Consumer Default, Credit Reporting and Borrowing Constraints[⋆]

Mark J. Garmaise and Gabriel Natividad[*]

ABSTRACT

Why do negative credit events lead to long-term borrowing constraints? Exploiting banking regulations in Peru and utilizing currency movements, we show that consumers who face a credit rating downgrade due to bad luck experience a three-year reduction in financing. Consumers respond to the shock by paying down their most troubled loans, but nonetheless end up more likely to exit the credit market. For a set of borrowers who experience severe delinquency, we find that the associated credit reporting downgrade by itself accounts for 25%-65% of their observed decline in borrowing at various horizons over the following several years.

*Garmaise is at UCLA Anderson (mark.garmaise@anderson.ucla.edu). Natividad is at Universidad de Piura (gabriel.natividad@udep.pe).

⋆This document has been officially screened by Superintendencia de Banca, Seguros, y AFP del Peru (SBS) to ensure that no confidential information is revealed. We are grateful to SBS for access to the banking data, and to two anonymous referees, the editor and numerous seminar audiences for useful comments. Guillermo Ramirez-Chiang provided excellent research assistance.

The recovery from the recession of 2008 has been anemic. An influential stream of research has attributed this sustained period of lackluster growth to financial constraints that bind heavily indebted consumers and limit their participation in the economy (Eggertsson and Krugman 2012, Guerrieri and Lorenzoni 2015, Hall 2011, Mian, Rao and Sufi 2013 and Mian and Sufi 2010 and 2011). What explains the power and duration of these financial constraints? While it is clear that many households experienced negative credit events during the recession, what is less apparent is precisely why these events might have had such long-lasting consequences for access to loans. In this paper we provide an empirical analysis of the impact of unfavorable credit events on future financing for consumers, with a particular focus on the role played by formal credit reporting systems.

Our empirical setting is a broad panel of consumer loans in Peru. We begin by showing that in Peru, as in other countries, negative credit events are associated with serious medium-term restrictions in access to credit. Our main interest, however, is in analyzing the determinants of this relationship. To that end, we exploit features of local banking regulations to identify exogenous shocks to the risk classifications of some borrowers. These shocks have no information content, yet we show that they lead to a three year reduction in financing for the affected consumers. That is, consumers who experience a credit downgrade due simply to bad luck are subjected to an extended period of reduced financial access.

We then apply our methodology to a set of borrowers who have had their loans downgraded to the lowest level by all their lenders. We label this event "complete default." For some of these borrowers, complete default arose due to the exogenous rating shocks, while others were not subject to these shocks. Contrasting the outcomes for these two classes of borrowers, we disentangle the extent to which future lending restrictions are driven simply by negative credit reporting, as opposed to the persistent long-run real shocks that often cause default. At various horizons up to three years, we estimate that 25%-65% of the observed credit decline after complete default arises solely due to the sustained negative impact of the borrower's poor credit rating. These findings offer some of the first evidence that credit reporting documenting the defaults, foreclosures and bankruptcies of consumers by itself may be a key mechanism substantially reducing future borrowing, irrespective of expansionary central bank policies or other macroeconomic stimuli such as those implemented in the U.S. after the 2008 crisis.

Assessing the impact of exogenous credit rating shocks on consumers may be challenging, as credit performance is determined endogenously by the actions of the consumer and the evaluations of banks and other credit raters. The consumer borrowing market in Peru has two features that allow for an empirical examination of the central questions outlined above.[1] First, Peruvian banking regulations require that banks provide to a central credit registry a quantitative risk assessment of each client, which is available for anyone to see. For borrowers with more than one bank, the regulations further require that these ratings display a degree of alignment. In particular, a poor risk rating given by any bank with a share of 20% or more of a given borrower's total lending should be reflected in the ratings of all other lenders. Second, during our sample period of 2001-2011, Peruvian consumers routinely borrowed in a mix of local currency (sol) and U.S. dollar debt.

[1] We focus exclusively on pure consumers, not businesses; the individuals in this study do not have a personal tax ID for business purposes and have never received a business loan.

The strict 20% cutoff for the alignment requirement and the combination of sol and dollar borrowing create the possibility that a given borrower may have a poorly performing loan pushed across the 20% threshold purely by exchange rate movements, while a different borrower with a similar loan profile but a somewhat different currency exposure may remain below the threshold. We implement a regression discontinuity design comparing borrowers with banking relationships whose exchange-rate-adjusted balances (i.e., previous month's balances adjusted by the changes in the current month's exchange rate) are just above 20% with borrowers with relationships whose exchange-rate-adjusted balances are just below 20%. The borrower with the delinquent loan that crosses the 20% border will experience a downgrade imposed by regulation, leading to an overall rating record that appears very weak. The other borrower with the delinquent loan just below 20% of her total loan portfolio will experience none of these consequences, due simply to specific movements in the currency market. From an information perspective, there is no substantive difference between these two consumers, but one will suffer a rating downgrade while the second will not.

We show that our exchange-rate-adjusted balances clearly predict whether a borrower's actual loan balance will shift to over 20% of her overall balance, despite the fact that the former ignores any changes made in the current month (to avoid endogeneity concerns). We also document that, in terms of observable characteristics, borrowers with exchange-rate-adjusted balances just over 20% look very similar to those with exchange-rate-adjusted balances just below this threshold, which is not surprising given that currency movements are exogenous for any given consumer. We further show that borrowers with low-rated loans pushed above the threshold by exchange rate movements do experience a negative rating shock of moderate duration (the effect is statistically significant for no longer than five months though the estimated coefficients do not fall much over the first year). These effects are confined, as expected, to borrowers with highly heterogeneous loan ratings; borrowers whose loan ratings are all somewhat similar are unaffected by the alignment mandate and do not experience a significant rating change when a loan passes the threshold.

Next we consider the impact of this negative rating shock on the borrower's banking relationships. We find that above-threshold borrowers experience a reduction in their consumer loan balance and receive less new consumer financing over the next three years, relative to below-threshold borrowers. Moreover, these consumers are less likely to initiate new banking relationships and are subject to reductions in their unused credit line balance. Even though banks have access to all the information necessary for unraveling the source of the downgrade, it nonetheless has a meaningful negative impact on lending to the borrower.

We then consider the effect of the shock on the consumer's actions. First, we show that above-threshold consumers are more likely to pay down their most delinquent loans (loans that are subject to judicial collection) in the three years after the shock. Further, we find that borrowers receiving a negative shock are more likely to achieve a zero balance on their credit card accounts in the year following the shock. These results suggest that the rating shock serves as a wake-up call for the consumer, inducing her to improve her financial profile.

Despite these corrective actions taken by above-threshold consumers, however, we find that the medium-term impact of the shock is quite negative. Shocked clients are more likely to completely exit the consumer loan market in the subsequent two and three years. They are also more likely to have loans transition to the severely delinquent status of being subject to judicial collection. The negative rating shock appears to lead consumers down a slippery slope towards very negative outcomes, even in the face of their efforts to ameliorate their credit conditions. This may be driven by the reduced financial flexibility and restricted access to finance that follow the shock.

Our final analysis decomposes the relationship between the very negative event of complete default and future borrowing. We find that a substantial proportion of the future decrease in lending arises solely due to the low credit rating associated with complete default. That is, the formal credit reporting system is an important driver of deleveraging by constrained consumers, a phenomenon that is often held to blame for at least a meaningful part of the sluggish post-recession recovery.

