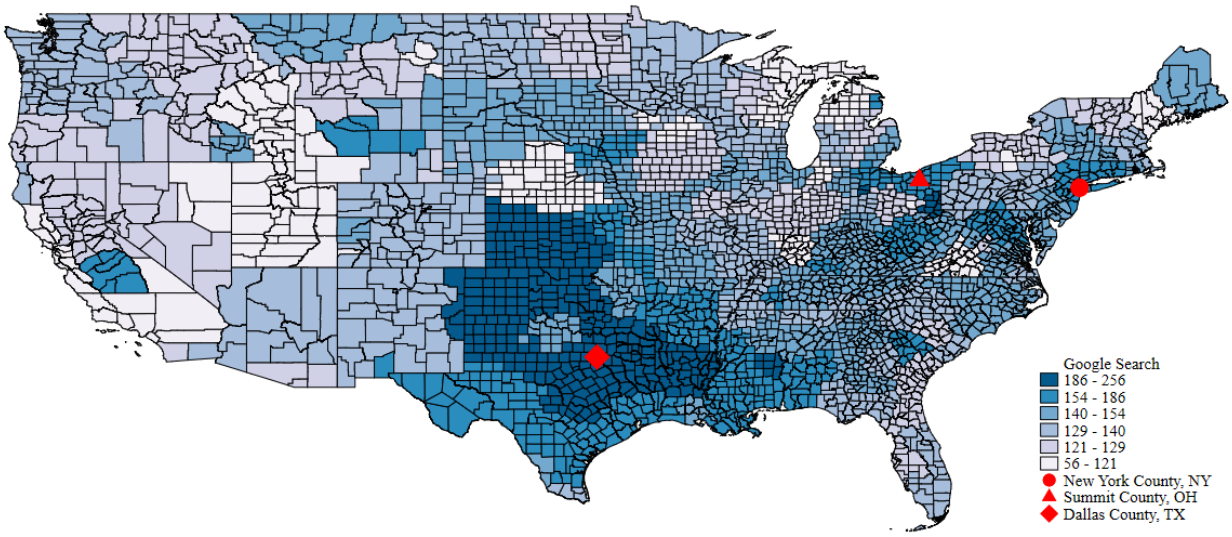
Online Appendix for "Deadly Disease, Fear, and Ostracism in the Credit Market"

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A Figure and Tables

Figure A1: Google Search Volume of Ebola



Note: This figure illustrates the county-level spatial distribution of the Google search volume of Ebola in 2014. The color classification is based on quantile levels, including 0%, 10%, 25%, 50%, 75%, 90%, and 100%. The darker the color, the more people search for information about Ebola. Counties that witness Ebola cases are marked in the heatmap by different symbols.

