Internet Appendix

This Internet Appendix contains supplemental figures and tables.

A. Supplemental figures

Figure IA1: Persistence of leniency measure

This figure shows a graph of loan officer by branch by year average leniency on its one year lag. The dashed line shows the best linear fit on the officer by branch by year data. The slope is 0.48.

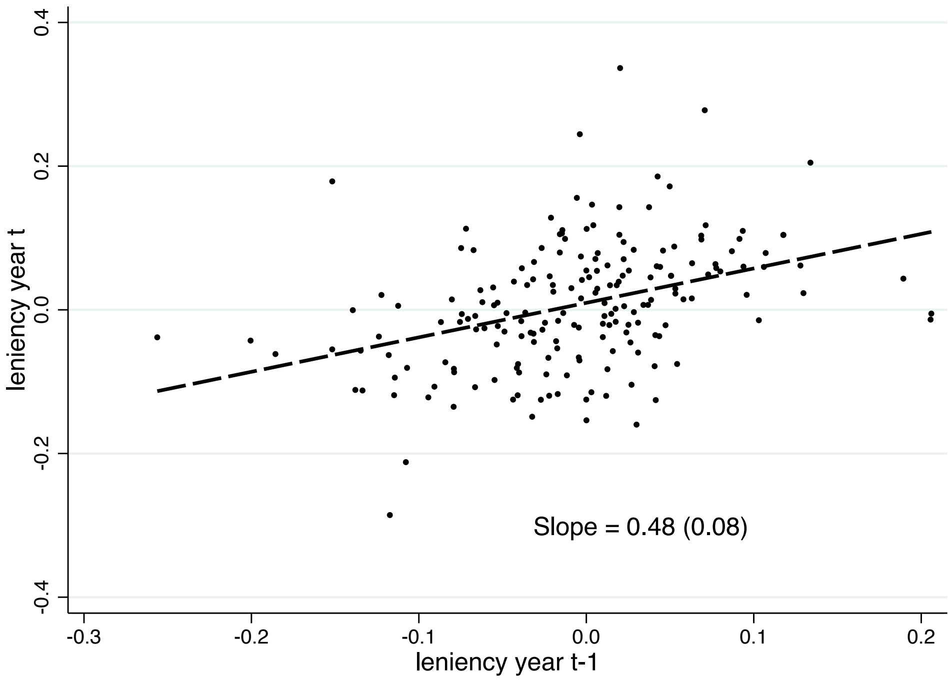


Figure IA2: Cross-sectional correlations of leniency

The figure shows the cross-sectional correlation between the yearly average measure of loan officer leniency and yearly average NPV of the borrower's full relationship with The Lender across all applications, defined as total payments made by borrower minus all loan amounts net of fees (top left graph), the yearly average of the number of monthly applications by officer (top right graph), the total number of first-time loans in our sample (bottom left), and the default rate of the individual's first loan with The Lender (bottom right). The sample includes loan officers with at least 10 applications per month. Data is aggregated at the officer by year level. The straight line represents the best linear fit on the underlying micro-level data, at the individual level for the NPV measure, and at the officer by month level for the number of applications. Standard errors are clustered at the store by year level.