In addition to informing the debate about the determinants of consumer recovery cycles, our study of negative credit events and lending also connects with literatures studying the equilibrium effects of personal bankruptcy law (Athreya 2002, Chatterjee et al. 2007 and Livshits, MacGee and Tertilt 2007) and asset pricing and portfolio choice in the presence of default (Alvarez and Jermann 2000 and 2001 and Cocco, Gomes and Maenhout 2005). A standard, central, but largely untested assumption in these models is that a consumer's choice to enter bankruptcy will also lead her to a prolonged exclusion from credit markets. Bankrupt consumers do borrow less in the the future (Jagtiani and Li 2013), but it may be argued that this reflects the underlying strained conditions that led to bankruptcy rather than resulting as an actual consequence of the bankruptcy decision. In other words, the jobless or ill who become bankrupt would perhaps not borrow much even if they did not declare bankruptcy. Our results, however, provide clear support for this important modeling assumption: the decision to enter bankruptcy, through its effect on the consumer's credit report, leads to restricted future borrowing, even controlling for the borrower's current economic circumstances.

Our study of consumer default and credit reporting thus sheds new light on the causes of borrowing constraints. Prior work has focused on the removal of derogatory information from credit reports. Musto (2004) and Bos and Nakamura (2014) study the timing of this information removal and show that lending increases when borrowers' negative reports are eliminated from their credit files, just as we find that a negative credit event leads to less lending. Our approach differs in that it we consider not the timing but whether a consumer receives a random credit shock at all. We are also able to quantify the fraction of the post-bankruptcy reduction in lending that is due to the reporting system. Moreover, we focus on borrowers who are entering financial distress rather than those who are exiting it. Given that entry into distress is far more common in economic downturns, our results have implications for policymakers interested in increasing consumer lending during a contraction. Elul and Gottardi (2015) provide a theoretical analysis of the equilibrium effects of requiring banks to forget some borrower defaults, and they argue that such a rule has both negative ex ante and positive ex post effects. These ex post benefits are likely to be most important during a recession. Our results suggest that it may be worth considering policies that link the regulated length of consumer retained credit histories to the state of the macroeconomy.

I Data

We analyze monthly consumer bank loan data from Peru over the period 2001-2011. The data are supplied by the Peruvian banking regulator, *Superintendencia de Banca, Seguros, y AFPs* (SBS) and are labeled the RCD (*Reporte Crediticio de Deudores*) consumer loan database, which is different from the business loan database. Our analysis focuses on purely consumer clients with no personal tax ID for business purposes (per the Tax Authority's registry) and no prior history of receiving business loans. The data describe for each Peruvian financial institution the monthly loan balances of every consumer borrower, the classification rating granted by the bank to each loan per SBS's regulation (described in more detail below), and the currency (i.e., Peruvian soles, U.S. dollars) in which the loan has been granted.[2] The exchange rate, as well as debt balances, are officially calculated at the end of each month by SBS. Over the term of the sample period, 72% of the loan balances of the clients are in Soles, with this fraction increasing over time. The mean exchange rate is 3.19 Soles per dollar, with a standard deviation of 0.28. This exchange-rate variability plays a central role in our empirical strategy, as described below in Section II.

Banking regulations in Peru mandate that all financial institutions report on the risk classification of each client, on a five-point integer scale from normal (a score of 0) to loss (a score of 4).[3] The risk classification of consumer loans is determined by the extent of the borrower's delinquency in days. These regulations require that banks make loan loss

[2]Consumer account-level financial data have been used in Gross and Souleles 2002, Agarwal and Qian 2014 and Gelman et al. 2014. Our data cover the formal sector and exclude informal lending, which is not insignificant in Peru (World Bank 2016).

[3]These classifications are publicly available at `http://www.sbs.gob.pe/app/pu/ReporteDeudasSBS/Default.aspx` (accessed August 3, 2016).

provisions that vary according to the risk classification, ranging from 1% for normal loans to 100% for loss loans.[4]

II Empirical Specification

A Borrower Risk Classifications and the "Rule of Twenty"

We are interested in the effect of an exogenous shock to a consumer's risk classification. Peruvian banking regulations state that there should be an alignment of debt classifications for a given borrower across relationships. Specifically, whenever there is a discrepancy in risk classifications across banks of the same client in a given month, the client should receive the worst classification assigned by any bank that holds *at least 20% of the client's total debt balance*.[5] We refer to this regulation, which places weight only on the risk classifications of banks with at least 20% of a borrower's balance, as the "rule of twenty".

Borrower risk classifications are, of course, highly endogenous and depend on the borrower's payment history. The rule of twenty, however, suggests a potential regression discontinuity design to measure the causal impact of an exogenous shock to a borrower's risk classifications. Specifically, if a borrower has a loan with a high risk classification that makes

[4] There is a stream of work showing the importance of consumer credit scores in predicting loan defaults (Agarwal, Skiba and Tobacman 2009) and in determining access to finance (Keys et al. 2008) and payment behavior (Mayer, Piskorski and Tchistyi 2013 and Liberman 2016).These themes are also discussed in the broad literature on the effects of consumer credit (Campbell 2006, Carrell and Zinman 2014, Melzer 2011 and Morse 2010), and in studies of the impact of incentives and regulations on shifts in consumer financial behavior over time (Karlan and Zinman 2009 and Agwarwal et al. 2015).

[5] See, for example, SBS resolution 808-2003 available at `www.sbs.gob.pe/repositorioaps/0/0/jer/sf_csf/0808-2003.doc` (accessed October 26, 2015).

up just less than 20% of the borrower's overall balance and this loan transitions to just above 20% of the borrower's balance, the rule of twenty would then require all the borrower's others lenders to adjust their risk classifications upwards. Loan balances are endogenous, but the use of two currencies in Peruvian banking that we described above allows for a design that exploits currency-driven shifts in the relative sizes of a consumer's bank loans.[6]

A consumer with one loan in Soles and a second loan in U.S. dollars will experience shifts in her loan balances that are generated by exogenous exchange rate movements. Consider, for example, a consumer with 19% of her total debt balance in a U.S. dollar loan with a high risk classification and 81% of her total debt balance in a low risk classification Sol loan. If the U.S. dollar strengthens relative to the Sol, then the U.S. dollar loan will now rise to more than 20% of the overall loan balance. In this case, the rule of twenty will require that the risk classification on the Sol loan be increased, thereby raising the required loss provision that the Sol lender must take against this loan. A similar consumer who had 19% of her total loan balance in a high risk classification Sol loan and 81% of her total balance in a low risk classification U.S. dollar loan would not be subject to any adjustments in her risk classifications. In this sense, the first consumer experienced an exogenous, exchange-rate driven shock to her risk classification.

As this example suggests, for currency movements to have an effect on the relative sizes of the loan balances across banking relationships, it is crucial that the currency exposures

[6]In common with the balance sheet literature (e.g., Aguiar 2005, Calvo, Izquierdo and Mejia 2004, Céspedes, Chang and Velasco 2004), we consider the impact of exchange rates on emerging markets. Our focus, however, is on consumers, not firms, and our interest is in using currency movements to exploit the discontinuity features of local banking regulations, rather than considering the macroeconomic consequences of the exchange rates themselves.

and risk ratings of a consumer's various relationships be very different. We therefore focus on a specific set of consumers with the following characteristics: the consumer must borrow from multiple banks, borrow in multiple currencies, all of her loans in one currency must come from one bank and the consumer must have a loan that is substantially (at least two rating classes) more risky than the loan-weighted average classification of her other loans. The conditions that the consumer borrow from multiple banks in multiple currencies are required to allow for at least some potential currency-driven variability in the shares of total lending. It is also important that different banks lend in different currencies, which explains the third condition that one bank be responsible for all lending in one currency. Finally, the rule of twenty mandates that all loans reflect the *worst* classification of any 20% or larger loan, so only relatively risky loans will influence the rating of other loans. Classifications range from zero to four, so we use ratings differences relative to the middle value of two to define high and low risk loans. In the data, there are 236,811 consumer-bank-month observations that meet these criteria. Summary statistics are given in Table I.