Table A1: Variable Definitions

Variable	Definition
	Panel A: Loan Characteristics in HMDA
Applicant Gender (Female)	Dummy that equals 1 if the applicant is female; and 0 otherwise.
Applicant Gender (Male)	Dummy that equals 1 if the applicant is male; and 0 otherwise.
Applicant Gender (Missing)	Dummy that equals 1 if the gender information of applicant is not provided; and 0 otherwise.
Applicant Gender (Not Applicable)	Dummy that equals 1 if the requirement to report the applicant's gender does not apply to the covered loan or application that the corresponding institution is reporting; and 0 otherwise.
Applicant Income	Applicant's gross annual income (measured in one hundred thousand dollars).
Asian	Dummy that equals 1 if the applicant's race is Asian; and 0 if White.
Black	Dummy that equals 1 if the applicant's race is Black; and 0 if White.
Deny	Dummy that equals 1 if the loan application is denied; and 0 if originated.
Lien Status (First)	Dummy that equals 1 if the property is a first lien; and 0 otherwise.
Lien Status (No Lien)	Dummy that equals 1 if the property has no lien; and 0 otherwise.
Lien Status (Subordinate)	Dummy that equals 1 if the property is a subordinate lien; and 0 otherwise.
Ln(Applicant Income)	The natural logarithm of applicant's gross annual income (measured in one hundred thousand dollars).
Loan Amount	Amount of the loan (measured in one hundred thousand dollars).
Loan Purpose (Home Improvement)	Dummy that equals 1 if the transaction is for home improvement; and 0 otherwise.
Loan Purpose (Home Purchase)	Dummy that equals 1 if the transaction is for home purchase; and 0 otherwise.
Loan Purpose (Refinancing)	Dummy that equals 1 if the transaction is for refinancing; and 0 otherwise.
Loan Type (Conventional)	Dummy that equals 1 if the loan is not insured or guaranteed by FHA, VA, RHS, or FSA; and 0 otherwise.
Loan Type (FHA)	Dummy that equals 1 if the loan is insured by Federal Housing Administration (FHA); and 0 otherwise.
Loan Type (RHS or FSA)	Dummy that equals 1 if the loan is guaranteed by USDA Rural Housing Service or Farm Service Agency (RHS or FSA); and 0 otherwise.
Loan Type (VA)	Dummy that equals 1 if the loan is guaranteed by Veterans Affairs (VA); and 0 otherwise.
Non-Hispanic	Dummy that equals 1 if the applicant's ethnicity is neither Hispanic nor Latino; and 0 otherwise.
Property Type (Manufactured)	Dummy that equals 1 if the property is manufactured housing; and 0 otherwise.
Property Type (One To Four Family)	Dummy that equals 1 if the property is one-to-four-family housing; and 0 otherwise.
Purchaser Type (Affiliate Institution)	Dummy that equals 1 if the loan is purchased by affiliate institutions; and 0 otherwise.
Purchaser Type (Commercial Bank)	Dummy that equals 1 if the loan is purchased by commercial banks, savings banks, or savings associations; and 0 otherwise.
Purchaser Type (FAMC)	Dummy that equals 1 if the loan is purchased by Farmer Mac; and 0 otherwise.
Purchaser Type (FDMC)	Dummy that equals 1 if the loan is purchased by Freddie Mac; and 0 otherwise.
Purchaser Type (Finance Company)	Dummy that equals 1 if the loan is purchased by credit union, mortgage company, or finance company; and 0 otherwise.
Purchaser Type (FNMA)	Dummy that equals 1 if the loan is purchased by Fannie Mae; and 0 otherwise.
Purchaser Type (GNMA)	Dummy that equals 1 if the loan is purchased by Ginnie Mae; and 0 otherwise.
Purchaser Type (Not Applicable)	Dummy that equals 1 if the loan is not purchased; and 0 otherwise.
Purchaser Type (Other)	Dummy that equals 1 if the loan is purchased by other type of purchasers; and 0 otherwise.
Purchaser Type (Private)	Dummy that equals 1 if the loan is purchased by private securitizers; and 0 otherwise.
SARS Outbreak	Dummy that equals 1 if the loan is applied in 2003; and 0 if the loan is applied in 2001 and 2002.
Soft Reason	Dummy that equals 1 if the denial reason is employment history, credit history, unverifiable information, credit application incomplete, or other; 0 if the denial reason is debt-to-income ratio, collateral, insufficient cash (down payment, closing costs), or mortgage insurance denied.
	Panel B: Variables in CPS
Age	Loan applicant's age.
Black	Dummy equals 1 if the respondent's race is Black; and 0 if White.
Employment	Dummy equals 1 if the respondent is in the labor force and employed; and 0 if the respondent is in the labor force but unemployed.
High School	Dummy equals 1 if the respondent has a degree above high school; and 0 otherwise.
Hourly Earning	Respondent's hourly earnings (measured in dollars).
Labor Force	Dummy equals 1 if the respondent is in the labor force; and 0 otherwise.
Ln(Age)	The natural logarithm of loan applicant's age.
Married	Dummy equals 1 if the respondent is married; and 0 otherwise.

