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Does Economic Stress Enhance Racial Bias in the P2P Lending Market?

An Investigation on the disproportionate effect of Exogenous Economic Shocks on different peer-to-peer borrowers

Team 4

Contents

1 Executive Summary

1.1 Introduction

Peer-to-peer (P2P) lending is a form of financial technology that allows people to lend or borrow money from one another without going through a bank. LendingClub was among the earliest pioneers of peer-to-peer unsecured personal loans. It went on to become the largest marketplace lending platform in the United States (US).

LendingClub screens potential borrowers and enables them to create loan listings on its website by supplying details about themselves and the requested loans. On the basis of the applicant's credit score, history, loan amount and debt-to-income ratio, LendingClub determined whether the borrower was creditworthy and assigned to its approved loans a credit grade that determined the interest rate and fees.

Investors were able to browse loan listings on LendingClub's website and **select loans they wanted to invest in based on the borrower's details and loan characteristics (loan amount, loan grade, loan purpose)**. Loans could only be chosen at the interest rates assigned by LendingClub, but **investors could decide how much to fund** each borrower.

Unlike traditional banking, which tends to be more regulated and scrutinized, this free-choice model brings in an element of behavioral finance to P2P lending. When making investments, investors are expected to make rational economic decisions. We wondered whether this ability is affected in times of economic stress, especially by exogenous factors such as scandals, controversies, terrorist attacks, etc.

Specifically, we tried to find out:

Research Question 1

Do economic shocks or market uncertainty, possibly caused by external events, enhance (or create) the previously present (or possibly non-existent) racial biases towards certain communities in context of the P2P lending market?

Research Question 2

If yes, are these effects directed towards a certain community and does the type of event determine which race gets affected?

1.2 Findings

We first identified the racial classes and shock types we could explore. By observing the racial distribution in the United States (by region), we identified Black, Islamic and Asian population as communities of interest. We needed two different shocks happening between 2014-2018 (time interval of the data given) to investigate the differential effects of various shocks.

Our primary analysis is based on the LendingClub Scandal in early 2016. An investigation found problems with LC loans which forced CEO Renaud Laplanche to resign. We then borrow our learning from this analysis to apply it to another event, namely the terrorist bombing in NYC in late 2016. The bombing in Manhattan injured 29; additional bombs were found at other locations in Manhattan and nearby New Jersey but were safely detonated or defused.

Using a thorough statistical framework, we find that racial bias in the p2p lending market is indeed very sensitive to economic stress. Moreover, the different shocks can trigger or enhance different kinds of biases in the lending community as shown in Table 1.

Shock Type \ Minority Class	**Mistrust (2016 LC Scandal)**	**Terrorist Activiy (NYC Bombing)**
Blacks	Negative Bias	Can't Say/Unaffected
Islamic	Can't Say/Unaffected	Negative Bias
Asians	Can't Say/Unaffected	Can't Say/Unaffected

Key	Negative Bias	Can't Say/Unaffected

Table 1: The table shows the effects of the considered shocks on p2p lending for different minority classes. The red boxes indicate there is concrete statistical evidence towards enhanced racial bias towards that race in the p2p lending community the period immediately after the attack. The yellow boxes show either the race was relatively unaffected or the data does not reveal a clear relationship.

We also establish that the bias is without reason, i.e. there is no evidence that the race degraded in its financial performance after the shock. Because if it had been the case, there would have existed a financial rationale for the community getting fewer and lower quality loans after the event.

1.3 Significance

Financial Mistrust The study indicates that the black community is still mentally associated with poor economic performance and trust. In the absence of regulation, the biases emerge due to the free will of the investor. Hence, there exists a need to mitigate behavioral biases to improve financial inclusion and optimize returns by means of rational financial decisions.

Terrorism This goes on to show that there is a subtle mental correlation of terrorist activity with the Islamic population. The investor trust deteriorates even if the event is completely unrelated to the borrower because investors may draw oversimplified connections based on religion.

The framework is very general and can be applied to all sorts of time events. This can be a potential way to find out further biases in unregulated markets and alert financial policy makers to devise more inclusive laws to for the disadvantaged communities and raise awareness to remove the element of race from financial decision making.

2 Technical Exposition

2.1 Literature Review

Discrimination is defined as "the unjust or biased treatment of distinct groups of people or things, notably on the grounds of race, age, or sex" by the American Oxford Dictionary (2006). Numerous economists have worked to identify, quantify, and comprehend prejudice in the marketplace. This interest stems in large part from the possibility that these unfair or discriminatory actions against a certain set of individuals could prevent them from having access to the financial markets and the opportunities they present. This has significant ramifications for public policymakers who frequently seek to lessen these discrepancies. Becker [2]'s theory of taste-based discrimination is one of the most well-known economic ideas still in use today. This model suggests that some economic agents may have a preference for particular types of people (mostly coming from majority backgrounds) and a taste for discrimination, for which selecting, collaborating with, or receiving services from a member of the discriminated group has a psychological cost. Such agents would then be willing to incur financial costs to do so, harming thus both their incomes and those of the targeted group, resulting in an overall welfare loss.