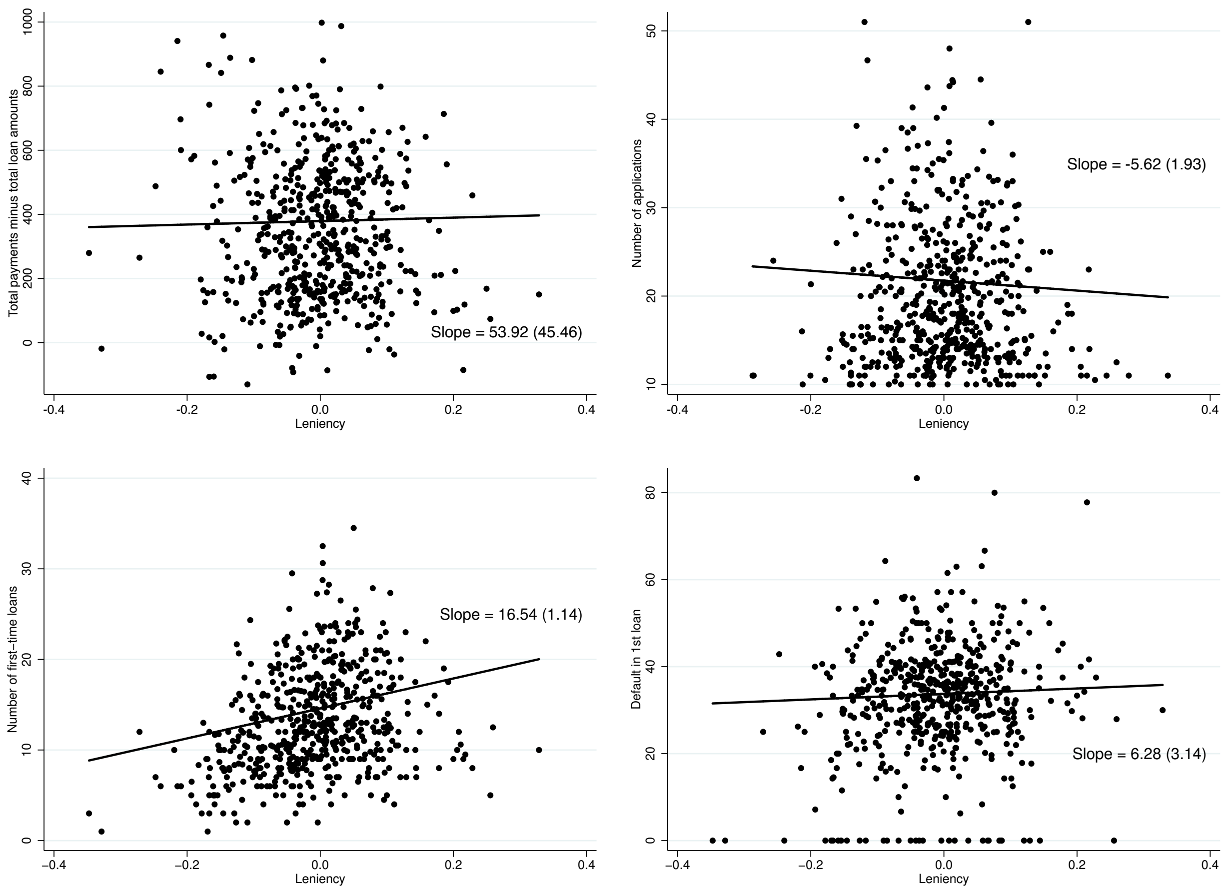


Figure IA3: Testing the monotonicity assumption

This figure shows that more lenient officers are not less likely to approve loans across observably different applicants, consistent with the monotonicity assumption of the identification strategy. Each graph shows the cross-sectional correlation between the measure of loan officer leniency and average loan approval rates, where each graph splits the sample