Table A1 – Continued

Outbreak	Dummy equals 1 if the survey time is in the 4th quarter of 2014; and 0 otherwise.
Weekly Earning	Respondent's weekly earnings (measured in dollars).
	Panel C: Variables in Call Report
ROA	Annualized ROA (in%) in each quarter, calculated as net income (RIAD4300, adjust year-to-date reporting to within quarter) divided by beginning assets (RCON2170).
ROE	Annualized ROE (in%) in each quarter, calculated as net income (RIAD4300, adjust year-to-date reporting to within quarter) divided by beginning equity (RCFD3210).
Tier 1 Capital Ratio	Tier 1 capital (RCON8274) divided by risk-weighted assets (RCONA223).
Total Capital Ratio	Tier 1 and tier 2 capital (RCON8274+RCON8275) divided by risk-weighted assets (RCONA223).
	Panel D: Variables in FNMA and FDMC
60-day Delinquency	Dummy equals 1 if the loan is delinquent at least for 60 days in our sample period; and 0 otherwise.
Below 620	Dummy equals 1 if the applicant's credit score is smaller than 620; and 0 otherwise.
Credit Score	Credit score of the applicant.
Credit Score Rank	Ordered variable that equals 1 if the credit score lies in [300, 579]; 2 if in [580, 619], 3 if in [620, 669], 4 if in [670, 739], 5 if in [740, 799], 6 if in [800, 850].
Half-year Modification	Dummy equals 1 if the default loan is modified in the half year following the last default; and 0 otherwise.
Ln(Credit Score)	The natural logarithm of credit score of the applicant.
One-year Modification	Dummy equals 1 if the default loan is modified in the one year following the last default; and 0 otherwise.
	Panel E: Other Variables
African-born Immigrant Ratio	The share of African-born immigrants in total immigrants.
COVID-19 Outbreak	Dummy that equals 1 if the loan is applied in 2020; and 0 if the loan is applied in 2019.
Close County	Dummy that equals 1 if the county is closer to Ebola cases than the national median; and 0 otherwise.
Community Bank	Dummy that equals 1 if the bank is with total assets less than ten billion dollars; and 0 otherwise.
Distance	County-level straight-line distance to the nearest county where Ebola cases are diagnosed (i.e., Dallas County, Cleveland County, and New York County).
Ebola State	Dummy that equals 1 if the state is with Ebola diagnoses (i.e., Texas, Ohio, and New York); and 0 otherwise.
FinTech Bank	Dummy that equals 1 if the bank is a FinTech banks; and 0 otherwise (Buchak et al., 2018).
Google(Ebola)	Standardized MDA-level Google search volume of "Ebola" in 2014.
Google(Ebola+death)	Standardized MDA-level Google search volume of "Ebola+death" in 2014.
Google(election)	Standardized MDA-level Google search volume of "election" in 2014.
HBR County	Dummy that equals 1 if the ratio of black people in the county is above the median; and 0 otherwise. The ratio of Black people is calculated from the 2010 Census.
High Google Search	Dummy that equals 1 if the county has a higher Google search volume on "Ebola" than the national median; and 0 otherwise.
Ln(Job Posting + 1)	The natural logarithm of the number of job postings plus one at the county-month level.
Ln(Num of Loans)	The natural logarithm of the number of loans at the county-month level.
National Bank	Dummy that equals 1 if the bank is with total assets more than one hundred billion dollars; and 0 otherwise.
Newsletter(Ebola)	Standardized county-level number of Ebola-related electronic newsletters sent by politicians representing the county in 2014.
Non-FinTech Bank	Dummy that equals 1 if the bank is not a FinTech banks; and 0 otherwise (Buchak et al., 2018).
Outbreak	Dummy that equals 1 if the loan application is during the Ebola outbreak, i.e., the loan sequence number is larger than its corresponding threshold; and 0 otherwise.
Outbreak (2014Q4)	Dummy that equals 1 if the loan application is in the fourth quarter of 2014; and 0 otherwise.
Outbreak (2015Q1)	Dummy that equals 1 if the loan application is in the first quarter of 2015; and 0 otherwise.
Outbreak (2015Q2–Q4)	Dummy that equals 1 if the loan application is in last three quarters of 2015; and 0 otherwise.
Outbreak (Census Tract Match)	Dummy that equals 1 if the loan application is during the Ebola outbreak, i.e., the loan sequence number is larger than its corresponding threshold, which relies on census-tract-based matching; and 0 otherwise.