Consider a consumer meeting these conditions with some U.S. dollar and Sol debt balances in period $t-1$. We evaluate the impact of changes in the period t Sol per Dollar exchange rate R_t on the probability that a given loan balance will exceed 20% of the overall consumer loan balance. If the exchange-rate-adjusted balance on the loan is more than 20% of the exchange-rate-adjusted overall balance, we would expect this loan to now be subject to the rule of twenty:

$$ShareAboveTwenty(1/0)_{i,t} = \alpha + \beta(Exchange\, rate\, adjusted\, Share_{i,t} \geq 20\%) \tag{1}$$

$$+F(Exchange\, rate\, adjusted\, Share_{i,t}) + controls + \epsilon_{i,t}$$

$$= \alpha + \beta \left(\frac{(USD\, balance_{i,t-1} * R_t + Soles\, balance_{i,t-1})}{\sum_{i=1}^{N} (USD\, balance_{i,t-1} * R_t + Soles\, balance_{i,t-1})} \geq 20\% \right)$$

$$+F \left(\frac{(USD\, balance_{i,t-1} * R_t + Soles\, balance_{i,t-1})}{\sum_{i=1}^{N} (USD\, balance_{i,t-1} * R_t + Soles\, balance_{i,t-1})} \right) + controls + \epsilon_{i,t},$$

where F is a flexible function of the exchange-rate-adjusted share, typically a polynomial, and the equation is estimated via OLS. The set of controls includes year-month fixed effects. We expect $\beta > 0$ if exogenous movements in R_t push bank shares above the rule of twenty threshold. We do not make use of the actual period t loan balances, as these are endogenous. Instead we consider whether applying exogenous exchange rate changes to the past-month balances will make it likely that the loan is subject to the rule of twenty. In this sense, we implement a fuzzy regression discontinuity design. We cluster t-statistics by each individual consumer. For ease of reference, we will refer to loans with exchange-rate-adjusted shares of 20% or higher as above-threshold loans.

The choices of borrowers and banks undoubtedly have an impact on the exchange-rate-adjusted share, and they may select loan levels that take into account the rule of twenty. To what extent does this undermine the regression discontinuity design? Even if consumers and lenders affect the exchange-rate-adjusted share, as long as their control is in some respect less than absolutely total, then the regression discontinuity model remains identified (Lee 2008). The noise introduced by exchange rate variability and the fact that we use the previous month's balances in the calculation together prevent borrowers and banks from entirely determining the current exchange-rate-adjusted balances. This introduction of a random element enables us to make causal inferences from our econometric approach.

We are primarily interested in the effect of ratings classification shocks on various client outcomes, including financing effects, so we estimate

$$ClientOutcome_{i,t+12} = \gamma + \delta(Exchange\, rate\, adjusted\, Share_{i,t} \geq 20\%) \tag{2}$$

$$+G(Exchange\, rate\, adjusted\, Share_{i,t}) + controls + \nu_{i,t},$$

where G is a polynomial and $\nu_{i,t}$ is an error term.

III Results

A Complete Default and Credit Outcomes

A.1 Random Sample of Full Data Set

We begin our analysis by considering the relationship between a negative credit event for a consumer and her future access to financing. We focus on the serious negative event in which all of a consumer's banks have assigned her the highest credit rating of loss. That is, all of the consumer's lenders have completely written off her loans. This occurrence is unambiguously unfavorable for the consumer, and we label entry into this event "complete default".

What are the implications of complete default for the future lending to this consumer? To address this question, we analyze a random subsample of 8.4 million consumer-bank-month observations from the *RCD*. Summary statistics are provided in Table II. We perform some descriptive regressions on these data to provide evidence on the observed correlations between complete default and future credit access, though we do not interpret these results in a causal manner.

In the first panel of Table III we show that consumers who experience complete default have significantly lower future loan balances. Specifically, a regression of the change in the log of the balance of total consumer loan financing over the following year on an indicator for complete default yields a coefficient of -4.318 (t-statistic=-145.78), as shown in the first column of the first panel of Table III. This corresponds to a reduction of almost 99% in lending. In other words, lending to borrowers who undergo complete default is essentially shut down. This effect continues into the second and third years, as shown in the second and third columns of the first panel. This finding is consistent with the long lasting negative effects of bankruptcy on credit access in the U.S. documented by Jagtiani and Li (2013).

Consumers subjected to complete default are also much more likely to exit the financial system and be left with no active banking relationships. As detailed in the first column of the second panel of Table III, complete default is associated with a 49.0 percentage point increase (t-statistic=117.04) in the probability of financial system exit. Effects of similar magnitudes are also experienced at two- and three-year horizons, as shown in the second and third columns of the second panel.

Last, complete default is also linked to a higher probability that the consumer will have debt that is subject to judicial collection. The regression result displayed in the first column of the third panel of Table III shows that complete default is associated with a 4.0 percentage point increase (t-statistic=19.15) in the probability of judical collection. Analogous results are observed at leads of two and three years.

Table III provides strong evidence that the negative event of complete default is followed by highly restricted credit access and very negative credit outcomes in a broadly representative sample of borrowers. Our main interest, however, lies in untangling the causes of this relationship and, specifically, in analyzing the role played by the credit reporting system.

B Shocks to Risk Classifications

B.1 Crossing the Twenty Percent Threshold

In Section II we described the empirical approach and specific study sample that we use to examine the effects of exogenous shocks to risk classifications. This approach allows us to isolate the causal impact of negative credit reports on borrowers. Any credit impact on borrowers who endure an exogenous change in their risk classifications can be attributed solely to the credit rating decline- it will not be driven by any of the other shocks (such as unemployment or extended illness) typically associated with negative credit events.

Our tests make use of the special characteristics of the study sample. To what extent does the study sample resemble the overall population of borrowers? A comparison of Tables I and II shows that the study sample borrowers tend to have somewhat larger loan balances, higher (riskier) loan classifications and are more likely to have debt subject to judicial collection and to enter complete default. These differences are not surprising, as our empirical design required that we select the study sample to consist of borrowers with multiple banking relationships in which at least one of the relationships was quite risky.

Borrowers in the study sample may experience a shock in their risk classification due to the rule of twenty. Specifically, as described in Section II, the risk rating of banking relationships that constitute 20% or more of a consumer's total outstanding loans should have an effect on all of the borrower's relationship ratings. Due to endogeneity concerns, rather than analyzing the actual loan balances in a given month, we proxy for above-twenty-percent relationships using measures of the consumers' previous month balances and exchange-rate shocks. This approach has the virtue of mitigating endogeneity considerations, but it comes at the cost of not using current information about the consumer's loan balances. Accordingly, our first tests examine whether this proxy is an effective predictor of above-twenty-percent relationships. Specifically, we analyze whether there is a discontinuous jump in the probability of an above-twenty-percent relationship when the exchange-rate-adjusted balance is just above 20%.