Throughout the literature, there are plenty of examples of observed discrimination biases in financing decisions. A notable one is represented by discrimination following terrorist attacks, as described by Kumar et al. [5], who show how flows to fund managers with Middle-Eastern-sounding names declined abnormally after attacks associated with Islamic beliefs. Furthermore, also within the FinTech realm, discriminating trends have been identified, in particular by Pope and Sydnor [6], using data taken from Prosper.com (one of LendingClub's main competitors). The authors found out that black borrowers with comparable credit profiles pay up to 80 basis points more interest than white borrowers. It's interesting to note that peer-to-peer lenders are less inclined to fund requests without pictures and tend to prioritize perceived racial features from the picture when making investments. This evidence suggests the existence of discrimination based on personal preference in the peer-to-peer lending landscape.

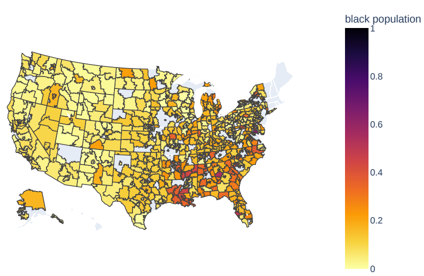
2.2 Datasets Used

Lending Club The datasets consist of two tables: one table with all accepted loan applications from 2014 to 2018, and one table with all rejected loan applications from 2014 to 2018. The accepted loan applications table includes a wide array of demographic and financial data pursuant to both the debtor, and any secondary applicants. Information is also included on the funding for the loan, and the loan terms. The rejected loan applications table includes a handful of data elements detailing the applicant's demographic profile with some additional indicators on financial risk and credit worthiness.

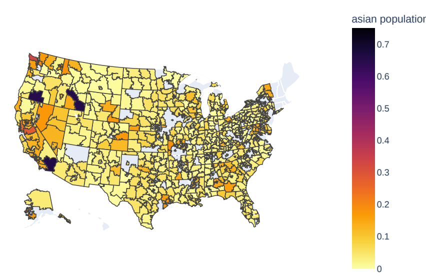
FDIC Bank Database We compile the bank lending trends between 2014-2018 using FDIC. We use the SDI reports for all FDIC insured institutions. Each ZIP file contains data for one reporting quarter. The database has bank branch wise level information for several variables outlined at https://www7.fdic.gov/sdi/sitemap.asp. We specifically use the consumer and credit card loan data and get it at the zip code level.

US Census Data We collected demographic related data from the Current Population Survey (CPS), a monthly U.S. labor force survey jointly conducted by the U.S. Flood et al. [3] Census Bureau and the Bureau of Labor Statistics. We pulled county-level data on household income, racial composition, education, and employment status, and then mapped to zip code. For zip codes that do not have enough reported data, we filled in missing data using state-level average.

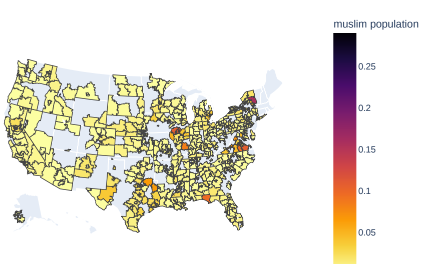
Top Muslim Zip Codes The US census data does not include data for Muslims as we desire. So we obtain top county data from www.thearda.com/ql2010/QL_C_2010_1_28c.asp and convert it to zip code level using a rough mapping.



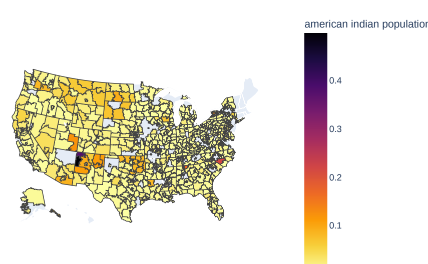
(a) Black population



(b) Asian population



(c) Muslim population

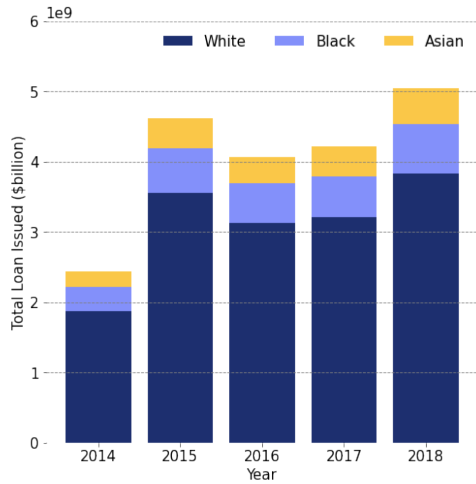


(d) Indian American population

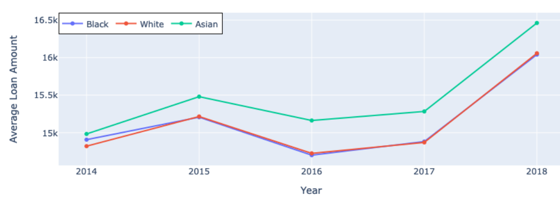
Figure 1: Map visualisation of population by group for each 3-digit Zip Code

2.3 Exploratory Data Analysis

Figure 1 gives the distribution of various communities across the United States. Our primary interest was to analyze the given data from a demographic angle, and we performed a number of race-based analyses to find correlations between lending characteristics and racial identity. We have Muslim population data for only the top zip codes, hence the community has not been included in some of exploratory data analysis. All plots are present in Figures 2 and 3.