Table A1 – Continued

Outbreak (Equal Dist)	Dummy that equals 1 if the loan application is during the Ebola outbreak, i.e., the loan sequence number is above its 75th percentile threshold; and 0 otherwise.
Outbreak (FNME Dist)	Dummy that equals 1 if the loan application is during the Ebola outbreak, i.e., the loan sequence number is in the 4th quarter under the monthly distribution of 2014 Fannie Mae dataset; and 0 otherwise.
Regional Bank	Dummy that equals 1 if the banks with total assets between ten billion dollars and one hundred billion dollars; and 0 otherwise.
SARS Outbreak	Dummy that equals 1 if the loan year is in 2003; and 0 if the loan year is in 2001 or 2002.
Social Connectedness	County-level socioeconomic connectedness statistics, defined as two times the share of high-socioeconomic status (SES) friends among low-SES individuals, averaged over all low-SES individuals in the county (Chetty et al., 2022) (last accessed: Dec 30, 2025).
Western-African-born Immigrant Ratio	The share of Western-African-born immigrants in total immigrants.

Table A2: Descriptive Statistics of 2014 HMDA

	Black		White	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Applicant Income	0.731	(1.005)	1.034	(0.420)
Loan Amount	1.469	(1.460)	1.962	(1.517)
Applicant Sex (Male)	0.549	(0.498)	0.708	(2.158)
Applicant Sex (Female)	0.448	(0.497)	0.290	(0.455)
Applicant Sex (Missing)	0.003	(0.056)	0.002	(0.454)
Applicant Sex (Not Applicable)	0.000	(0.001)	0.000	(0.046)
Loan Type (Conventional)	0.648	(0.477)	0.790	(0.002)
Loan Type (FHA)	0.219	(0.414)	0.121	(0.407)
Loan Type (VA)	0.116	(0.320)	0.063	(0.326)
Loan Type (RHS or FSA)	0.017	(0.128)	0.025	(0.243)
Property Type (One To Four Family)	0.949	(0.221)	0.963	(0.157)
Property Type (Manufactured)	0.051	(0.221)	0.037	(0.188)
Loan Purpose (Home Purchase)	0.450	(0.498)	0.507	(0.188)
Loan Purpose (Home Improvement)	0.158	(0.364)	0.089	(0.500)
Loan Purpose (Refinancing)	0.392	(0.488)	0.404	(0.285)
Lien Status (First)	0.854	(0.353)	0.922	(0.491)
Lien Status (Subordinate)	0.038	(0.191)	0.039	(0.269)
Lien Status (No Lien)	0.107	(0.310)	0.039	(0.194)
Purchaser Type (FNMA)	0.092	(0.288)	0.163	(0.498)
Purchaser Type (GNMA)	0.102	(0.303)	0.071	(0.369)
Purchaser Type (FDMC)	0.048	(0.214)	0.099	(0.257)
Purchaser Type (FAMC)	0.000	(0.008)	0.000	(0.298)
Purchaser Type (Private)	0.003	(0.055)	0.005	(0.010)
Purchaser Type (Commercial Bank)	0.066	(0.249)	0.084	(0.074)
Purchaser Type (Finance Company)	0.058	(0.234)	0.069	(0.278)
Purchaser Type (Affiliate Institution)	0.010	(0.101)	0.014	(0.254)
Purchaser Type (Other)	0.037	(0.190)	0.042	(0.118)
Purchaser Type (Not Applicable)	0.583	(0.493)	0.453	(0.194)
Obs.	511,937		5,828,197	

Note: This table presents the detailed descriptive statistics of HMDA data in 2014. The sample consists of loans whose applicants are either Black or White, with an outcome of loans being either denied or approved.

Table A3: Robustness—Adding Fixed Effects

	Deny (1)	Deny (2)	Deny (3)
Outbreak × Black	0.038*** (0.002)	0.016*** (0.002)	0.016*** (0.002)
Control	Yes	Yes	Yes
Race FE	No	Yes	No
County-Month FE	Yes	Yes	Yes
Race-County FE	Yes	No	Yes
Bank-Month FE	No	Yes	Yes
Observations	6,284,239	6,277,682	6,277,363
Adj. R-Square	0.534	0.594	0.594

Note: This table presents robustness checks of the effect of the Ebola outbreak on the mortgage denial rate of Black applicants. *Outbreak* is a dummy that equals 1 if the loan sequence number is larger than its corresponding threshold; and 0 otherwise. *Black* is a dummy that equals 1 if the applicant's race is Black; and 0 if White. *Deny* is a dummy that equals 1 if the loan application is denied; and 0 if originated. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors are clustered at the county level and reported in parentheses.