As described in equation (1), we regress an indicator for whether a banking relationship constitutes more than 20% of a borrower's total loans on an indicator for whether the exchange-rate-adjusted share exceeds 20% and on a flexible function of the exchange-rate-adjusted share. When the flexible function takes the form of a seventh-degree polynomial on either side of the cutoff, we find that there is a jump of 0.127 (t-statistic=6.73) in the probability that a relationship share is above 20% when the exchange-rate-adjusted share is above 20%, as detailed in the first column of Table IV (t-statistics are clustered by individual consumer and we include year-month fixed effects). This is clear evidence that exchange rate shocks can push relationships into the above-twenty-percent category. We find significant jumps as well in specifications using third and tenth degree polynomials, as detailed in the second and third columns of Table IV. As shown in columns four through seven of Table IV, we also estimate equation (1) using OLS and an indicator for above threshold exchange-rate-adjusted balances in various narrow windows around 20% as well as using a local linear estimator with the Imbens and Kalyanaraman (2012) optimal bandwidth. Although there is some variation in the estimated magnitudes, all the estimation methods support the argument that when a banking relationship's exchange-rate-adjusted balance crosses the 20% threshold, the relationship is significantly more likely to constitute more than 20% of the consumer's actual total loan balance.[7]

Figure 1 illustrates the estimate for the seventh-degree polynomial model. The red and blue lines illustrate the fitted polynomials above and below the threshold and the surrounding black lines depict the 95% confidence interval (which is very tight in this figure). The points describe the average values of the large (above 20%) loan indicator for each of the buckets of 0.8% in the exchange-rate-adjusted share. For clarity of presentation, the figure presents the regression results and bucket averages for the model without year-month fixed effects (this has only a minimal effect on the estimated coefficients).

B.2 Local Characteristics and Distribution around the Threshold

Our estimation technique exploits the exchange-rate-adjusted balance and is therefore directly affected by the noise of currency movements. This introduces quasi-randomness into whether a given relationship falls just above or just below the 20% threshold. Nonetheless, there may still be a concern that relationships with exchange-rate-adjusted balances just above and below 20% are somehow different. We analyze this question by considering the distributions of relationship characteristics for borrowers just above and below the threshold.

Our study focuses on consumer lending, ratings and delinquency. As a consequence, we consider the following variables: the log of bank debt, the number of banks from which the

[7]Section A1 in the Supplementary Appendix presents a discussion of the robustness of our empirical findings to other samples and specifications.

consumer borrows, the loan-weighted mean debt rating classification, the log of the amount of highly delinquent debt subject to judicial collection, the fraction of debt that is subject to judicial collection, the log of total debt plus lines of credit, number of years in the *RCD* and client sex. Although all our borrowers are consumers without business IDs, we also consider some characteristics of the businesses located within 500 meters of each client when available: the log of the number of such businesses, the fraction involved in mining (Peru's number one export) and the fraction involved in oil-related firms (Peru's number one import). As shown in Table V, none of these variables exhibits a discontinuity at the threshold. Figure 2 provides graphical evidence that these variables are all indistinguishable for just above- and just below-threshold relationships.

As further evidence on the possible manipulation of exchange-rate-adjusted balances on the part of banks or borrowers (which seems highly implausible on its face given the difficulty in precisely forecasting currency movements), we implement a McCrary (2008) test of the continuity of the density function around the 20% threshold which yields a coefficient of 0.014 (t-statistic=0.78). This result is graphically displayed in Figure 3 and it indicates no evidence of strategic manipulation of the exchange-rate-adjusted balances around 20%. The thick line represents the density estimate and the surrounding thin lines depict the 95% confidence interval. Along with the null findings on local characteristics, these results indicate that the variation between relationships just above and just below the threshold is plausibly quasi-random.

B.3 Crossing the Threshold and Borrower Risk Classifications

In this section we consider to what extent the Peruvian banking regulation mandating rating alignment is observed, and we analyze the impact of currency movements that push a relationship across the 20% threshold. We estimate (2) with the change in the mean borrower risk classification as the dependent variable. Using a seventh-degree polynomial model we find, as described in the first panel of Table VI, that borrowers with risky loans with exchange-rate-adjusted balances just above 20% have significantly higher (worse) average risk classifications across all relationships than borrowers with exchange-rate adjusted balances just below 20%. The magnitude of this effect is 0.063 ratings classes (t-statistic=2.97) in the next month and 0.089 (t-statistic=2.93) two months out. The mean average rating classes for these borrowers is 1.44, so these increases are meaningful and quite large in magnitude.

The results for the first sixth months are displayed graphically in Figure 4. The effect is somewhat persistent: although the impact on the average risk classification is not statistically significant beyond the fifth month, the estimated coefficient does not drop substantially over the course of the first year after the shock. By the second year, there is no evidence of any impact. These findings indicate that exchange-rate-driven movements across the 20% threshold have a substantial moderate-term effect on the overall portfolio of a borrower's ratings. Beyond a year, borrowers can presumably make adjustments to their balances to undo the effects of the currency shocks.

We argued above that loan relationships with relatively low (safe) risk classifications should not be expected to have any effect on a borrower's other loan risk classifications;

the regulations require that risky classifications for one large loan should downgrade the classification of other loans, but a large safe loan will not have any impact on other loan risk classes. As a placebo test, we therefore consider the sample of relatively safe loans (with rating less than 2 classes above the loan-weighted average of other loans). In the bottom panel of Table VI, we estimate the same model for the set of relatively safe relationships. As expected, we find no difference between the overall ratings classifications of consumers with above- and below-threshold relationships. These relatively safe loans have no impact on the risk ratings of other loans and are not considered in the subsequent analysis.

B.4 Financing Conditions for Shocked Borrowers

We showed in Table VI that the transition of a relatively risky loan relationship across the 20% threshold results in a worsening of a borrower's overall classifications for a period of at least five months. What are the broader implications of this negative risk classification shock for a borrower?

We estimate (2), with the log of the balance of total consumer loan financing serving as the dependent variable. We find that, as documented in the first panel of Table VII, for consumers who remain in the banking system, those with above-threshold exchange-rate-adjusted balances experience no impact on their total consumer debt balance in the year after the shock. Above-threshold borrowers do, however, experience negative and significant declines in total consumer financing in the second and third years (t-statistics of -2.82 and -2.87, respectively). Total loan balances drop by more than 30% in the second year and by more than 35% by the third year. The reduction in total financing occurs two and three years after the rating shock.

This finding provides clear evidence that credit rating downgrades lead to the consumer deleveraging that is emphasized by Eggertsson and Krugman (2012), Guerrieri and Lorenzoni (2015), Hall (2011), Mian, Rao and Sufi (2013) and Mian and Sufi (2010 and 2011) in their accounts of the slow post-2008 recovery. Our results suggest that after a recession in which many consumers experienced default and foreclosure, their negative credit reports will continue to depress lending for several years.

Consistent with the result on total loan balances, we also find that consumers with above-threshold exchange-rate-adjusted balances do not experience any significant change in the log of total new consumer loan financing in the year subsequent to the rating shock but do experience significant reductions in new consumer financing in the second and third years after the shock, as detailed in the second panel of Table VII (t-statistics of -1.69 in the second year and -1.93 in the third year).

Above-threshold borrowers also initiate significantly fewer new banking relationships in the second and third years after the shock, though there is no significant effect in the first year, as shown in the third panel of Table VII. The estimated impact on new banking relationships in the second year following the shock is -0.069 (t-statistic=-1.74) and is especially large in the third year at -0.144 (t-statistic=-2.85). These are meaningful magnitudes compared to the sample average of 0.62 new relationships. In the fourth panel of Table VII we show that above-threshold consumers experience significant reductions in the log of their unused credit line balances (relative to the initial balance) two and three years after the shock, with no significant effect in the first year. Figure 5 illustrates these financing results.

