005	0.005	0.005
	[0.154]	[0.170]	[0.172]
Median Income	-0.000	-0.000	-0.000
	[0.124]	[0.131]	[0.127]
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Constant	3.049***	3.327***	3.194***
	[0.000]	[0.000]	[0.000]
Observations	3,661,310	3,661,310	3,661,310
Pseudo R2	0.634	0.637	0.634
Marginal effect of interaction term	0.0022	-0.0732***	0.0074***

Table 6-2

Trump election analysis – Interest Rate

This table reports coefficients and p-values (in brackets). The dependent variable is at the top of the column and all variables are defined in Table 2. Estimation method is OLS regression. The regression is robust to heteroscedasticity and we use 3-digit clusters. *, **, *** denote statistical significance at the 10%, 5%, 1% level respectively.

	(1) Int. Rate	(2) Int. Rate	(3) Int. Rate
AFAM	0.081***	0.068***	0.071***
	[0.000]	[0.000]	[0.000]
Trump M-3	0.262***		
	[0.000]		
AFAM × Trump M-3	-0.026		
	[0.495]		
Trump		-0.540***	
		[0.000]	
AFAM × Trump Election		0.082**	
		[0.026]	
Trump M+3			0.493***
			[0.000]
AFAM × Trump M+3			0.064
			[0.129]
Log(Amount)	0.104***	0.111***	0.107***
	[0.000]	[0.000]	[0.000]
Grade	3.983***	3.981***	3.982***
	[0.000]	[0.000]	[0.000]
Business	0.042***	0.042***	0.040***
	[0.006]	[0.006]	[0.008]
Car financing	-0.036**	-0.037**	-0.037**
	[0.017]	[0.014]	[0.013]
Credit card refinancing	-0.102***	-0.105***	-0.102***
	[0.000]	[0.000]	[0.000]
Debt consolidation	-0.024***	-0.029***	-0.026***
	[0.000]	[0.000]	[0.000]
Home buying	0.023	0.042*	0.028
	[0.354]	[0.080]	[0.242]
Home improvement	-0.039***	-0.043***	-0.040***
	[0.000]	[0.000]	[0.000]
Other	0.050***	0.054***	0.050***
	[0.000]	[0.000]	[0.000]
Debt to Income Ratio	0.004***	0.004***	0.004***
	[0.000]	[0.000]	[0.000]
Past Delinquency	-0.000	-0.002	-0.001
	[0.810]	[0.133]	[0.426]
Employment length	0.000	0.001	0.000
	[0.277]	[0.100]	[0.443]
Historical Default Rate	0.034	0.031	0.033
	[0.155]	[0.202]	[0.174]
Log(Annual Income)	-0.097***	-0.103***	-0.098***
	[0.000]	[0.000]	[0.000]
House Owner	0.022***	0.026***	0.023***
	[0.000]	[0.000]	[0.000]
House Rent	0.038***	0.039***	0.038***
	[0.000]	[0.000]	[0.000]
Poverty Rate	0.002	0.002	0.003*
	[0.103]	[0.118]	[0.088]
Unemployment Rate	-0.007**	-0.007**	-0.007**
	[0.015]	[0.020]	[0.015]
Internet Rate	0.001	0.000	0.000
	[0.347]	[0.396]	[0.418]
High School Rate	0.000	-0.000	0.000
	[0.966]	[0.873]	[0.897]
Median Income	0.000***	0.000***	0.000***
	[0.005]	[0.006]	[0.005]
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Constant	1.854***	1.862***	1.659***
	[0.000]	[0.000]	[0.000]
Observations	817,492	817,492	817,492
R^2	0.935	0.936	0.936
Adjusted R^2	0.935	0.936	0.936

Table 6-3
Trump election analysis – Short Term

This table reports coefficients and p-values (in brackets). The dependent variable is at the top of the column and all variables are defined in Table 2. Estimation method is logistic regression and marginal effects for interaction are displayed at the end of the table. The regression is robust to heteroscedasticity and we use 3-digit clusters. *, **, *** denote statistical significance at the 10%, 5%, 1% level respectively.