Table A4: Robustness—Labor Market Consequences

	Labor Force (1)	Employment (2)	Weekly Earning (3)	Hourly Earning (4)
Outbreak × Black	-0.004	0.005	-6.021	-0.198
	(0.006)	(0.004)	(9.573)	(0.153)
Controls	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
State-Month FE	Yes	Yes	Yes	Yes
Obs.	4,397,207	2,731,779	576,460	341,025
Adj. R^2	0.333	0.035	0.334	0.246

Note: This table presents the robustness test on the effect of Ebola on labor market. We relax county-month fixed effects to state-month fixed effects and cluster standard errors at the state level. *Outbreak* is a dummy that equals 1 if the loan sequence number is larger than its corresponding threshold; and 0 otherwise. *Black* is a dummy that equals 1 if the applicant's race is Black; and 0 if White. *Labor Force* is a dummy that equals 1 if the respondent is in the labor force; and 0 otherwise. *Employment* is a dummy that equals 1 if the respondent is in the labor force and employed; and 0 if the respondent is in the labor force but unemployed. *Weekly Earnings* are the respondent's weekly earnings. *Hourly Earnings* are the respondent's hourly earnings. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors are clustered at the state level and reported in parentheses.

Table A5: Robustness—Demographic Composition

	High School (1)	Married (2)	Age (3)	Ln(Age) (4)
Outbreak × Black	-0.003	-0.003	0.016	-0.002
	(0.004)	(0.004)	(0.227)	(0.008)
Race FE	Yes	Yes	Yes	Yes
State-Month FE	Yes	Yes	Yes	Yes
Obs.	6,833,486	5,958,106	5,958,106	5,899,522
Adj. R^2	0.004	0.015	0.009	0.007

Note: This table presents the robustness test on the demographic composition during the Ebola outbreak. We relax county-month fixed effects to state-month fixed effects and cluster standard errors at the state level. *Outbreak* is a dummy that equals 1 if the loan sequence number is larger than the corresponding outbreak threshold; and 0 otherwise. *Black* is a dummy that equals 1 if the applicant's race is Black; and 0 if White. *Deny* is a dummy that equals 1 if the loan application is denied; and 0 if originated. *High School* is a dummy that equals 1 if the respondent has a degree above high school; and 0 if otherwise. *Married* is a dummy that equals 1 if the respondent is married; and 0 if otherwise. *Age* is the age of the respondent. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors are clustered at the state level and reported in parentheses.

Table A6: Robustness—Credit Score and Delinquency Rate of Approved Applicants (with County-Month Fixed Effects)

	Credit Score (1)	Ln(Credit Score) (2)	Credit Score Rank (3)	Below 620 (4)	60-day Delinquency (5)
Outbreak × Black	23.602**	0.032**	0.734***	-0.015	-0.335**
	(9.783)	(0.013)	(0.224)	(0.011)	(0.151)
Controls	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes
County-Month FE	Yes	Yes	Yes	Yes	Yes
Obs.	20,114	20,114	20,114	20,114	20,125
Adj. R^2	0.061	0.062	0.051	0.052	0.022

Note: This table presents the results of the effects of Ebola outbreak on the loan quality among approved applicants in non-FinTech samples. We use county-month fixed effects. *Outbreak* is a dummy that equals 1 if the loan sequence number is larger than its corresponding threshold; and 0 otherwise. *Black* is a dummy that equals 1 if the applicant's race is Black; and 0 if White. *Credit Score* is the credit score of the applicant. *Credit Score Rank* is an ordered variable that equals 1 if the credit score lies in [300, 579]; 2 if in [580, 619], 3 if in [620, 669], 4 if in [670, 739], 5 if in [740, 799], 6 if in [800, 850]. *Below* 620 is a dummy that equals 1 if the applicant's credit score is smaller than 620; and 0 otherwise. 60-*day Delinquency* is a dummy equals 1 if the loan is delinquent at least for 60 days in our sample period; and 0 otherwise. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level and reported in parentheses.