into applicants based on an observable characteristic: above and below median age; male and female; and above and below median credit score. Details on the construction of the graphs are as shown in Figure 2. The straight line represents the best linear fit on the underlying data.

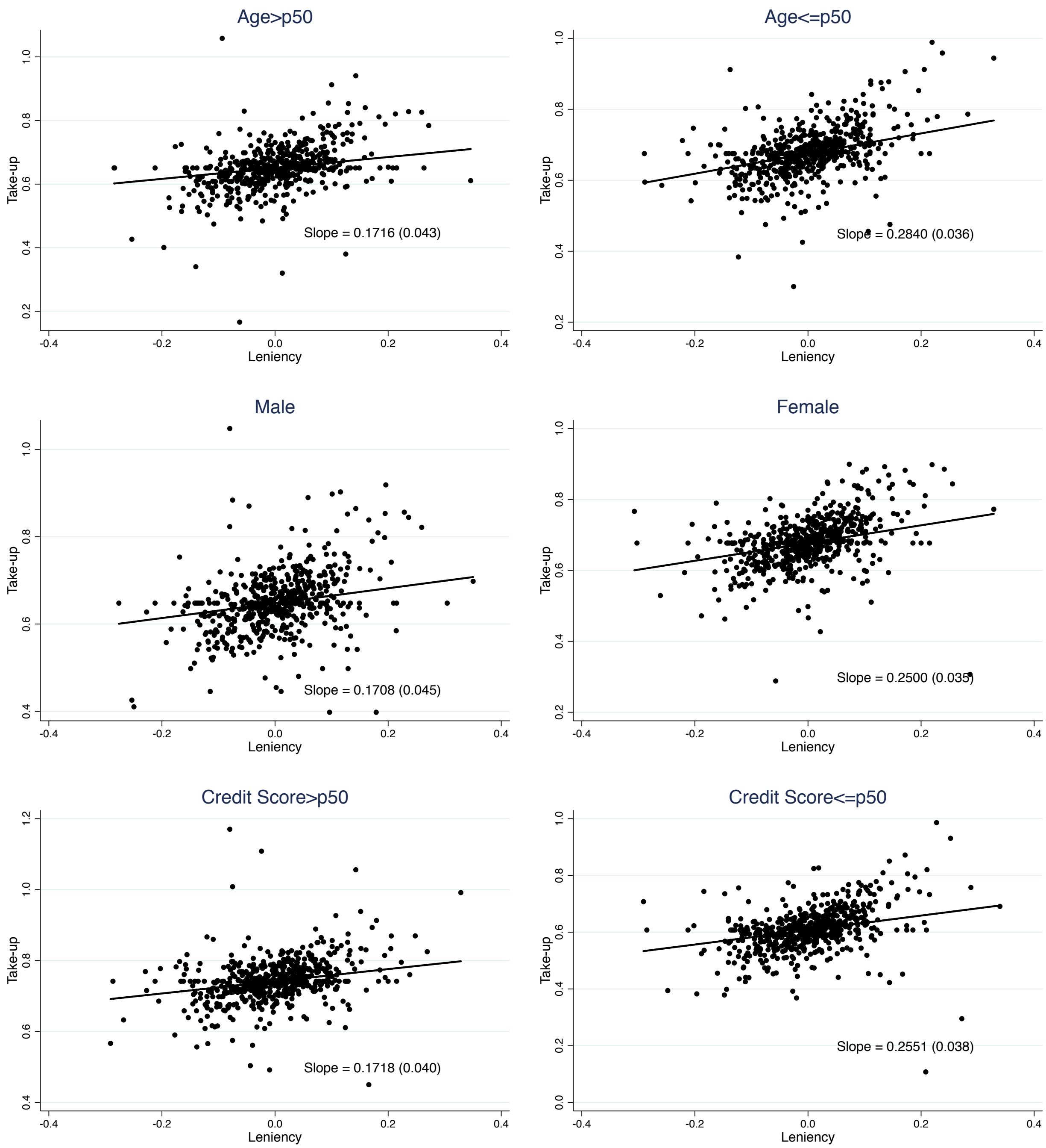
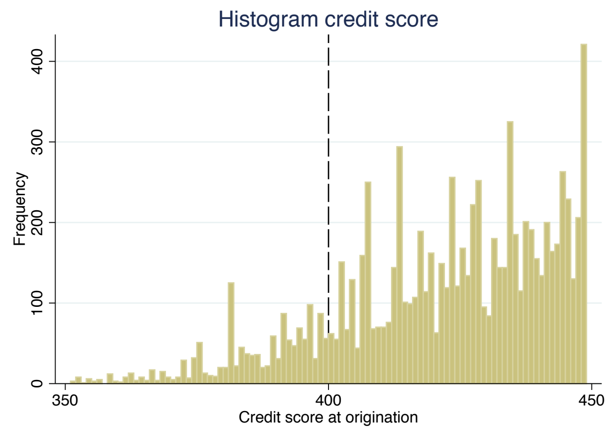
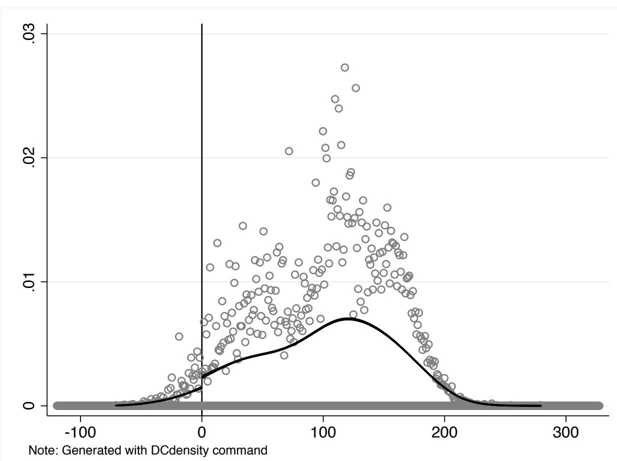
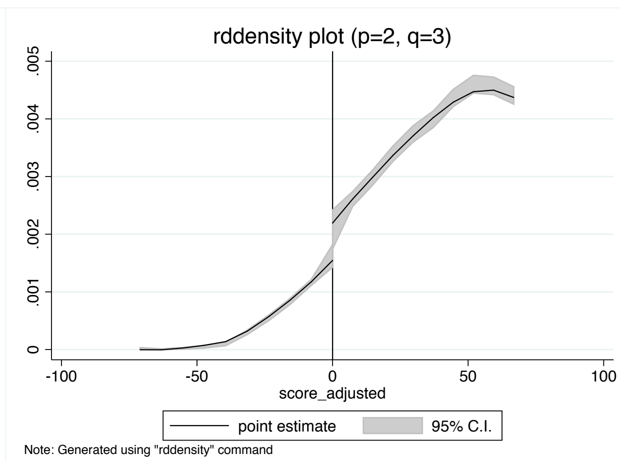