(a) Yearly Dollar Amount of Issued Bank Loans



(b) Trends of average loan amount over time

Figure 2: We analyze trends for loan amounts by race

Total loans issued (dollar amount) As the very first step, we look for the racial split of the dollar value of loans issued. White people make up the majority here, as expected from their population and income level (Figure 2a)

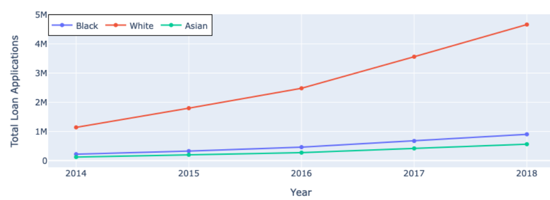
Average loan amount Next we study the average value of loans issued to people of various races. Asians appear to receive larger loans on average with the difference especially pronounced around 2016 (Figure 2b). It is interesting to note that this corresponds to the same time Lending Club was embroiled in controversy, leading to a downturn in loans issued.

Loan applications and acceptance rate Next, we include into our purview the entire Lending Club loan data (not just accepted applications). This gives us a better insight into borrower activity and investor behaviour.

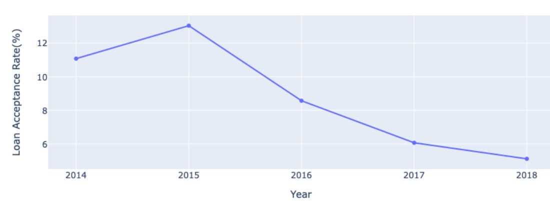
Total loan applications are a good indicator of the demand for p2p loans. We see that the number of applications has consistently increased for the given time period, increasing by at least 5 times for all races. The white community has the most applications while the Asian community has the least (Figure 3a).

Looking at the fraction of loans which get accepted is also important to analyze investor behavior. Acceptance rates as a whole appear to have taken a dive post 2015, falling to almost half their maximum levels by 2018 (Figure 3b). Asians consistently enjoy the highest acceptance rates and the black community the lowest (Figure 3c).

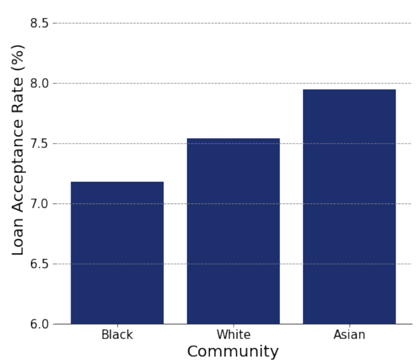
Analyzing minority neighbourhoods Another way to understand the data is by checking the trends for neighborhoods with the most minority percentage. This avenue yields interesting correlations with external events and is explored further in this paper. The tables with quarterly trends are present in the appendix (Tables 8 and 9).



(a) Trends of total loan applications over the time period 2014-2018



(b) Trends of acceptance rate between 2014 and 2018



(c) Acceptance Rates by race, averaged over the time period 2014-2018

Figure 3: We analyze several trends by race over the time 2014-2018 to get a sense of how loan factors change.

2.4 Motivation and Preliminary Analysis

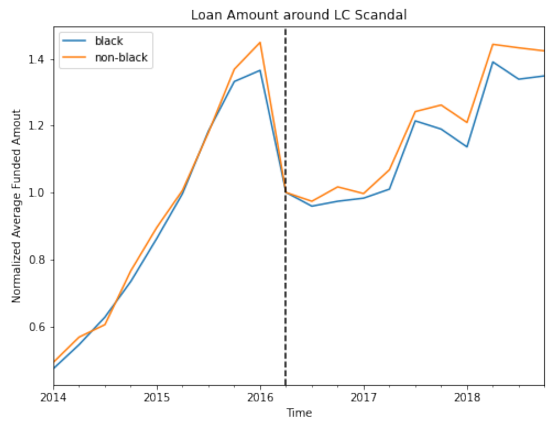
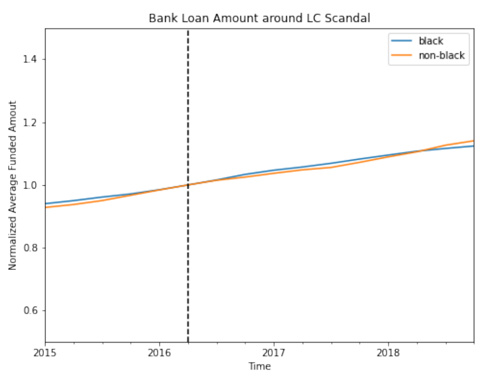
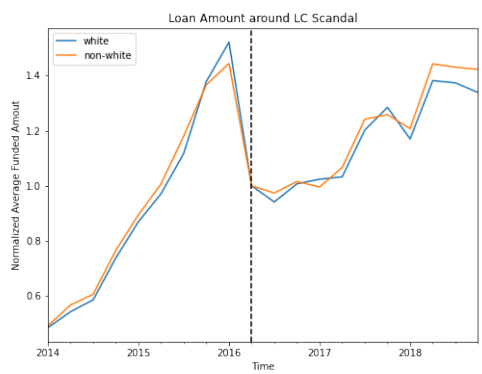


Figure 4: LC funding amount for black dominated zip codes vs the rest. The amounts are normalized to 1 at the onset of the LC Scandal. We can clearly see the disproportionate effect the mistrust environment has on the black community i.e. the graphs display a consistently widening gap after the shock.