Table A7: Data Structure for Three Epidemics

Epidemic	SARS (1)	Ebola (2)	COVID-19 (3)
Treatment	Asian	Black	Asian
Pre	2001, 2002	2014 Q1-Q3	2019
Post	2003	2014 Q4	2020
Time Unit	Year	Month	Year
Total Observation	39,886,404	6,340,134	22,494,287
Efficient Observation	39,886,157	6,284,559	22,369,093
Fixed effect	County-year	County-month	County, year
Control Variable	Applicant Income, Applicant Sex, Loan Amount, Loan Type, Loan Purpose, Purchaser Type (no Property Type and Lien Status)	Applicant Income, Applicant Sex, Loan Amount, Loan Type, Property Type, Loan Purpose, Lien Status, Purchaser Type	Applicant Income, Applicant Sex, Loan Amount, Loan Type, Property Type, Loan Purpose, Lien Status, Purchaser Type

Note: The efficient observation refers to the observation excluding singletons after controlling fixed effects.

B Procedures of Merging Datasets

B.1 Procedure of Creating HMDA-FNMA-FDMC Match Database

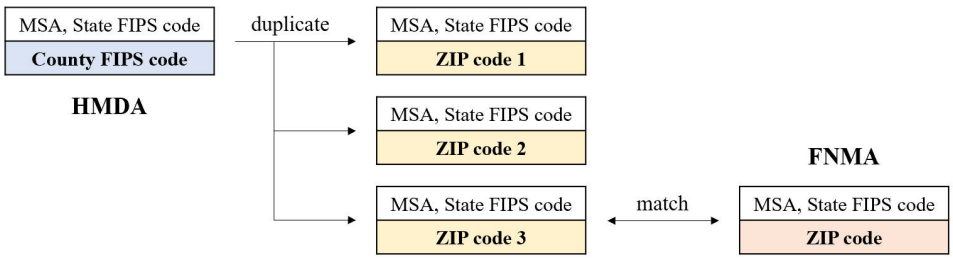
In this part, we introduce how we match 2014 HMDA data with corresponding FNMA and FDMC data. The matched dataset covers information on the loan origination month, the applicant's credit score at origination, and the dynamic performance of the loan from its origination to the latest updated status.

We first document the progress of matching HMDA with FNMA. Following Sun and Gao (2019), we merge HMDA data with FNMA by a series of variables. Intuitively, loans are matched between HMDA and FNMA by region and loan characteristics.

For geographical variables, three databases share MSA and the state FIPS code in common. While FNMA and FDMC uses 3-digit ZIP codes, HMDA do not. Conversely, HMDA use county FIPS codes, which FNMA and FDMC does not incorporate. However, county FIPS codes and 3-digit ZIP codes do not have a one-to-one match.

To increase the granularity of loan matching across databases, we create multiple duplicates of each HMDA sample, illustrated by Figure B1. The number of duplicates is determined by the number of possible ZIP codes for the original loan's county FIPS code. All samples duplicated from the same loan have the same county FIPS code but different ZIP codes. The loan would have three common geographic variables, including MSA, the state FIPS code, and the ZIP code. At the end, the loan will be matched to FNMA at most once.

Figure B1: Illustration of Geographical Matching



For other loan characteristics, we consider loan amount, loan purpose, property type, owner occupancy, and the existence of co-applicants. We unify variable definitions of HMDA and FNMA. The look-up table is as follows.

Table B1: HMDA-FNMA-FDMC Look Up Table

	HMDA	FNMA	FDMC
Property type	1	CO, PU, SF	CO, PU, SF
	2	MH	MH
	3	CP	CP
Owner occupancy	1	P	P
	2	S	S
	3	I	I
	.	U	9
Loan purpose	1	P	P
	3	R, C	R, C, N
	.	U	9
Co-applicant	1 if co_applicant_ethnicity value is not 5 (5 means no co-applicant); and 0 otherwise.	1 if number of borrowers is greater than 1; and 0 otherwise.	

Before merging HMDA data with 2014 FNMA data, we retain all originated loans in HMDA that are subsequently purchased by FNMA. We keep only loans that are unique in our matching variables, both in HMDA and FNMA. In the end, we can match HMDA with FNMA by locations (MSA, state FIPS code, and ZIP code) and loan characteristics (loan amount, loan purpose, property type, owner occupancy, and existence of co-applicants).