Figure IA4: Assumptions for regression discontinuity design

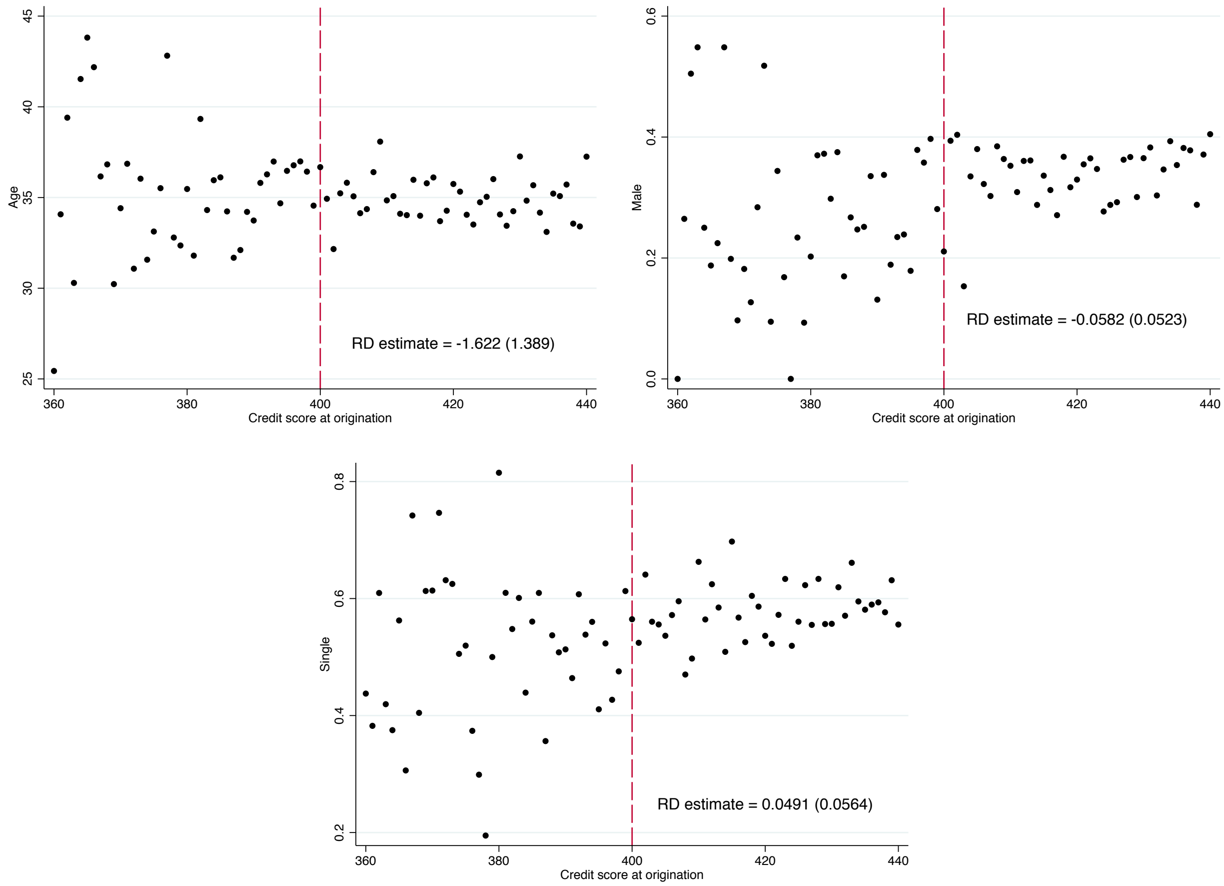
This figure shows the graphical setup of a regression discontinuity design to estimate the causal effect of loan approval on credit outcome based on the credit score cutoff. The top panel shows the histogram around the discontinuity for a window of 50 points around the credit score discontinuity, as well as histograms generated with the DCdensity commands, provided by Justin McCrary (see McCrary, 2008) and rddensity (see Calonico, Cattaneo, and Titiunik, 2014) The middle panel shows plots of average age, a dummy for male, and a dummy for single applicants, by credit score at application. Each graph shows the RD estimate of the discontinuity. The bottom panel shows a plot of the first stage, which shows the fraction of loan take-up by credit score at application, and OLS estimates of the relationship between take-up and credit score on both sides of the cutoff.







Panel B: continuity of covariates



Panel C: first stage

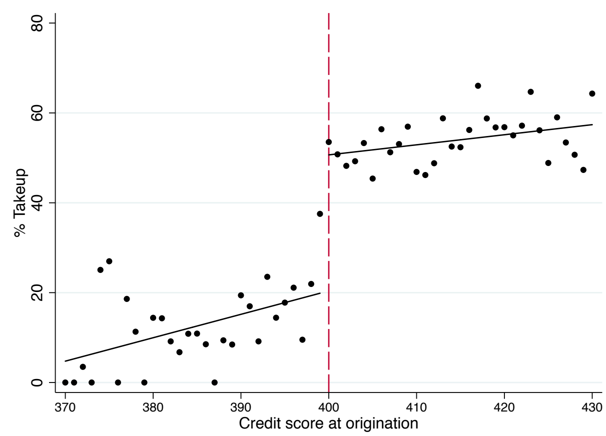


Figure IA5: Regression discontinuity design graphs

This figure shows graphical results of the RD design on credit scores by quarter after application.