	(1) Short Term	(2) Short Term	(3) Short Term
AFAM	0.321***	0.318***	0.310***
	[0.000]	[0.000]	[0.000]
Trump M-3	0.089***		
	[0.000]		
AFAM × Trump M-3	-0.084		
	[0.388]		
Trump		-0.433***	
		[0.000]	
AFAM × Trump Election		-0.069	
		[0.358]	
Trump M+3			0.480***
			[0.000]
AFAM × Trump M+3			0.032
			[0.735]
Log(Amount)	-1.913***	-1.909***	-1.911***
	[0.000]	[0.000]	[0.000]
Grade	-0.766***	-0.770***	-0.769***
	[0.000]	[0.000]	[0.000]
Business	0.808***	0.810***	0.808***
	[0.000]	[0.000]	[0.000]
Car financing	-0.231***	-0.233***	-0.232***
	[0.000]	[0.000]	[0.000]
Credit card refinancing	-0.116***	-0.121***	-0.117***
	[0.000]	[0.000]	[0.000]
Debt consolidation	0.015	0.009	0.013
	[0.347]	[0.583]	[0.446]
Home buying	0.336***	0.351***	0.343***
	[0.000]	[0.000]	[0.000]
Home improvement	-0.084***	-0.089***	-0.085***
	[0.000]	[0.000]	[0.000]
Other	0.294***	0.297***	0.295***
	[0.000]	[0.000]	[0.000]
Debt to Income Ratio	0.012***	0.012***	0.012***
	[0.000]	[0.000]	[0.000]
Past Delinquency	0.067***	0.066***	0.067***
	[0.000]	[0.000]	[0.000]
Employment length	-0.013***	-0.013***	-0.013***
	[0.000]	[0.000]	[0.000]
Historical Default Rate	0.018	0.014	0.017
	[0.884]	[0.909]	[0.891]
Log(Annual Income)	0.268***	0.262***	0.266***
	[0.000]	[0.000]	[0.000]
House Owner	0.364***	0.368***	0.365***
	[0.000]	[0.000]	[0.000]
House Rent	0.404***	0.406***	0.405***
	[0.000]	[0.000]	[0.000]
Poverty Rate	0.011	0.011	0.011
	[0.154]	[0.156]	[0.145]
Unemployment Rate	-0.012	-0.011	-0.012
	[0.485]	[0.501]	[0.495]
Internet Rate	0.015***	0.015***	0.015***
	[0.000]	[0.000]	[0.000]
High School Rate	-0.024***	-0.024***	-0.024***
	[0.000]	[0.000]	[0.000]
Median Income	0.000	0.000	0.000
	[0.158]	[0.165]	[0.158]
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Constant	18.963***	18.984***	18.788***
	[0.000]	[0.000]	[0.000]
Observations	3,661,310	3,661,310	3,661,310

Pseudo R2	0.634	0.637	0.634
Marginal effect of interaction term	-0.0114	-0.0094	0.0044

Table 7
South analysis

This table reports coefficients and p-values (in brackets). The dependent variable is at the top of the column and all variables are defined in Table 2. Estimation method is logistic regression in columns (1) and (4), and is OLS regression in other columns. The regression is robust to heteroscedasticity and we use 3-digit clusters. *, **, *** denote statistical significance at the 10%, 5%, 1% level respectively.