We further match HMDA and FDMC. The only difference is that we don't use the existence of co-applicants as a matching variable, because FDMC lacks this information. Lastly, we append HMDA-FNMA and HMDA-FDMC matched databases to form our targeted HMDA-FNMA-FDMC database.

B.2 Procedure of Creating Default FNMA and FDMC Database

Default loan sample construction is based on the HMDA-FNMA-FDMC matching method described in Online Appendix B.1. We collect HMDA origination data from 2007 to 2014 and match it with corresponding FNMA and FDMC origination data. After creating such a matched origination database, we can combine it with performance data from FNMA and FDMC.

Next, we describe our selection of default loans. We focus on loan performance in 2014. First, we retain only loans that have at least one default record in 2014. We then check a loan's last default time. The last default time refers to the beginning month of the latest default duration in the sample period. If a loan's last default time is earlier than Jan 2014, we exclude it from the sample.

For FNMA data, if a loan is modified in month t, at least one condition should be satisfied: (1) modification status changes from "N" in $t-1$ to "Y" in t, (2) current interest rates are different between $t-1$ and t, (3) maturity dates are different between $t-1$ and t, (4) current actual UPBs are different between $t-1$ and t. As for FDMC performance data, modification status change is documented, so we just define the modification month when the loan's modification status change from "N" to "Y".

C Validating the Chronological Order of Sequence Numbers in HMDA Data

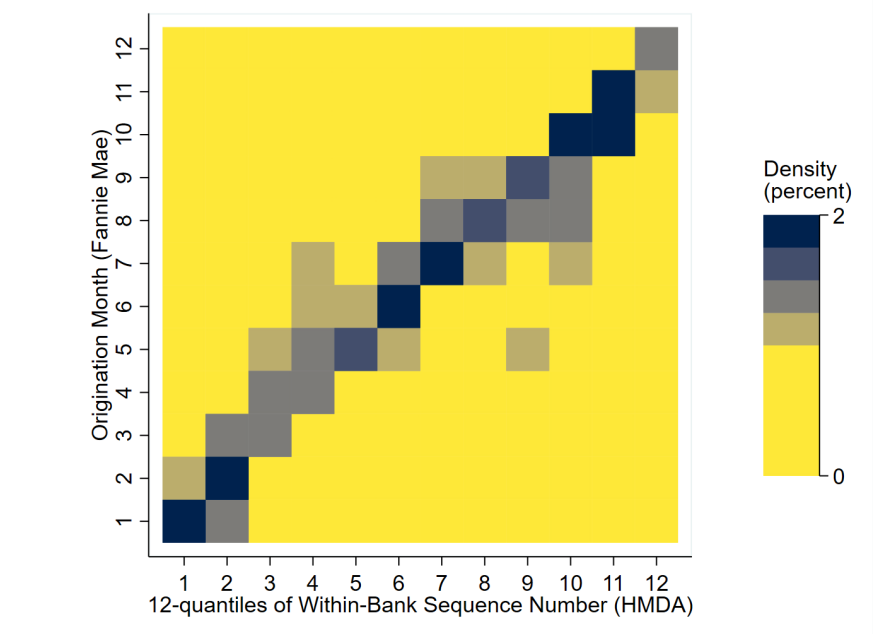
One caveat in our classification of pre- and post-Ebola loans is that the public version of HMDA data does not provide detailed information on the application month. In contrast, it contains the sequential number of loans initiated for each institution in each year. In this section, we demonstrate that the sequence number in HMDA data could retain the chronological order of loan originations for individual lenders. To validate this, we leverage the HMDA-FNMA matched dataset (see Online Appendix B) and analyze the correlation between the origination month (sourced from FNMA) and the 12-quantile of the HMDA sequence number (a normalized measure of application timing).

Figure C1 plots the joint distribution of origination months and sequence number quantiles. High-density cells (exceeding 1%) cluster tightly along the diagonal from the lower left (earlier months/lower quantiles) to the upper right (later months/higher quantiles), while off-diagonal cells exhibit negligible density. This visual pattern strongly supports a chronological alignment between sequence numbers and origination timing.