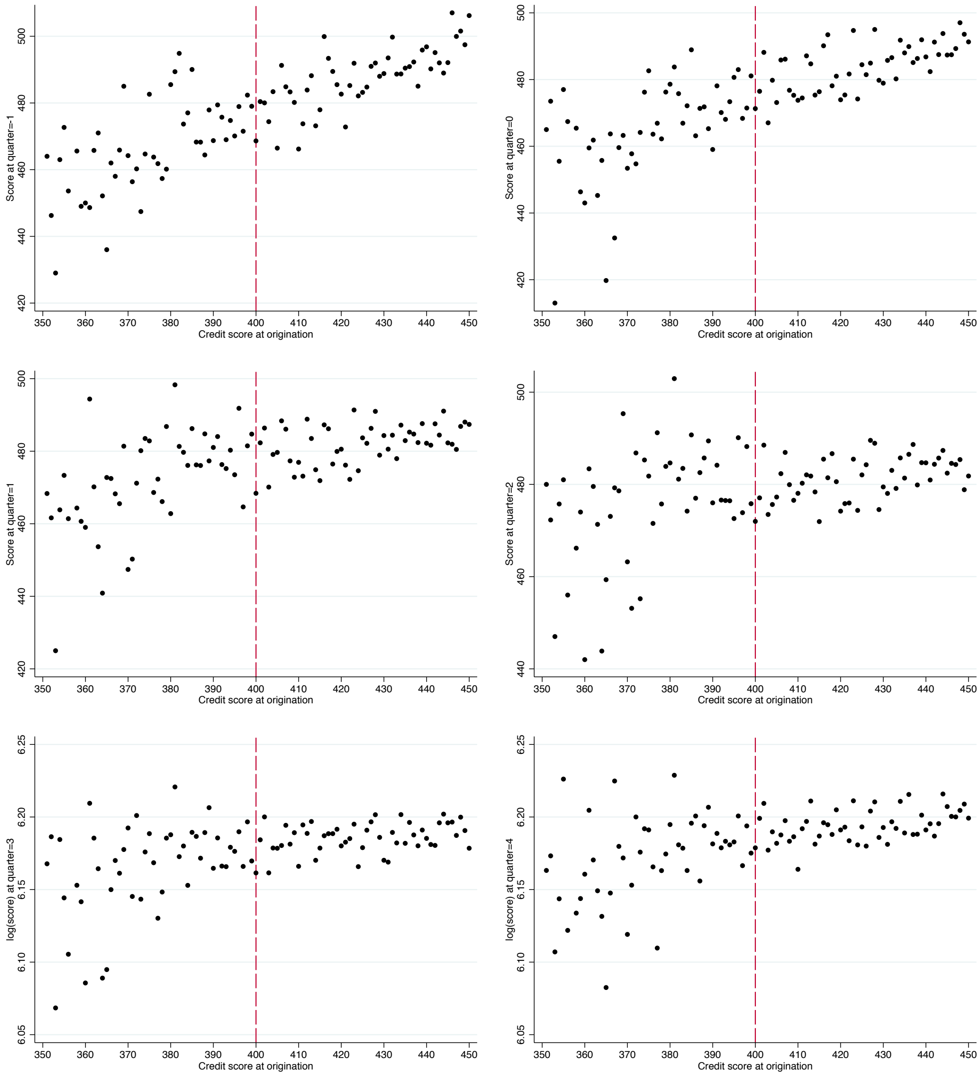


Figure IA6: Marginal Treatment Effects

This figure presents the distribution of marginal treatment effects (MTEs) for the change in credit score in t=0. The excluded instrument corresponds to leniency residualized by store by nationality by month of application fixed effects. We include credit score at application as a control variable. Plot produced using the STATA command “margte”.

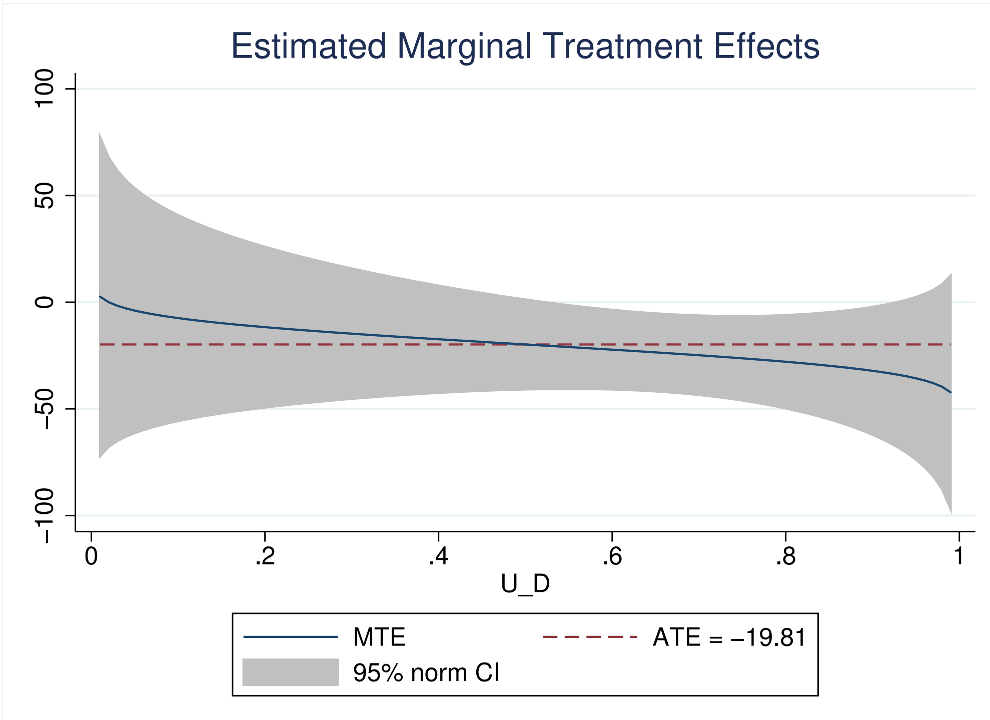


Figure IA7: Debt and credit scores

This figure plots the average credit score by 100 pound bin of debt outstanding at application, and a polynomial fit.