	(1) Obtain	(2) Obtain	(3) Int. Rate	(4) Short Term	(5) Short Term
AFAM	-0.160	0.002	0.099***	0.646***	0.088***
	[0.132]	[0.790]	[0.000]	[0.000]	[0.000]
South	-0.015	-0.002	0.006	0.029	0.005
	[0.678]	[0.512]	[0.305]	[0.273]	[0.212]
AFAM × South	-0.083	-0.005	-0.041*	-0.543***	-0.073***
	[0.573]	[0.614]	[0.078]	[0.000]	[0.000]
Log(Amount)	0.027***	-0.008***	0.102***	-1.914***	-0.223***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Grade	-1.197***	-0.107***	3.984***	-0.766***	-0.123***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Business	-0.626***	-0.046***	0.042***	0.809***	0.127***
	[0.000]	[0.000]	[0.006]	[0.000]	[0.000]
Car financing	-1.321***	-0.048***	-0.036**	-0.230***	-0.010***
	[0.000]	[0.000]	[0.019]	[0.000]	[0.007]
Credit card refinancing	0.695***	0.041***	-0.101***	-0.117***	0.008***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Debt consolidation	0.646***	0.033***	-0.023***	0.016	0.025***
	[0.000]	[0.000]	[0.000]	[0.329]	[0.000]
Home buying	-0.495***	-0.023***	0.021	0.334***	0.066***
	[0.000]	[0.000]	[0.389]	[0.000]	[0.000]
Home improvement	0.264***	0.009***	-0.039***	-0.084***	0.008***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Other	0.157***	0.004***	0.050***	0.293***	0.038***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Debt to Income Ratio	-0.024***	-0.002***	0.004***	0.012***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Employment length	0.437***	0.062***	0.001	-0.013***	-0.002***
	[0.000]	[0.000]	[0.124]	[0.000]	[0.000]
Historical Default Rate	-0.470***	-0.046***	0.033	-0.017	-0.011
	[0.002]	[0.000]	[0.174]	[0.880]	[0.483]
Poverty Rate	-0.031***	-0.002***	0.002	0.014**	0.003***
	[0.000]	[0.000]	[0.128]	[0.047]	[0.005]
Unemployment Rate	0.002	0.000	-0.007**	-0.023	-0.004*
	[0.933]	[0.757]	[0.016]	[0.179]	[0.083]
Internet Rate	-0.009**	-0.001***	0.001	0.015***	0.002***
	[0.012]	[0.001]	[0.312]	[0.000]	[0.000]
High School Rate	0.005	0.000	-0.000	-0.024***	-0.003***
	[0.183]	[0.314]	[0.997]	[0.000]	[0.000]
Median Income	-0.000*	-0.000	0.000**	0.000	0.000
	[0.073]	[0.107]	[0.010]	[0.412]	[0.413]
Past Delinquency			-0.000	0.067***	0.011***
			[0.811]	[0.000]	[0.000]
Log(Annual Income)			-0.096***	0.271***	0.011***
			[0.000]	[0.000]	[0.000]
House Owner			0.022***	0.362***	0.054***
			[0.000]	[0.000]	[0.000]
House Rent			0.038***	0.398***	0.062***
			[0.000]	[0.000]	[0.000]
Month dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	3.227***	0.774***	1.872***	19.055***	3.058***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	3,661,310	3,661,310	817,492	817,492	817,492
R^2		0.629	0.935		0.277
Adjusted R^2		0.629	0.935		0.277
Pseudo R^2	0.634			0.281	
Marginal effect of interaction term	0.0045*			-0.073*	

Table 8
Estimations by loan purpose

This table reports coefficients and p-values (in brackets). The dependent variable is *Obtain*, *Int. Rate*, or *Short Term*, as mentioned below the number of the column. The loan purpose is mentioned at the top of the column and all variables are defined in Table 2. Estimation method is logistic regression when the dependent variable is *Obtain* or *Short Term*, and OLS regression when the dependent variable is *Int. Rate*. The regression is robust to heteroscedasticity and we use 3-digit clusters. *, **, *** denote statistical significance at the 10%, 5%, 1% level respectively.