(a) Consumer Bank Loans over 2015-2018 (black vs rest)



(b) LC Bank Loans over 2014-2018 (white vs rest)

Figure 5: We further try a confirmation that the effect demonstrated in Figure 4 is indeed due to the 2016 Scandal and acts against black minority specifically.

We first tried to find out if there was an indication that our conjecture was true. Since LC data provides zip codes along with funded loan amounts, we can use these parameters together. We take top-k (k=30) zip codes with the highest percentage of black population. We find the average funded amount by quarter in all those zip codes. We do the same for the rest of the zip codes. We then plot these together, normalizing them to 1 at the onset of the shock in Figure 4. The figure clearly showed a drastic change happening in 2016 Quarter 1 as the amounts drastically drop. What is even more interesting is they change differently for the two sets of zip codes.

After the shock, the black community was getting affected more than the rest of the population. To pinpoint the trend and the cause, we plotted the graphs in Figure 5. As shown in (a), those exact same zip codes did not show a similar trend wrt consumer bank lending in the same time frame. This suggests it is something specific to LC i.e. the trend is likely due to the 2016 scandal. And as shown in (b), if we do the same analysis for say, top-k white zip codes, the trend does not hold. This suggested that something very specific in happening in those earlier zip codes.

We also look at the zip wise race correlation data as well, outlined in Figure 6. We do not want high positive correlation between two races as it leaves open the possibility that we attribute one race's effect to another i.e. we want to make sure that the top-k zip codes have the intended race as the only special/common feature as much as possible.

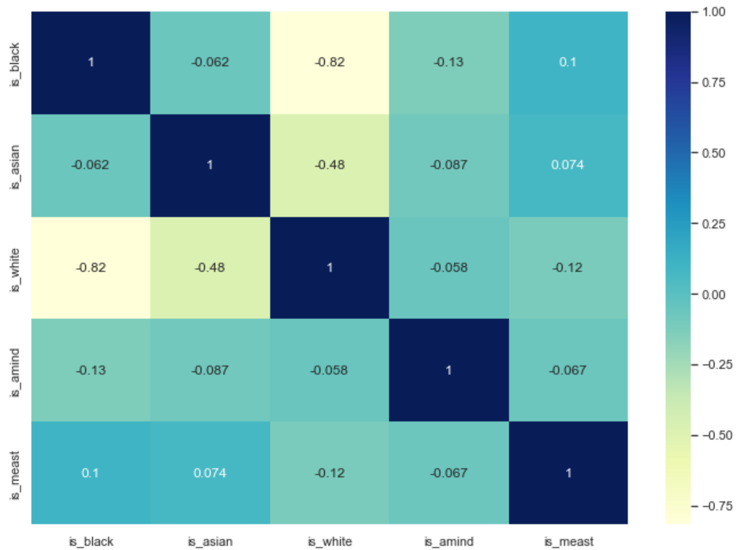


Figure 6: Race correlations among our compiled zip code data. This acts as sanity check when we filter zip codes by race in our regression analysis. As there is no high positive correlation, it is unlikely that we will mistakenly attribute one race's effect to another.

2.5 Hypothesis Development

We aim to provide statistical evidence for enhanced bias in peer-to-peer lending. If certain races are associated with certain lines of thought (poor financial performance, terrorism beliefs etc.), then investors will be willing to avoid interaction with those communities during and after correspondingly related events.

Applying this to peer-to-peer lending, lenders would avoid interaction with areas that have a high minority race ratio. This would result in a lower funding likelihood for these high minority ratio areas.

Hypothesis 1: After the LC scandal, zip codes with high black ratio lead to a lower likelihood of funding than before.

Moreover, due to the bias, investors perceive a higher risk associated with loans to a particular race. As investors can handpick the loans from the LC website, they will tend to fund only higher interest rate loans originating from that race. This brings us to our second hypothesis.

Hypothesis 2: After the LC scandal, zip codes with high black ratio lead to a higher interest rate than before.

We also aim to disentangle the racial bias from true financial performance. The zip codes of interest should not be also associated with an inferior financial performance (repayment of loans). Otherwise, the investors have a rational, rather than social, reason for animus towards the geographical area. To test for this, we formulate our third and final hypothesis.

Hypothesis 3: After the LC scandal, zip codes with high black ratio do not lead to a higher default rate than before.

2.6 Regression Analysis

We adapt a variation of the difference in difference approach for hypothesis testing. Taking inspiration from the approaches outlined in Albouy [1] and Geven [4], we run two regressions for every hypothesis and interpret the coefficients.

2.6.1 Difference In Difference Approach

Notation We wish to evaluate the impact of **belonging to a certain race** on an outcome Y over a population. The two groups are indexed by race $T = 0, 1$ where 0 indicates individuals who do not belong the race of interest, i.e. the control group, and 1 indicates individuals who do i.e the treatment group. Assume that we observe individuals in two time periods, $t = 0, 1$ where 0 indicates a time period before the shock, i.e. pre-shock, and 1 indicates a time period after the shock, i.e. post-shock. For the sake of notation, let $\bar{Y}_0^T$ and $\bar{Y}_1^T$ be the sample averages of the outcome for **race of interest (treatment)** before and after shock, respectively, and let $\bar{Y}_0^C$ and $\bar{Y}_0^C$ be the corresponding sample averages of the outcome for the **rest (control)**. Subscripts correspond to time period and superscripts to the race status.
Note: There are several other possible relevant variables for the outcome. We denote them by $\{\lambda\}_{i=1..k}$ We aim to separate their effect from the above variables of interest as much as possible.