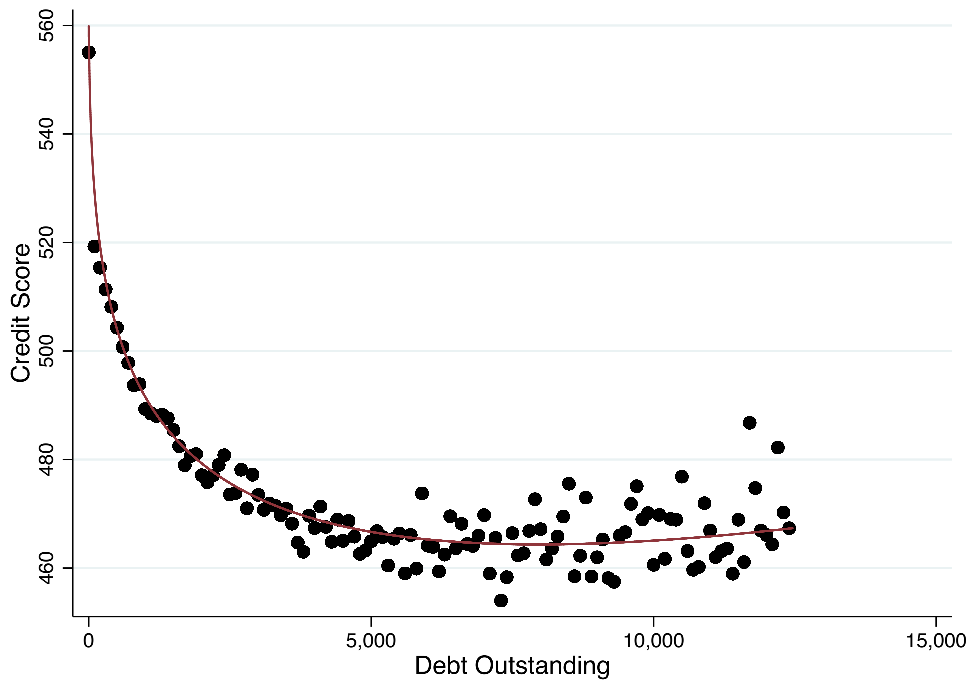
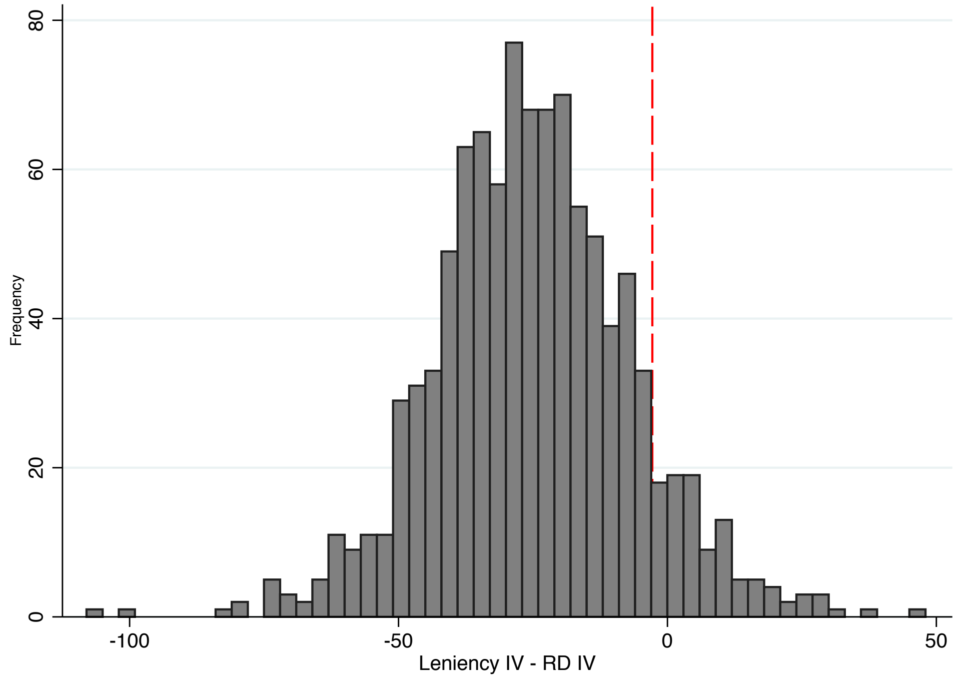


Figure IA8: Bootstrap distribution of differences in IV estimates at t=0

This figure presents a histogram of 1,000 bootstrap estimates of the difference between the leniency IV and RD estimates of the effect of loan take-up on the change in credit score during the quarter of application. The vertical line represents the 90th percentile.



B. Supplemental tables

Table IAI: Additional randomization test

This table presents additional evidence in support of the exclusion restriction for the leniency as an instrument of loan approval. Each row lists the OLS coefficient of a regression of each covariate on z_i, the measure of advisor leniency, and week of application by store by nationality of applicant fixed effects. The sample corresponds to all loan applicants at the lender's physical stores who were between 18 and 75 years old at the time of application. Standard errors clustered at the store by year level. *, **, and *** represent 10, 5, and 1 percent significance level, respectively.

	(1)
	x
$Credit\ score$	3.8540
	(3.2611)
$Single$	−0.0380
	(0.0525)
$Male$	0.0549*
	(0.0288)
Age	0.1356
	(0.6793)
$Salary$	53.9792
	(41.5546)
$Loan\ for\ emergency$	−0.0446
	(0.0932)
$Years\ of\ residence\ UK$	2.1934
	(2.2417)
$Loan\ amount\ requested$	17.6845
	(27.2366)
Observations	51,355

Table IAII: Change in credit score by probability of take-up

This table shows the output of the IV regression

$$\Delta Score_{it} = \alpha + \beta_0 Takeup_i + \sum_{k=2}^{4} \beta_k Takeup_i \times \hat{p}_{k(i)} + \alpha^{swc} + \epsilon_i,$$

of credit score at quarter t minus log credit score at quarter -1, where quarter is measured relative to the application date, on $Takeup$ and the interactions of $Takeup$ and $\hat{p}_k$. Each $\hat{p}_k$ is a dummy variable that represents quartile k of the predicted probability of take-up conditional on: credit score at origination, a dummy for single applicants, a dummy for male applicants, age, salary, a dummy for whether the stated purpose of the loan is an emergency, years of residence in the UK, and loan amount requested, all measured at the time of application, as well as week of application by branch by nationality of applicant fixed effects, α^{swc}. We instrument for $Takeup$ and the three $Takeup \times \hat{p}_k$ endogenous variables with leniency z and the three interactions of leniency z and $\hat{p}_k$ for $k \in \{2, 3, 4\}$. Each column shows the outcome of a regression that varies quarter t from 0 to 4. The sample corresponds to all loan applicants at the lender's physical stores who were between 18 and 75 years old at the time of application. Standard errors clustered at the store by year level. *, **, and *** represent 10, 5, and 1 percent significance level, respectively.