The timing and duration of all these negative financing effects are quite consistent: no meaningful impact in the year following the shock and large and significant effects in both the second and third years after the downgrade. The results in Table VII make clear that a negative credit rating shock due to exogenous currency movements leads to restricted credit provision for borrowers for three years: consumers are punished for bad luck. This may occur for several reasons. It is possible that information about borrowers is always necessarily so imperfect that banks can never fully attribute a low rating to purely exogenous factors. The bank may also worry that outside observers (including other borrowers) may misinterpret any leniency granted to unlucky borrowers as weakness on the part of the bank. Or it may be that banks simply do not find it worthwhile to devote resources to untangling all the causes of a downgrade and instead adopt clear and unconditional rules penalizing borrowers with low ratings in all cases.[8]

Financing Results–Supply or Demand Effects?

One question is whether the effects in Table VII are driven by reduced demand for or supply of credit. It seems quite implausible, however, that minor exchange-rate-generated shocks in relative loan balances could have an influence on a borrower's fundamental risk

[8]We focus on the impact of credit downgrades on future consumer borrowing. Other studies have emphasized the effects of income shocks (Agarwal, Liu and Souleles 2007, Bertrand and Morse 2009 and Agarwal and Qian 2014) and changes in regulations and market liquidity (Assunção, Benmelech and Silva 2014 and Benmelech, Meisenzahl and Ramcharan 2015) on the supply of consumer credit.

preferences or consumption plans. The only potential impact of these shocks is on the lending environment and the supply of loans.

A more difficult question is whether the terms offered by banks to the consumer have actually changed or whether the borrower merely perceives that her lending environment has worsened. Our data do not permit us to answer this second question. We do not observe loan applications, and we certainly do not observe conversations between the consumer and her banks, or subtle cues that may indicate a change in the consumer's relationships with her lenders. In this sense, while we are considering the effect of a change in the supply of financing, we cannot say whether this is a true or simply perceived shift in supply.

Financing Results–Mechanical Response?

Given that banking regulations in Peru require larger loss provisions for loans with higher risk classifications, it might be argued that the decrease in financing after a credit downgrade that we describe in Table VII is simply a mechanical response. Even though the downgrade conveys no new information, it is now more costly for the bank to continue providing this loan, so it reduces the supply of credit. Similarly, it is possible that the downgrade triggers a higher interest rate for the borrower (perhaps to offset the bank's loss provision costs) and that this is what drives the decreased borrowing.

While these explanations are certainly plausible, we argue that they are not supported by the timing of the financing response. Specifically, the results in Table VI show that the impact of the rating shock is statistically significant for only the subsequent five months. The financing declines in Table VII, by contrast, are insignificant in the first year and significant after both the second and third years for all four outcome variables. That is, we observe no impact on financing during the period in which the rating increase is statistically significant and large, and we observe a large decrease in financing over the subsequent two years, by which point the loss provision penalties do not exist. This response pattern is not consistent with banks reducing the supply of loans with high loss provisions. It is consistent with a rating shock having a long-run negative impact on a consumer's reputation and access to financing.

B.5 Client Actions After the Shock

How do consumers respond to negative credit rating shocks generated by exogenous events? The results described above show that these shocks lead to less financing. There are two reasonable hypotheses for the more general effects of a risk rating downgrade. The first is that the shock initiates a series of negative outcomes. Relationships with banks begin to deteriorate and the consumer therefore loses financial flexibility. Without the cushion of credit availability, the consumer is led down a slippery slope and is perhaps eventually pushed out of the financial system entirely. The second hypothesis is that a negative rating shock has a chastening effect on a consumer. Realizing that her banking relationships have become potentially endangered, the consumer takes steps to improve her position. The consumer's caution and focus on her financial status may lead to better medium-term outcomes, as the negative rating shock serves as a wake-up call leading to ameliorative action.

To test these contrasting hypotheses, we examine the impact of a negative rating shock on the actions of the consumer. Specifically, we consider the way the consumers manage their most delinquent accounts, those that are subject to judicial collection. These are the accounts that are likely to be most irritating to banks and to generate the most negative consequences for borrowers. We restrict attention to the consumers in our sample who have loans that have been consigned to the judicial collection category. In the first column of the first panel of Table VIII, we show that above-threshold borrowers are 12.4 percentage points more likely (t-statistic=2.33) to fully pay down at least one judicial status loan in the year following the shock. They are also more likely to pay down judicial status loans in the two and three year periods after the shock. These are relatively large effects showing that after a negative rating shock consumers do act to improve their credit profile.

One concern may be that the zero balances of these judicial loans may reflect a debt discharge by a bank rather than a payment or negotiated settlement by the borrowers. To check this hypothesis, we only consider judicial loans that are paid down by borrowers who later receive new debt from the same bank. The zero balances associated with these judicial loans are unlikely to result from write-offs, as the banks would typically be very wary of lending again to borrowers whose loans had to be discharged without accompanying payments. As shown in the second panel of Table VIII, we continue to find strong evidence that above-threshold borrowers are significantly more likely to pay down judicial loans with this feature as well, over the both the year (t-statistic=2.19), two years (t-statistic=2.14) and three years (t-statistic=2.17) after the shock.

We also consider the consumer's actions on her credit card account, a revolving account with a balance that is subject to direct consumer control. If a consumer views a negative rating shock as a wake-up call, she may move to reduce her credit card balance to zero to indicate to banks that she can behave responsibly. For consumers who remain in the banking system, we regress an indicator for a zero credit card balance on the above-threshold indicator and the usual controls. We find that above-threshold consumers are 12.5 percentage points more likely (t-statistic=1.70) to have a zero credit card balance one year after the shock, as shown in the third panel of Table VIII. There is no impact two or three years after the shock. The results on client actions are displayed graphically in Figure 6.

We interpret these findings to show that the above-threshold borrowers who receive an exogenous credit rating shock make efforts to ameliorate their relationships with banks and their overall credit record. It is striking that these actions take place quite quickly- effects are observed one year after the shock, quicker than the financing reductions detailed in Table VII. Consumers respond rapidly to the wake-up call of a negative rating shock. Our results are therefore consistent with recent research arguing that focusing the attention of market participants can lead to better outcomes for them (Hirshleifer and Teoh 2003 and Lee and Malmendier 2011); in our setting, the negative shocks may serve to alert consumers to their credit status and encourage them to manage their financial profile more skillfully.

B.6 Broader Impacts

If, as shown in Table VIII, borrowers who suffer from a negative credit rating shock do make an effort to improve their financial position, what impact does this have on their overall prospects? We first consider the impact of the shock on borrowers' participation in the consumer loan market. We regress an indicator for whether the borrower subsequently exits the consumer loan market on the above threshold exchange-rate-adjusted indicator. We find, as displayed in the first panel of Table IX, that a negative credit shock has an insignificant impact on the probability of exit one year after the shock but leads to a significant increase in the probability of an exit from the consumer loan market two (t-statistic=1.72) and three (t-statistic=2.41) years after the shock. Three years after the shock, above threshold consumers are 3.7 percentage points more likely to exit the market, which is a substantial impact given that the overall rate of market exit after three years is 15%. Thus, not only do shocked clients who remain banked have smaller consumer loan balances, as shown in Table VII, but over the medium-term shocked clients are actually more likely to completely exit the consumer loan market.

These findings are consistent with the hypothesis that a negative credit shock will lead to a downward spiral resulting in the consumer being forced out of the formal lending market. Despite the evidence in Table VIII that above-threshold borrowers do respond proactively to negative credit rating shocks, the overall impact of these shocks is so negative that the affected clients are more likely to eventually end all consumer banking relationships.