Modeling The outcome Y_i is modeled by the following equation

$$Y_i = \alpha + \beta T_i + \gamma t_i + \delta(T_i \cdot t_i) + \sum_k \lambda_k \cdot v_k + \epsilon_i \tag{1}$$

where the coefficients given by the greek letters $\alpha, \beta, \gamma, \delta, \{\lambda\}_i$ are all unknown parameters and ϵ_i is a random, unobserved "error" term which contains all determinants of Y_i which our model omits. By inspecting the equation, the coefficients have the following interpretation:

- α = constant term
- β = race specific effect (to account for average permanent differences between treatment and control)
- γ = time trend common to control and treatment groups
- δ = true effect of treatment
- λ = control for effect of other variables

The purpose of the program evaluation is to find a good estimate of δ, given the data that we have available.

Pre-shock Analysis For $t_i = 0$, the modeling breaks down to

$$Y_i = \alpha + \beta T_i + \sum_k \lambda_k \cdot v_k + \epsilon_i \tag{2}$$

If we do a regression over the pre-shock population (following the equation above), the coefficient for T i.e. $\hat{\beta}$, gives us an estimator for β.

Post-shock Analysis For $t_i = 1$, the modeling breaks down to

$$Y_i = (\alpha + \gamma) + (\beta + \delta) T_i + \sum_k \lambda_k \cdot v_k + \epsilon_i \tag{3}$$

Under these assumptions we can use these equations to determine the expected values of the average outcomes:

If we now do a second regression over the post-shock population (following the equation above), the coefficient for T i.e. $\widehat{\beta + \delta}$, gives us an estimator for $\beta + \delta$.

Comparing the Coefficients As $\delta = (\beta + \delta) - (\beta)$, we can get an estimate for the sign and magnitude of δ by comparing the coefficients we get from the 2 regressions.

The additional assumption (to make the estimator unbiased) here from normal regression is that T and t are uncorrelated with other variables in the equation Albouy [1]. We also verify this property in each of our regressions performed.

2.7 Modeling

Data As outlined in the approach before, we divide the initial population into applications before and after the shock. Depending on context, the initial population is either the accepted loan data or the combined accepted and rejected loan data.

Feature Engineering We construct our dependent variable depending on context and definition. We also add normalized versions of features which show high variability like loan amounts, annual income, debt-to-income-ratio and add them to the future set. We also add binary variables *{ black_zip, white_zip, asian_zip, meast_zip }* for each zip code which take 1 if they belong to top-k for that ethnicity and 0 otherwise.

Feature Selection We first start with the maximum set of features that are available and appropriate. We evaluate regression fit using metrics such as adjusted R-squared, and select features using a combination of forward and backward selection based on AIC and BIC criteria. We also perform statistical tests to ensure OLS assumptions are sufficiently met. From a heat-map of feature correlation matrix, we ensure there is no multicollinearity. We also examine the scatter plot of regression residuals to confirm there is no major heteroskedasticity.

Space and Time Control We control for space, time and space * time variations in all our modeling. The $C(year)$ represents the categorical variable for year and $C(region)$ represents the categorical variable for region i.e. where the zip code is from among *{West, SouthWest, SouthEast, MidWest, NorthEast}*. We also include each possible combination of space*time among these two sets to control for general unknown effects due to space and time.

2.7.1 Experiments

Hypothesis 1: We take the full dataset of accepted and rejected loans and divide it into two subsets: pre-scandal and post-scandal. A dependent variable is_funded is constructed according to whether the loan is funded or not. We run a regression for each subset, try to predict the probability of funding. For analysing high black proportion zip codes vs the rest, the results are shown in Table 2. For additional rigor, we also verify that T and t are uncorrelated with the other variables as shown in Appendix A.3.

	Dependent variable: is_funded	
	(1) Pre-shock	(2) Post-shock
C(year):C(region)	✓	✓
Intercept	-0.018***	-0.038***
	(0.001)	(0.000)
black_zip	**-0.001***	**-0.004*****
	(0.001)	**(0.000)**
dti	-0.001***	-0.000***
	(0.000)	(0.000)
emp_length	0.070***	0.056***
	(0.000)	(0.000)
loan_amnt_norm	0.035***	0.046***
	(0.000)	(0.000)
Observations	5,672,809	21,316,583
R^2	0.304	0.234
Adjusted R^2	0.304	0.234
Residual Std. Error	0.279(df = 5672790)	0.209(df = 21316564)
F Statistic	137929.405*** (df = 18.0; 5672790.0)	360829.448*** (df = 18.0; 21316564.0)

*p<0.1; **p<0.05; ***p<0.01

Table 2: Regression for probability of funding vs probability of being from a black majority zip code (black_zip) and other relevant variables. *Left:* Pre-shock population. The coefficient for black_zip is not significant. *Right:* Post-shock population. The coefficient is much more negative than in pre-shock and is quite significant at the highest level.