	Business			Debt Consolidation			Home improvement			Car financing			Credit card refinancing		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Obtain	Int. Rate	Short Term	Obtain	Int. Rate	Short Term	Obtain	Int. Rate	Short Term	Obtain	Int. Rate	Short Term	Obtain	Int. Rate	Short Term
AFAM	-0.092	0.034	0.237	-0.250***	0.077***	0.249***	-0.468***	0.095**	0.497***	-0.712***	0.255**	0.406	-0.137	0.065**	0.417***
	[0.543]	[0.777]	[0.357]	[0.002]	[0.000]	[0.000]	[0.000]	[0.035]	[0.000]	[0.000]	[0.044]	[0.255]	[0.175]	[0.015]	[0.000]
Log(Amount)	-0.165***	0.054***	-1.412***	0.058***	0.123***	-1.826***	-0.060***	0.061***	-1.828***	-0.700***	0.068***	-2.919***	0.144***	0.114***	-1.958***
	[0.000]	[0.007]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
Grade	-0.731***	4.072***	-0.516***	-1.185***	4.002***	-0.776***	-1.037***	3.995***	-0.641***	-1.353***	3.954***	-0.754***	-1.493***	3.863***	-0.938***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Debt to Income Ratio	-0.005***	0.004**	0.003	-0.031***	0.004***	0.014***	-0.016***	0.002***	0.005***	0.005***	0.004**	0.010**	-0.036***	0.006***	0.014***
	[0.000]	[0.013]	[0.369]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.027]	[0.017]	[0.000]	[0.000]	[0.000]
Employment length	0.323***	-0.004	0.007	0.442***	0.002***	-0.012***	0.420***	0.002	-0.011***	0.447***	-0.008**	-0.024**	0.384***	0.002**	-0.011***
	[0.000]	[0.343]	[0.363]	[0.000]	[0.005]	[0.000]	[0.000]	[0.184]	[0.000]	[0.000]	[0.026]	[0.026]	[0.000]	[0.025]	[0.000]
Historical Default Rate	-0.015	0.514*	0.539	-0.461***	0.010	0.109	-0.750***	0.022	-0.240	-0.770**	0.098	1.561**	-0.185	0.130**	-0.157
	[0.966]	[0.063]	[0.412]	[0.003]	[0.780]	[0.373]	[0.002]	[0.786]	[0.296]	[0.041]	[0.687]	[0.030]	[0.352]	[0.015]	[0.362]
Poverty Rate	-0.028*	-0.024*	-0.022	-0.038***	0.001	0.013*	-0.040***	0.001	-0.005	0.111***	0.005	-0.016	-0.053***	0.009***	0.012
	[0.087]	[0.060]	[0.485]	[0.000]	[0.562]	[0.082]	[0.001]	[0.836]	[0.737]	[0.000]	[0.712]	[0.638]	[0.000]	[0.002]	[0.220]
Unemployment Rate	0.049	-0.013	0.009	0.019	-0.006	-0.025	0.017	0.001	0.040	-0.253***	0.019	0.030	0.035	-0.009	0.010
	[0.196]	[0.632]	[0.880]	[0.405]	[0.112]	[0.152]	[0.593]	[0.958]	[0.175]	[0.000]	[0.489]	[0.694]	[0.135]	[0.109]	[0.607]
Internet Rate	-0.002	-0.002	0.005	-0.007*	-0.000	0.014***	-0.015***	0.002	0.009**	0.022***	0.003	0.030**	-0.018***	0.002*	0.021***
	[0.743]	[0.723]	[0.588]	[0.072]	[0.827]	[0.000]	[0.006]	[0.170]	[0.047]	[0.006]	[0.557]	[0.021]	[0.000]	[0.074]	[0.000]
High School Rate	0.005	-0.007*	-0.021**	0.000	0.000	-0.023***	0.019***	-0.000	-0.022***	0.057***	-0.001	-0.049***	0.010**	-0.001	-0.026***
	[0.377]	[0.072]	[0.017]	[0.998]	[0.955]	[0.000]	[0.000]	[0.791]	[0.000]	[0.000]	[0.732]	[0.000]	[0.018]	[0.495]	[0.000]
Median Income	-0.000	-0.000	-0.000	-0.000**	0.000	0.000*	-0.000*	0.000	-0.000	0.000*	-0.000	0.000	-0.000**	0.000***	0.000
	[0.366]	[0.840]	[0.832]	[0.013]	[0.109]	[0.077]	[0.068]	[0.619]	[0.757]	[0.089]	[0.973]	[0.461]	[0.021]	[0.000]	[0.655]
Past Delinquency		-0.019	0.040		-0.002	0.069***		0.010**	0.057***		-0.000	0.037		-0.008**	0.067***
		[0.122]	[0.148]		[0.258]	[0.000]		[0.049]	[0.000]		[0.996]	[0.292]		[0.027]	[0.000]
Log(Annual Income)		-0.066**	0.101*		-0.103***	0.234***		-0.095***	0.265***		-0.100***	0.166**		-0.102***	0.340***
		[0.023]	[0.068]		[0.000]	[0.000]		[0.000]	[0.000]		[0.000]	[0.038]		[0.000]	[0.000]
House Owner		-0.005	0.386***		0.022***	0.370***		0.040***	0.428***		0.035	0.526***		0.016	0.327***
		[0.926]	[0.000]		[0.001]	[0.000]		[0.004]	[0.000]		[0.343]	[0.000]		[0.109]	[0.000]
House Rent		0.019	0.341***		0.033***	0.391***		0.067***	0.544***		0.043	0.554***		0.063***	0.446***
		[0.540]	[0.000]		[0.000]	[0.000]		[0.000]	[0.000]		[0.176]	[0.000]		[0.000]	[0.000]
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.785**	2.741***	17.155***	3.938***	1.720***	18.502***	3.000***	2.145***	18.469***	1.323	2.188***	29.804***	4.573***	1.811***	18.459***
	[0.033]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.194]	[0.004]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	68,258	9,441	9,441	1,879,786	461,239	461,239	193,718	65,141	65,141	171,401	9,447	9,447	538,217	170,691	170,691
R^2		0.946			0.935			0.938			0.932			0.924	
Adjusted R^2		0.946			0.935			0.938			0.932			0.924	
Pseudo R^2	0.413		0.195	0.622		0.261	0.609		0.268	0.639		0.402	0.667		0.282