We further regress origination months on the 12-quantile of sequence numbers (excluding a constant term to isolate proportional relationships). The estimated coefficient exceeds 0.9 (Table C1), confirming a near-linear association. This result implies that a one-unit increase in the sequence number quantile corresponds to a 0.9-month advancement in origination timing.

Both graphical and regression-based evidence robustly support the use of HMDA sequence numbers as a reliable proxy for chronological loan origination order. This validation underpins our empirical strategy, ensuring that temporal patterns in lending behavior are accurately captured. In this study, the loans are classified into pre- and post-Ebola periods and do not rely heavily on the exact time of each loan.

Figure C1: Joint Density of Origination Month (Fannie Mae) and 12-quantile of Sequence Number (HMDA)



Note: This figure plots the joint distribution of origination months and sequence number quantiles.

Table C1: Correlation between Origination Month (Fannie Mae) and 12-quantile of Sequence Number (HMDA)

	Origination Month (1)
12-quantile of Sequence Number	0.906***
	(0.003)
Constant	No
Obs.	29,041
Adj. R^2	0.783

Note: This table presents the correlation between the origination month (Fannie Mae) and the 12-quantile of the sequence number (HMDA). The constant is forced to be zero. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors are reported in parentheses.

D Alternative Outbreak Measurements

Despite our preferred HMDA month division method, we explore two alternative methods to check the robustness of our baseline results.

First, we use a straightforward but crude method to impute the missing monthly information in the HMDA data. As the HMDA data records loan sequence numbers by time order for each institution, we simply divide the loans into 12 groups based on their sequence numbers within each institution, and we regard these groups sequentially from January to December. This method assumes that loan numbers across each month within each institution are the same, which is a crude but straightforward way to fill in the missing information.

Second, we leverage time information from the FNMA to impute the missing month information in the HMDA data. The FNMA data record the origination year and month of loans delivered to Fannie Mae. We obtain the monthly distribution of the loan numbers from the 2014 FNMA data and apply this distribution to each institution in the 2014 HMDA. Under this method, the loan numbers vary across months, but every institution shares the same cumulative distribution of "October 1". This method allows us to incorporate the time information from the FNMA data into the HMDA data and fill in the missing month information more accurately.

Third, we use a new method to match time information from FNMA with loan information from HMDA. We match at census tract level, which is more granular than the county level. The process is almost the same as our baseline method (see Section B.1), except replacing county FIPS code with census tract code, as FNMA loan-level data do not include census tract identifiers. Accordingly, we produce a new tract-level outbreak cutoff.

We denote *Outbreak (Equal Dist)*, *Outbreak (FNME Dist)*, and *Outbreak (Census Tract Match)* as Outbreak calculated by these three methods, respectively. Regression results using three month-division methods are shown in Table D1. We find that the our key interested variable are still significantly positive. It suggests that our month division method is valid and baseline results are robust.

Table D1: Alternative Outbreak Measurements

	Deny (1)	Deny (2)	Deny (3)	Deny (4)	Deny (5)	Deny (6)
Outbreak (Equal Dist) × Black	0.023***	0.024***				
	(0.002)	(0.002)				
Outbreak (FNME Dist) × Black			0.019***	0.021***		
			(0.002)	(0.002)		
Outbreak (Census Tract Match) × Black					0.045***	0.046***
					(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	No	Yes	Yes	Yes	Yes
County FE	Yes	No	Yes	No	Yes	No
State-Month FE	Yes	No	Yes	No	Yes	No
County-Month FE	No	Yes	No	Yes	No	Yes
Observations	6,285,464	6,284,555	6,285,464	6,284,505	6,285,464	6,284,541
Adj. R-Square	0.529	0.534	0.529	0.534	0.529	0.534

Note: This table presents the effects of the Ebola outbreak on the mortgage denial rate of treatment groups, under alternative outbreak measurements. *Outbreak* (*Equal Dist*), *Outbreak* (*FNME Dist*), *Outbreak* (*Census Tract Match*) are dummies that equal 1 if the sequence number is larger than its corresponding threshold of 4th quarter; and 0 otherwise. *Black* is a dummy that equals 1 if the applicant's race is Black; and 0 if White. *Deny* is a dummy that equals 1 if the loan application is denied; and 0 if originated. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors are clustered at the county level and reported in parentheses.

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