We see the coefficient shifts towards the negative side in post-shock than in pre-shock population. In the post-shock population, being from a black neighborhood decreases funding probability by 0.4%. Note that the average funding probability during post shock is 5.92%. So there is an effective 7% decrease in funding if coming from a black majority neighborhood.

We also run the same experiment for other races. For example, the asian zip code analysis is shown in Table 3. Here, the conclusion as before cannot be made as such i.e. the Asian majority zip codes were probably not affected by the shock in this regard.

Hypothesis 2: We do a similar regression, but this time with interest rate as the dependent variable. Our population is now only the accepted loan population, so now we can do feature selection from a lot of variables given in the schema. We also make categorical variables out of grade and subgrade of the loan as we only want to look at investor bias (these grades are assigned by LC) and remove LC bias as much as possible i.e. it is not the investor's fault if a loan gets a interest rate higher than it should be. This still counts as a rational decision on the investor's part. The results are shown in Table 4.

	Dependent variable: is_funded	
	(1) Pre-shock	(2) Post-shock
C(year):C(region)	✓	✓
Intercept	-0.018***	-0.038***
	(0.001)	(0.000)
asian_zip	**0.003*****	**0.004*****
	(0.000)	**(0.000)**
dti	-0.001***	-0.000***
	(0.000)	(0.000)
emp_length	0.070***	0.056***
	(0.000)	(0.000)
loan_amnt_norm	0.034***	0.046***
	(0.000)	(0.000)
Observations	5,672,809	21,316,583
R^2	0.304	0.234
Adjusted R^2	0.304	0.234
Residual Std. Error	0.279(df = 5672790)	0.209(df = 21316564)
F Statistic	137933.339*** (df = 18.0; 5672790.0)	360836.438*** (df = 18.0; 21316564.0)

*p<0.1; **p<0.05; ***p<0.01

Table 3: Regression for probability of funding vs probability of being from a asian majority zip code (asian_zip) and other relevant variables. *Left:* Pre-shock population. *Right:* Post-shock population. The coefficient is almost the same as in pre-shock and it is less likely that shock had a profound effect on the amount of asian bias in investors.

Upon comparison, we clearly observe that the interest rate for accepted loans increased in the post shock population for black majority areas. Although both coefficients are at only a moderate significance level, the post shock one is much higher i.e. it represents a 0.6% higher interest rate in post shock population just due to an applicant being from one of the selected zip codes.

	Dependent variable: int_rate	
	(1) Pre-shock	(2) Post-shock
C(year):C(region)	✓	✓
C(grade):C(subgrade)	✓	✓
Intercept	6.121***	5.304***
	(0.015)	(0.012)
black_zip	**0.000**	**0.006****
	(0.003)	**(0.003)**
delinq_2yrs	-0.002***	0.002***
	(0.001)	(0.001)
dti	-0.000***	-0.000***
	(0.000)	(0.000)
emp_length	0.001***	-0.001***
	(0.000)	(0.000)
fico_range_low	0.000	-0.000***
	(0.000)	(0.000)
loan_amnt_norm	0.019***	-0.053***
	(0.003)	(0.002)
Observations	728,613	1,299,628
R^2	0.073	0.041
Adjusted R^2	0.073	0.041
Residual Std. Error	4.227(df = 728594)	5.016(df = 1299609)
F Statistic	3175.113*** (df = 18.0; 728594.0)	3064.892*** (df = 18.0; 1299609.0)

*p<0.1; **p<0.05; ***p<0.01

Table 4: Regression for determinants of loan interest rate for black zip codes. *Left:* Pre-shock population. *Right:* Post-shock population. We see quite a difference between the coefficients, indicating that accepted loans from those zip codes had to pay higher interest rates than before to get accepted.

2.7.2 Causal Analysis Sensibility Check

Hypothesis 3: To establish the validity of our hypothesis that investors choice for loans is driven more by mental bias rather than an a correlation between black zip and default probability, we regress binary variable *is_default* on selected features. The results in Table 5 show that the higher black ratio does not have a significant effect on the probability of default.

Random Date To establish whether it the quarter of scandal that is causing the shift, we try random dates far away from 2016 i.e. dates from 2015 and 2017 respectively. None of them show as strong a difference as in our original regression. Consider for example, Table 6. The difference has diminished by a lot and significance levels have worsened on account of the fact that we are now doing an earlier date (from 2015).

	Dependent variable: is_default	
	(1) Pre-shock	(2) Post-shock
C(year):C(region)	✓	✓
Intercept	1.261***	1.428***
	(0.011)	(0.013)
black_zip	**-0.000**	**0.001**
	(0.003)	**(0.004)**
delinq_2yrs	-0.003***	0.001
	(0.001)	(0.001)
dti	0.005***	0.004***
	(0.000)	(0.000)
emp_length	-0.003***	-0.006***
	(0.000)	(0.000)
fico_range_low	-0.002***	-0.002***
	(0.000)	(0.000)
loan_amnt_norm	0.156***	0.169***
	(0.002)	(0.003)
Observations	662,604	462,841
R^2	0.035	0.041
Adjusted R^2	0.035	0.041
Residual Std. Error	0.390(df = 662591)	0.419(df = 462828)
F Statistic	1994.924*** (df = 12.0; 662591.0)	1668.180*** (df = 12.0; 462828.0)

*p<0.1; **p<0.05; ***p<0.01

Table 5: Regression for determinants of default probability vs probability of being from a black majority zip code (black_zip) and other relevant variables. Left: Pre-shock population. Right: Post-shock population. The coefficient is negligible in pre-shock. It is also negligible in post-shock (as it is insignificant), conveying that these zip codes were actually performed almost the same in paying back their loans.