This result relates closely to an important assumption in both models of the equilibrium effects of personal bankruptcy law (Athreya 2002, Chatterjee et al. 2007 and Livshits, MacGee and Tertilt 2007) and studies of asset pricing and portfolio choice when households can default (Alvarez and Jermann 2000 and 2001 and Cocco, Gomes and Maenhout 2005). These theoretical papers presume that a consumer who chooses to default will be excluded from future borrowing for some period. We show that this assumption is empirically verified:

irrespective of a consumer's current economic circumstances, a credit downgrade (such as the one associated with entrance into formal bankruptcy) does lead to exclusion from the credit market, though we do find that the impact may not be immediate.

To provide some insight on the mechanism that leads from credit downgrades to credit market exit, we analyze the effect of the rating shock on the probability that a consumer will have a loan that is subject to judicial collection, which arises after severe delinquency. In the second panel of Table IX, we show that shocked consumers are not significantly more likely to have a judicial status loan in the first or second year after the shock, but they are 4.3 percentage points (t-statistic=2.57) more likely to have a judicial status loan in the third year after the shock. This may be compared with the average probability 13% of having a judicial debt balance. Shocked consumers are not only more likely to simply have judicial status loans in the third year, they are also more likely (t-statistic=2.03) to have loans transition into judicial from non-judicial status, as detailed in the third panel of Table IX. These results indicate that shocked consumers slowly descend into severe delinquency, despite the fact that their overall consumer loan balances are decreasing over time.

The increased probability of loan market exit and transition to judicial status for shocked consumers contrasts with the results in Table VIII that these consumers are more likely to pay down their existing judicial status loans. To reconcile these findings, we again consider the sample of borrowers who have a judicial status loan at the time of the shock. In the fourth panel of Table IX we show that above-threshold consumers in this sample are significantly more likely to have a different non-judicial status loan transition into judicial status at horizons of one, two and three years after the shock. In other words, while shocked consumers are more likely to pay down existing judicial status loans, at the same time they are more likely to have different loans newly enter the judicial category. The credit rating shock initiates a dangerous slide into delinquency and loan market exit, despite the apparent efforts of consumers to better their situations.

The shock may have an influence not only on consumer lending to the borrower but also on a consumer's ability to start a new business, which can be affected by her personal credit rating and access to consumer loans (Berger and Frame 2007 and Chatterji and Seamans 2012). The sample of consumers in our data have no business interests at the time of the shock: they do not possess the business tax ID that is required for conducting business in any sort of entrepreneurial venture in Peru. We analyze the impact of the shock on the probability that a consumer subsequently obtains a business tax ID, an essential precursor to entrepreneurship. As shown in the final panel of Table IX, shocked consumers are less likely to acquire a business tax ID at horizons of one and two years, though the effect is insignificant three years after the shock. The graphical counterparts of the results on broader impacts are provided in Figure 7.

Taken together, the results in Tables VIII and IX indicate support for both the hypothesis that a negative credit rating shock serves as a wake-up call to consumers and for the hypothesis that the shock leads them down a slippery slope to unfortunate outcomes. Consumers subject to the shock do take actions to improve their financial standing. Unfortunately, these actions are insufficient to protect them from the broad negative effects of the shock: restricted credit provision, increased frequency of severe delinquency, decreased entrepreneurship and eventual consumer loan market exit.

C Complete Default, Rating Shocks and Credit Outcomes

The results presented in Section A document that complete default is clearly followed by reduced credit access. Complete default is often engendered by persistent adverse shocks like ill health, loss of income or unemployment (Domowitz and Sartain 1999) and it is associated with a reduced credit rating. It is difficult to disentangle the roles played by the adverse shocks and the credit downgrade in creating the lasting undesirable outcomes associated with complete default. In Section B we show that negative rating changes by themselves can lead to unfavorable medium-term financial outcomes even in the absence of any real shock. In this section, we make use of the approach developed in Section B to measure the extent to which a complete default's long-run damaging consequences arise solely from the negative credit report experienced by the borrower.

Broadly speaking, our strategy is to compare outcomes for two classes of borrowers who experience complete default. The first set of borrowers undergo complete default in the absence of any exogenous credit rating shocks. The second set of borrowers experience a large plausibly exogenous shock to their rating classifications due to the rule of twenty that causes them to enter complete default. The first group of borrowers will experience negative consequences from both the endogenous events that led to complete default as well as from the credit rating downgrade. The second group of borrowers will only suffer from the credit rating change. The contrast between the severity of the negative outcomes in the two cases supplies an estimate of the fraction of the consequences of complete default that arises exclusively from credit rating classification effects.

In order to exploit the rule of twenty to generate exogenous credit rating shocks, we employ observations from the study sample in these tests. As described in more detail below, we will consider differences between above- and below-threshold borrowers with exchange-rate-adjusted shares within ten percentage points of the rule of the twenty cutoff. The first issue to consider is whether complete default has a comparable effect in the random sample and in this sample, so we begin the analysis by repeating the regressions described in Table III in the present sample. As shown in Table X, in general similar patterns emerge in the study sample: complete default is followed by a large decline in future borrowing, an increased probability of consumer loan market exit and a heightened likelihood that the borrower will have debt that is subject to judicial collection. The magnitudes of the negative effects are larger in the random sample for the outcomes of total loan balance and consumer market exit, while the effect on judicial collection is slightly larger in the study sample.[9] From a qualitative standpoint, however, it is clear that complete default is a severely adverse outcome for borrowers in both samples, followed by dramatic declines in credit access over the subsequent three years.

We now turn to an analysis of the study sample that exploits its particular characteristics to derive plausibly exogenous shocks to borrower risk ratings. For these tests, we make use of the expected change in a borrower's overall rating that arises from the imposition of the rule of twenty. We calculate this change by first finding the borrower's

[9]While it can be difficult to carefully analyze differences between results in descriptive regressions, we will note that the borrowers in the study sample are riskier than those in the random sample, so it may be that complete default is an even stronger negative outcome for borrowers in the latter group. This may explain the larger coefficients on complete default in the total borrowing and loan market exit regressions in the random sample. Judicial collection, though, is an extreme event that is almost never experienced by the generally safe borrowers in the random sample, which may explain the muted coefficient in that regression.

overall weighted risk rating when the rule of twenty regulation applies and then subtracting the borrower's current weighted risk rating. We then multiply this difference by an indicator for whether the borrower has an exchange-rate-adjusted share above 20%. We label this product the expected exogenous change in classification generated by the rule of twenty.

In the first column of the first panel of Table XI we display the results from a regression of the change of the log of the total loan balance in one year on the expected exogenous change in classification, an indicator for complete default, their interaction and year-month fixed effects. The key coefficient of interest is on the interaction. It describes the extent to which the outcomes are different for borrowers who undergo complete default due to a credit rating shock rather than due to an endogenous event. We find a positive and significant coefficient of 0.311 (t-statistic=3.42) on this interaction, indicating that the impact of complete default on future lending is smaller for those are driven into this state by a credit rating shock. The coefficients on complete default and the expected exogenous increase in credit rating are both negative (coefficients of -1.425 and -0.049 and t-statistics of -7.88 and -3.47, respectively), indicating that complete default and credit rating shocks both lead to reduced financing.

How much of the negative response of lending to complete default is due solely to the credit rating shock? For a borrower who experiences complete default without any exogenous change in credit rating, the future loan balance is reduced by $1 - exp(-1.425) = 75.9\%$. The loan-weighted average classification of a borrower in this narrow window sample is 0.738 on average (somewhat below the 1.44 value shown in Table I for the full study sample), so an increase of 3.262 is required to achieve complete default (i.e., a rating of 4). Borrowers who experience complete default due to an expected exogenous classification increase of 3.262 will realize a decline in their future loan balance of $1 - exp(0.311 * 3.262 - 1.425 - 0.049 * 3.262) =$ 43.5%. Comparing this 43.5% with the 75.9% overall reduction, we therefore estimate that 57.3% of the one-year decline in the future loan balance is due exclusively to the credit downgrade. As displayed in the second and third columns of the first panel of Table XI, the interaction is positive and significant in the two-year and three-year loan balance regressions as well. We estimate that the fraction of the loan balance decline due to the credit downgrade is 25.4% at the two-year horizon and 65.1% at the three-year horizon.