	(1) t=0	(2) t=1	(3) t=2	(4) t=3	(5) t=4
			$\Delta Score$		
Takeup	-36.05^{**}	-44.17^{*}	-59.41^{***}	-45.39^{*}	-50.36^{*}
	(17.65)	(23.36)	(19.31)	(25.82)	(28.81)
Takeup $\times \hat{p}2$	6.10	-4.09	-5.05	-8.58	-5.39
	(5.60)	(7.19)	(6.18)	(8.52)	(9.41)
Takeup $\times \hat{p}3$	7.81	-7.83	-8.92	-13.29	-9.52
	(7.59)	(9.85)	(8.41)	(11.18)	(12.72)
Takeup $\times \hat{p}4$	9.81	-9.04	-11.95	-19.82	-13.94
	(9.09)	(12.34)	(10.62)	(14.17)	(16.07)
Observations	40,771	40,608	38,487	34,811	31,445
R-squared	0.07	0.17	0.16	0.16	0.12
Clusters					

Table IAIII: Regression discontinuity design first stage

This table shows the first-stage coefficient of the regression discontinuity design using the minimum credit score cutoff to estimate the effects of high-cost credit on credit outcomes, estimated using local linear polynomials and the default optimal bandwidth, as per Calonico, Cattaneo, and Titiunik (2014), for t=0, 1, 2, 3, and 4 quarters after loan application. All coefficients and standard errors are robust to bias, as per Calonico, Cattaneo, and Titiunik (2014), estimated using the STATA command RDROBUST. Standard errors are clustered at the store by year level. *, **, and *** represent 10, 5, and 1 percent significance level, respectively.

	(1)	(2)	(3)	(4)	(5)
			$\Delta Score$		
	t=0	t=1	t=2	t=3	t=4
Above	0.2494***	0.2733***	0.2636***	0.2081***	0.1825***
	(0.0394)	(0.0378)	(0.0395)	(0.0452)	(0.0497)
Observations	44,723	44,549	41,866	37,315	33,101

Table IAIV: Change in credit score, no attrition

The table repeats Table III but conditions the sample on applicants for whom four quarters of credit score data are available after loan application.

Panel A: OLS

	(1)	(2)	(3)	(4)	(5)
			$\Delta Score$		
	t=0	t=1	t=2	t=3	t=4
Takeup	-4.37^{***}	-21.85^{***}	-29.38^{***}	-24.25^{***}	-20.44^{***}
	(0.54)	(0.93)	(1.21)	(0.99)	(0.87)
Observations	29,061	29,058	29,057	29,057	29,057
R-squared	0.16	0.19	0.21	0.19	0.18
Clusters	37	37	37	37	37

Panel B: Reduced Form

	(1)	(2)	(3)	(4)	(5)
			$\Delta Score$		
	t=0	t=1	t=2	t=3	t=4
z	-6.83^{**}	-10.58^{**}	-15.98^{***}	-11.93^{***}	-10.31^{**}
	(2.66)	(4.04)	(3.34)	(3.51)	(3.88)
Observations	29,061	29,058	29,057	29,057	29,057
R-squared	0.15	0.17	0.17	0.16	0.15
Clusters	37	37	37	37	37

Panel C: IV

	(1)	(2)	(3)	(4)	(5)
			$\Delta Score$		
	t=0	t=1	t=2	t=3	t=4
Takeup	-31.25^{**}	-48.37^{**}	-73.01^{***}	-54.52^{***}	-47.10^{**}
	(13.80)	(21.12)	(19.11)	(18.28)	(19.77)
Observations	29,061	29,058	29,057	29,057	29,057
R-squared	0.06	0.16	0.12	0.14	0.14
Clusters	37	37	37	37	37

Table IAV: Change in credit score by credit score at origination

The table runs our baseline regression (3) where we add two endogenous variables, the interactions of *Takeup* with *Tercile 2* and *Tercile 3*, dummies representing the second and third terciles of the distribution of credit scores at origination. The instruments include leniency, and the interactions of leniency with *Tercile 2* and *Tercile 3*. Standard errors are clustered at the store by year level. *, **, and *** represent 10, 5, and 1 percent significance level, respectively.