Random Zip Code Sets We try the same thing for several zip code sets and ascertain that the findings are related to those being rich in our race of interest. All of these show either no or much lower difference in the coefficients. In fact, the regression for Asian in Table 3 is one such example where the codes just happen to be selected by the asian population percentage.

2.8 Generalising: Terrorism vs The Islamic Population

Extending to Islamic Population Similar to the hypothesis development for bias against black neighborhoods, we wanted to test whether we see cognitive bias towards the Islamic population in events of terrorism. The association between Muslim and terrorists mostly come from political propaganda that relies on preexisting false ideologies, which is another way to describe racist stereotyping. We adopted similar methodology and the previous regression setup.

	Dependent variable: is_funded	
	(1) Pre-shock	(2) Post-shock
C(year):C(region)	✓	✓
Intercept	-0.020***	0.014***
	(0.001)	(0.000)
black_zip	**-0.001**	**-0.002******
	(0.001)	**(0.000)**
dti	-0.001***	-0.000***
	(0.000)	(0.000)
emp_length	0.070***	0.059***
	(0.000)	(0.000)
loan_amnt_norm	0.037***	0.046***
	(0.001)	(0.000)
Observations	2,336,248	24,653,144
R^2	0.310	0.254
Adjusted R^2	0.310	0.254
Residual Std. Error	0.276(df = 2336234)	0.221(df = 24653120)
F Statistic	80560.628*** (df = 13.0; 2336234.0)	364011.696*** (df = 23.0; 24653120.0)

*p<0.1; **p<0.05; ***p<0.01

Table 6: Sensibility check using random date in 2015. Left: New Pre-shock population. Right: New Post-shock population. We see there is negligible difference, which arises likely due to all the true post-shock population present in our new post-shock population (which already shows increased discrimination).

Population Selection Due to the local nature of the considered event, we only subset from the zip codes around New York and New Jersey. This gives us more direct results and more interpretability in what we are trying to measure i.e. it is likely that the event is televised more extensively in the region around it happened.

In Table 7, we see the coefficient shifts towards the negative side more in the post-shock than in the pre-shock population. In the post-shock population, being from a neighborhood with higher percentage of Muslims decreases funding probability by 0.3%. Note that the average funding probability during post shock is 5.92%. So there is an effective 5% decrease in funding if coming from a Muslim majority neighborhood.

2.9 Limitations and Future Work

We have tried to make our analysis as rigorous as possible. But we also take time to identify some limitations of our current approach and explore directions for future work.

Modeling We have resorted to linear regression due to the intrepretability of coefficients. However, this may not be the best approach. A non linear model may provide for better modeling and provide deeper insights.

	Dependent variable: is_funded	
	(1) Pre-shock	(2) Post-shock
C(year):C(region)	✓	✓
Intercept	0.078	-0.035
	(0.065)	(0.021)
islamic_zip	**-0.002*****	**-0.005*****
	(0.001)	**(0.001)**
dti	-0.000***	-0.001***
	(0.000)	(0.000)
emp_length	0.059***	0.074***
	(0.000)	(0.000)
loan_amnt_norm	0.031***	0.014***
	(0.001)	(0.001)
Observations	907,295	610,202
R^2	0.241	0.323
Adjusted R^2	0.241	0.323
Residual Std. Error	0.269(df = 907271)	0.198(df = 610188)
F Statistic	12528.952*** (df = 23.0; 907271.0)	22354.489*** (df = 13.0; 610188.0)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 7: Regression Islamic neighborhood

Assumptions Due to time as well as data limitations, we have made some oversimplifying assumptions. A more complex analysis can be done if we relax them. First, we assume that other variables (like fico, employment length) etc. are not correlated with neither T (i.e. the fact that a person belongs to a certain race or not) nor t (i.e. they don't really vary any differently after the shock). Second, during sensibility check for loan default probability, we assumed a linear relationship when in reality it could be nonlinear and determined by more features outside what we have been given.

Framework The framework we have used is very general and powerful. The method can be used to find out statistical significance for effects of sudden events on treatment vs the control group. Examples include effect of government policy changes on the affected parties, global or the effect of global catastrophic events on the demographic distribution of a region.

2.10 Conclusion

Our 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. Using a difference-in-difference approach, we examined the effect of external shocks, such as the 2016 LendingClub scandal and terrorist attack, on different racial subgroups.

The results show that living in a top decile 3-digit zip code areas in terms of black racial concentration after the LendingClub scandal in 2016 significantly decreases the likelihood of getting funded, although conditional on getting funded, it slightly increases the interest rate paid by the borrowers. Using a similar analytical framework, living in an area with high Muslim concentration also decreases the likelihood of getting funded following events of terrorist attack and political stress.

We established the validity of our argument by comparing the trends between control and treatment groups pre- and post-treatment. By randomizing zip code and date, we confirm the shocks are indeed relevant and specific to the treatment groups. Additionally, through a quick examination of default probability, we draw a likely conclusion that the observed racial bias does not significantly contribute to the likelihood of loan defaulting.