Although there is some variability in these magnitudes, all the estimates consistently indicate that a large portion of the credit decline following complete default arises simply because of the sustained negative impact of the borrower's poor credit rating. This suggests that a substantial fraction of the post-recession consumer deleveraging that is the focus of Eggertsson and Krugman (2012), Guerrieri and Lorenzoni (2015), Hall (2011), Mian, Rao and Sufi (2013) and Mian and Sufi (2010 and 2011) arises purely from features of the credit reporting system, independent of monetary or fiscal stimulus policies.

The analogous regressions for exit from the consumer loan market are shown in the second panel of Table XI. The interaction is insignificant at the one- and two-year horizons, but it is negative and significant at the three-year horizon (t-statistic=-1.68). At the three-year horizon, we estimate that 41.4% of the increased probability of credit market exit after complete default is driven purely by the credit downgrade. Results for the future presence of a loan subject to judical collection are shown in the third panel of Table XI. For this credit outcome, the interaction is negative and significant (t-statistic=-1.78) only at the one-year horizon. We estimate that 53.4% of the post-complete default increase in the likelihood of being subjected to judicial collection in one year is attributable solely to the change in credit rating.[10]

Across a variety of future outcomes, we find two robust findings. First, when complete default is caused by an exogenous change in risk classification the consequences for the borrower are less severe than when associated with endogenous events. Second, the fraction of the negative effects of complete default generated exclusively from the change in credit rating are nonetheless substantial, ranging from 25% to 65%.

IV Conclusion

One leading and compelling account for the disappointing recovery from the 2008 recession places the blame on household borrowing constraints that continued to restrict consumers who suffered financial distress during the downturn. We investigate the relationship between negative credit events and sustained limitations on financial access, with an emphasis on the role of credit reporting systems. We show that in our sample of Peruvian consumers, default is indeed followed by a reduction in borrowing in the medium term. We analyze the causal mechanism underlying this association by using a regression discontinuity design that exploits local credit rating alignment regulations and makes use of variation arising from currency movements. We show that consumers who experience a credit rating downgrade

[10] The analysis in Table XI is conducted in a window of ten percentage points on each side of the rule of twenty threshold. Tests using narrower windows of five or even three percentage points on either side of the cutoff continue to show the statistically significant finding that the reduction in loan balances for borrowers who experience complete default is driven to a large degree by the associated credit rating downgrade, though the results for exit and judicial collection are not significant in the smaller samples.

due simply to bad luck experience reduced consumer loan balances and receive fewer new consumer loans in the three years following the shock. We find evidence that consumers respond to the shock by proactively improving their credit profile by paying off their most delinquent loans. Unfortunately, despite this, consumers subject to the shock experience serious negative outcomes including increased probability of consumer loan market exit. We apply our methodology to a set of borrowers who experience severe delinquency. We show that the impact of their credit downgrade by itself accounts for 25%-65% of their observed decline in borrowing at various horizons over the following three years.

Our findings suggest that regulations linking credit history forgiveness to the overall state of the macroeconomy may have a place in the palette of options available to policymakers following a recession. Credit reporting systems bring many benefits, but the downward spiral in financial consequences following a negative credit rating shock that we document can be especially costly when the economy is struggling to grow.

References

Agarwal, Sumit, Chunlin Liu, and Nicholas S. Souleles. 2007. The reaction of consumer spending and debt to tax rebatesEvidence from consumer credit data. *Journal of Political Economy* 115: 986–1019.

Agarwal, Sumit, and Wenlan Qian. 2014. Consumption and debt response to unanticipated income shocks: Evidence from a natural experiment in Singapore. *American Economic*

Review 104: 4205–30.

Agarwal, Sumit, Paige Marta Skiba, and Jeremy Tobacman. 2009. Payday loans and credit cards: New liquidity and credit scoring puzzles? *American Economic Review* 99: 412–17.

Aguiar, Mark. 2005. Investment, devaluation, and foreign currency exposure: The case of Mexico. *Journal of Development Economics* 78: 95–113.

Alvarez, Fernando, and Urban J. Jermann. 2000. Efficiency, equilibrium, and asset pricing with risk of default. *Econometrica* 68: 775–797.

Alvarez, Fernando, and Urban J. Jermann. 2001. Quantitative asset pricing implications of endogenous solvency constraints. *Review of Financial Studies* 14: 1117–1151.

Assunção, Juliano J., Efraim Benmelech, and Fernando S.S. Silva. 2014. Repossession and the democratization of credit. *Review of Financial Studies* 27: 2661–2689.

Athreya, Kartik B. 2002. Welfare implications of the bankruptcy reform act of 1999. *Journal of Monetary Economics* 49: 1567–1595.

Benmelech, Efraim, Ralf R. Meisenzahl and Rodney Ramcharan. 2015. The real effects of liquidity during the financial crisis: Evidence from automobiles. *The Quarterly Journal of Economics*, forthcoming.

Berger, Allen N., and W. Scott Frame. 2007. Small business credit scoring and credit availability. *Journal of Small Business Management* 45: 5–22.

Bertrand, Marianne, and Adair Morse. 2009. Indebted Households and Tax Rebates. *American Economic Review* 99: 418–23.

Bos, Marieke, and Leonard I. Nakamura. 2014. Should Defaults Be Forgotten? Evidence from Variation in Removal of Negative Consumer Credit Information. FRB of Philadelphia Working Paper No. 14-21.

Calvo, Guillermo A., Alejandro Izquierdo, and Luis-Fernando Mejia. 2004. On the empirics of sudden stops: the relevance of balance-sheet effects.Working Paper 10520, National Bureau of Economic Research.

Campbell, John Y. 2006. Household finance. *Journal of Finance* 61: 1553–1604.

Carrell, Scott, and Jonathan Zinman. 2014. In harm's way? Payday loan access and military personnel performance. *Review of Financial Studies* 27: 2805–2840.

Céspedes, Luis Felipe, Roberto Chang, and Andrés Velasco. 2004. Balance sheets and exchange rate policy. *American Economic Review* 94: 1183–1193.

Chatterjee, S., Corbae, D., Nakajima, M., and Ríos-Rull, J. V. 2007. A quantitative theory of unsecured consumer credit with risk of default. *Econometrica* 75: 1525–1589.

Chatterji, Aaron K., and Robert C. Seamans. 2012. Entrepreneurial finance, credit cards, and race. *Journal of Financial Economics* 106: 182–195.

Cocco, Joao F., Francisco J. Gomes, and Pascal J. Maenhout. 2005. Consumption and portfolio choice over the life cycle. *Review of Financial Studies* 18: 491–533.

Domowitz, Ian, and Robert L. Sartain. 1999. Determinants of the consumer bankruptcy decision. *Journal of Finance* 54: 403–420.

Eggertsson, Gauti B., and Paul Krugman. 2012. Debt, deleveraging, and the liquidity trap: A Fisher-Minsky-Koo approach. *Quarterly Journal of Economics* 127: 1469–1513.

Elul, Ronel and Piero Gottardi. 2015. Bankruptcy: Is It Enough to Forgive or Must We Also Forget? *American Economic Journal: Microeconomics* 7: 294–338.