	(1)	(2)	(3)	(4)	(5)
			$\Delta Score$		
	t=0	t=1	t=2	t=3	t=4
Takeup	-23.37^{**}	-43.09^{***}	-69.85^{***}	-48.49^{***}	-34.11^{**}
	(10.65)	(15.42)	(15.50)	(13.52)	(16.77)
Takeup × *Tercile 2*	7.40	28.21	26.32	10.27	−7.03
	(15.72)	(18.51)	(22.58)	(19.47)	(22.24)
Takeup × *Tercile 3*	−21.53	18.19	3.74	−10.43	-46.22^{*}
	(22.74)	(26.84)	(33.31)	(27.89)	(27.54)
Observations	40,321	40,159	38,047	34,406	31,067
R-squared	0.10	0.24	0.22	0.23	0.20
Clusters	59	59	59	59	59

Table IAVI: Causal effect of loan take-up on profitability, future applications, and future loans

This table shows the causal effect of loan take-up on *Lender profits*, calculated as borrower payments minus disbursements, *Loan top-up*, defined as a dummy that equals one if a new loan is issued by the Lender to the borrower before the first loan is paid, *Future applications*, defined as the number of subsequent applications for new loans by the Lender made by the borrower, and *Future loans*, defined as the number of new loans issued by the Lender to the borrower after the first one. Estimates using the leniency IV and the RD are shown for each outcome. Standard errors are clustered at the store by year level. *, **, and *** represent 10, 5, and 1 percent significance level, respectively.

	(1)	(2)
ID Strategy	Leniency IV	RD
	Lender profits	
Takeup	248.88**	110.97
	(124.38)	(92.25)
	Loan top-up	
Takeup	44.4570***	44.6084***
	(11.7151)	(5.7233)
	Future applications	
Takeup	0.9600*	0.9258**
	(0.5056)	(0.3848)
	Future loans	
Takeup	1.0923**	0.9074***
	(0.4298)	(0.3334)

Table IAVII: Heterogeneity by initial level of debt

This table shows the causal effect of loan take-up by level of outstanding debt using the leniency IV identification strategy. Panel A presents the output of a regression of the change in credit score relative to one quarter before application on dummies for loan take-up, and loan take-up interacted with dummies for the second and third tercile of the level of debt outstanding at origination as endogenous variables, instrument by leniency, and leniency interacted with dummies for the second and third tercile of debt at origination. Panels B and C show the output for the same regression using measures of usage and search for bank credit. The regresion includes the uninteracted dummies for debt terciles (unreported). Standard errors are clustered at the store by year level (76 clusters). *, **, and *** represent 10, 5, and 1 percent significance level, respectively.

Panel A: change in credit score

	(1)	(2)	(3)	(4)	(5)
			Takeup		
	t=0	t=1	t=2	t=3	t=4
Takeup	−32.42*	−9.99	−54.32*	−43.77**	−45.68**
	(19.05)	(28.59)	(32.47)	(19.51)	(19.73)
Takeup × Tercile 2	19.00	−22.54	−1.73	4.16	6.22
	(15.67)	(28.15)	(34.78)	(23.83)	(26.95)
Takeup × Tercile 3	3.57	−39.24	−17.14	−20.99	−15.84
	(16.09)	(26.74)	(31.73)	(21.07)	(22.88)
Observations	40,771	40,608	38,487	34,811	31,445
R-squared	0.10	0.19	0.19	0.17	0.16
Clusters	59	59	59	59	59

Panel B: search for bank credit

	(1)	(2)	(3)	(4)	(5)
			Δ *Bank credit searches*		
	t=0	t=1	t=2	t=3	t=4
Takeup	−0.69	−0.09	−0.28	−0.23	1.22*
	(0.53)	(0.66)	(0.60)	(0.55)	(0.65)
Takeup × Tercile 2	0.80	0.04	0.76	0.63	−0.65
	(0.73)	(0.75)	(0.69)	(0.72)	(0.66)
Takeup × Tercile 3	0.92	0.79	0.79	2.14***	0.48
	(0.64)	(0.78)	(0.68)	(0.66)	(0.95)
Observations	40,845	40,682	38,559	34,879	31,501
R-squared	0.14	0.20	0.12	0.06	0.04
Clusters	59	59	59	59	59

Panel C: usage of bank credit

	(1)	(2)	(3)	(4)	(5)
			Δ *Accounts bank credit*		
	t=0	t=1	t=2	t=3	t=4
Takeup	-0.56^{**}	-0.92^{**}	-1.04^{**}	-0.84	-1.31^{*}
	(0.25)	(0.36)	(0.47)	(0.61)	(0.75)
Takeup $\times$ *Tercile 2*	0.34	0.41	0.43	0.28	0.54
	(0.31)	(0.52)	(0.63)	(0.78)	(0.94)
Takeup $\times$ *Tercile 3*	0.48^{*}	0.54	0.39	0.07	-0.21
	(0.26)	(0.45)	(0.56)	(0.67)	(0.97)
Observations	40,845	40,682	38,559	34,879	31,501
R-squared	0.10	0.07	0.08	0.11	0.07
Clusters	59	59	59	59	59

	(1)	(2)	(3)	(4)	(5)
			Δ log(*Bank credit*+1)		
	t=0	t=1	t=2	t=3	t=4
Takeup	-1.43	-1.67	-2.65^{**}	-1.93	-0.83
	(0.88)	(1.10)	(1.23)	(1.30)	(1.30)
Takeup $\times$ *Tercile 2*	1.10	0.69	1.05	1.04	0.37
	(0.99)	(1.07)	(1.26)	(1.31)	(1.28)
Takeup $\times$ *Tercile 3*	1.43^{*}	2.09^{*}	3.26^{***}	2.83^{**}	1.67
	(0.84)	(1.07)	(1.15)	(1.31)	(1.18)
Observations	40,845	40,682	38,559	34,879	31,501
R-squared	0.14	0.15	0.10	0.16	0.21
Clusters	59	59	59	59	59