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A Appendix

A.1 What did not work: Banks vs P2P Lending

Before the current approach was followed, several other hypothesis were tried. One of them was investigating the effect of p2p scandal on the banking sector. Specifically, we tried to find out whether banks and marketplace lenders were substitutes or compliments i.e. whether a p2p user is one who also had access to a bank loan or the situation was otherwise.

We took inspiration from the approach followed in [7]. The framework allows testing the above hypothesis using the the resulting change in the P2P borrower quality distribution from an exogenous shock.

However, we eventually concluded that p2p is just too small to have an measurable effect on commercial bank loans, due to large size and number of these loans. If it had been the other way around, the situation would have been much more amenable to analysis as p2p would show a large change owing to the customers not satisfied/rejected from the banks.

A.2 Quarter based Trends

Quarter	Black N'hoods (total loans $mm)	Other N'hoods (total loans amt $mm)	Black N'hoods (default rate %)	Other N'hoods (default rate %)
2014Q1	19.92	487.10	17.74	16.55
2014Q2	22.73	562.63	20.84	18.55
2014Q3	25.88	603.27	19.19	18.84
2014Q4	30.91	766.04	19.67	19.49
2015Q1	37.99	933.77	21.38	20.18
2015Q2	43.95	1039.63	21.54	20.64
2015Q3	52.23	1218.63	21.07	20.24
2015Q4	57.26	1413.67	21.06	19.84
2016Q1	36.38	1331.10	20.77	20.38
2016Q2	26.89	919.52	24.05	25.36
2016Q3	24.46	906.01	25.40	25.87
2016Q4	25.91	945.69	26.26	23.85
2017Q1	26.13	925.57	21.77	22.84
2017Q2	27.33	992.44	26.00	23.91
2017Q3	32.34	1154.09	25.20	23.86
2017Q4	31.27	1173.07	24.68	21.43
2018Q1	30.04	1116.86	20.66	19.69
2018Q2	37.43	1338.15	20.42	18.41
2018Q3	36.51	1323.16	10.31	10.34
2018Q4	35.89	1319.57	3.49	2.34

Table 8: Data for total loan amount and default rates for black neighbourhoods compared to other neighbourhoods. In the period starting 2016, the total loans for black communities falls to roughly half their maximum value, a markedly steeper decrease compared to other communities

Quarter	Muslim N'hoods (total loans $mm)	Other N'hoods (total loans amt $mm)	Muslim N'hoods (default rate %)	Other N'hoods (default rate %)
2014Q1	11.97	495.05	19.43	16.53
2014Q2	14.63	570.72	17.66	18.65
2014Q3	13.94	615.21	17.96	18.87
2014Q4	18.14	778.81	21.24	19.46
2015Q1	25.59	946.17	20.58	20.22
2015Q2	30.45	1053.12	21.21	20.66
2015Q3	33.82	1237.04	19.82	20.28
2015Q4	39.95	1430.98	19.54	19.90
2016Q1	42.15	1325.33	20.89	20.37
2016Q2	29.12	917.29	24.55	25.35
2016Q3	26.17	904.31	24.31	25.90
2016Q4	27.13	944.47	26.41	23.85
2017Q1	28.16	923.53	22.57	22.82
2017Q2	29.91	989.86	24.14	23.96
2017Q3	34.22	1152.21	22.05	23.94
2017Q4	33.39	1170.95	23.20	21.47
2018Q1	32.17	1114.73	20.37	19.69
2018Q2	38.03	1337.56	16.98	18.50
2018Q3	37.44	1322.23	8.99	10.38
2018Q4	36.04	1319.43	3.23	2.35

Table 9: Data for funding amounts and default rates for Muslim neighbourhoods compared to other neighbourhoods. There is a drop in funding amounts in 2016Q3 which suspiciously coincides with the NYC bombing in Sep 2016

A.3 Correlation Matrix of Selected Variables

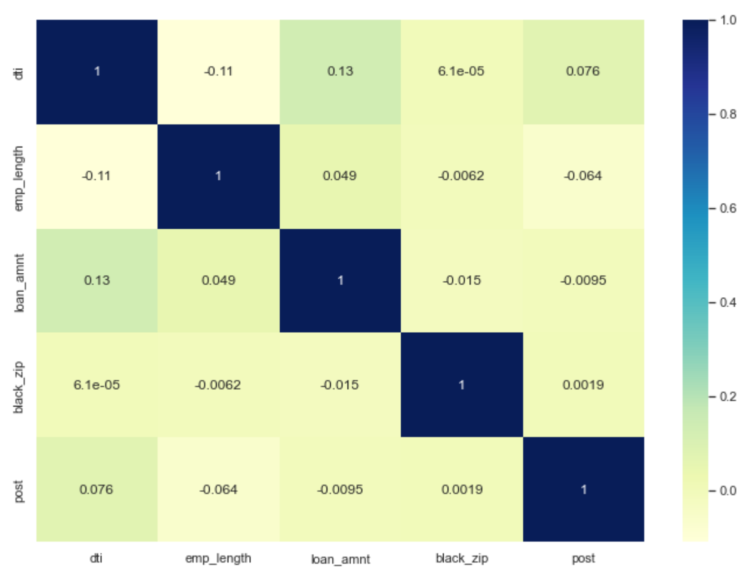

Figure 7: For Table 2, we verify the assumption that other variables are not correlated with T and t (*post* and *black_zip* here).