Gelman, Michael, Shachar Kariv, Matthew D. Shapiro, Dan Silverman, and Steven Tadelis. 2014. Harnessing naturally occurring data to measure the response of spending to income. *Science* 345: 212–215.

Gross, David B., and Nicholas S. Souleles. 2002. Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data. *Quarterly Journal of Economics* 117: 149–185.

Guerrieri, Veronica, and Guido Lorenzoni. 2015. Credit crises, precautionary savings, and the liquidity trap. Working Paper 17583, National Bureau of Economic Research.

Hall, Robert E. 2011. The long slump. *American Economic Review* 101: 431–469.

Hirshleifer, D., and S. Teoh. 2003. Limited Attention, Information Disclosure, and Financial Reporting. *Journal of Accounting and Economics* 36: 337–386.

Imbens, Guido, and Karthik Kalyanaraman. 2012. Optimal bandwidth choice for the regression discontinuity estimator. *Review of Economic Studies* 79: 933–959.

Jagtiani, Julapa, and Wenli Li. 2013. Credit access and credit performance after consumer bankruptcy filing: new evidence. Working Paper 13-24, Federal Reserve Bank of Philadelphia.

Karlan, Dean, and Jonathan Zinman. 2009. Observing unobservables: Identifying information asymmetries with a consumer credit field experiment. *Econometrica* 77: 1993–2008.

Keys, Benjamin, Tanmoy Mukherjee, Amit Seru, and Vikram Vig, 2010. Did securitization lead to lax screening? Evidence from subprime loans. *Quarterly Journal of Economics* 125: 307–362.

Lee, David. 2008. Randomized experiments from non-random selection in U.S. House elections. *Journal of Econometrics* 142:675–97.

Livshits, Igor, James MacGee, and Michele Tertilt. 2007. Consumer bankruptcy: A fresh start. *American Economic Review* 97: 402–418.

Lee, Young, and Ulrike Malmendier. 2011. The Bidder's Curse. *American Economic Review* 101: 749–787.

Liberman, Andres. 2016. The value of a good credit reputation: Evidence from credit card renegotiations. *Journal of Financial Economics* 120: 644–660.

Mayer, Chris, Tomasz Piskorski, and Alexei Tchistyi. 2013. The inefficiency of refinancing: Why prepayment penalties are good for risky borrowers. *Journal of Financial Economics* 107: 694–714.

McCrary, Justin. 2008. Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics* 142: 698–714.

Melzer, Brian T. 2011. The real costs of credit access: Evidence from the payday lending market. *Quarterly Journal of Economics* 126: 517–555.

Mian, Atif, Kamalesh Rao, and Amir Sufi. 2013. Household Balance Sheets, Consumption, and the Economic Slump. *Quarterly Journal of Economics* 128: 1687–1726.

Mian, Atif, and Amir Sufi. 2010. Household Leverage and the Recession of 200709. *IMF Economic Review* 58: 74–117.

Mian, Atif, and Amir Sufi. 2011. House prices, home equitybased borrowing, and the us household leverage crisis. *American Economic Review* 101: 2132–2156.

Morse, Adair. 2011. Payday lenders: Heroes or villains? *Journal of Financial Economics* 102: 28–44.

Musto, David K. (2004). What happens when information leaves a market? Evidence from post-bankruptcy consumers. *Journal of Business* 77: 725–749.

The World Bank. 2016. Global FINDEX database. Available at:
www.worldbank.org/en/programs/globalfindex.

Table I: Summary Statistics– Study Sample

Summary statistics are based on the 236,811 client-bank-month observations of the sample selected for the study: the consumer borrows from multiple banks, borrows in multiple currencies, all her loans in one currency come from one bank, and the loan of the observation studied is substantially (at least two rating classes) more risky than the loan-weighted average classification of her other loans. The exchange rate is in soles per U.S. dollar and described in monthly frequency. The bank share of lending is expressed at the client-bank-month level and is defined as the ratio of this bank's debt over the total consumer debt balance across all banks of the client. All other variables are expressed at the client-month level. Debt balance is the sum of all debt from all banks of the client this month and is expressed in soles. Amount of new consumer loan financing sums over all new debt received by the client from all banks in the next 12 months or 24 months and is expressed in soles. Number of banks is a count, and number of new banking relationships sums over all initiations of banking relationships over the next 12 months or 24 months. Loan-weighted average classification is the dot product of classifications and debt balances on all bank relationships of the client this month. Judicial debt is the sum of all loans of the client that are in judicial collection status expressed in soles, and judicial debt / debt is the ratio of this amount over the total consumer debt of the client. Amount of credit card debt is expressed in soles. Entered complete default is a dummy equal to one when all banking relationships are downgraded to the worst classification of the system, i.e., loss; this variable is calculated for this month or for the last 12 months, alternatively.

Variable	Mean	Median	Std.Dev.	1^{st} pctile.	99^{th} pctile.
Exchange rate (sol / U.S. dollar)	3.19	3.25	0.28	2.70	3.62
Bank share of lending	0.42	0.38	0.31	0.00	0.99
Debt balance	7659	3570	18939	254	59832
Amount of New Consumer Loan Financing *t+12*	6420	2350	17530	0	60789
Amount of New Consumer Loan Financing *t+24*	13250	5389	31363	0	119929
Number of Banks	2.45	2.00	0.79	2.00	5.00
Number of New Banking Relationships *t+12*	0.33	0.00	0.61	0.00	2.00
Number of New Banking Relationships *t+24*	0.62	0.00	0.89	0.00	4.00
Loan-Weighted Average Classification	1.44	1.22	1.12	0.00	3.95
Judicial Debt	997.59	0.00	8685	0.00	24691
Judicial Debt / Debt	0.05	0.00	0.19	0.00	0.97
Amount of Credit Card Debt	331	0	2208	0	8322
Entered complete default (this month)	0.02	0.00	0.14	0.00	1.00
Entered complete default (last 12 months)	0.07	0.00	0.26	0.00	1.00

Table II: Summary Statistics– Random Sample

Summary statistics for the 8,392,480 observations of the random sample. Debt balance is the sum of all debt from all banks of the client this month and is expressed in soles. Loan-weighted average classification is the dot product of classifications and debt balances on all bank relationships of the client this month. Judicial debt is the sum of all loans of the client that are in judicial collection status expressed in soles, and judicial debt / debt is the ratio of this amount over the total consumer debt of the client. Entered complete default is a dummy equal to one when all banking relationships are downgraded to the worst classification of the system, i.e., loss; this variable is calculated for this month or for the last 12 months, alternatively.

Variable	Mean	Median	Std.Dev.	1^{st} pctile.	99^{th} pctile.
Debt balance	6477	2393	13682	0	57301
Loan-Weighted Average Classification	0.29	0.00	0.77	0.00	3.67
Judicial Debt	34.95	0.00	1181.88	0.00	0.00
Judicial Debt / Debt	0.00	0.00	0.05	0.00	0.00
Entered complete default (this month)	0.004	0.00	0.065	0.00	0.00
Entered complete default (last 12 months)	0.019	0.00	0.138	0.00	1.00

Table III: Complete Default and Credit Outcomes- Random Sample

This table reports estimates of regressions of financing and broader outcome variables on complete default using the random sample described in Table II. Observations are at the client-bank-month level. The change of log of total consumer loans balance is calculated in $t + 12$, $t + 24$ or $t + 36$ with respect to month t. Exit consumer loan market is based on future sustained lack of activity in outstanding debt and unused credit line balances through months $t + 12$, $t + 24$ or $t + 36$.

	Dependent Variables:		
	While Remaining Banked, Change of Log of Total Consumer Loans Balance		
through period:	*t+12*	*t+24*	*t+36*
	(III.1)	(III.2)	(III.3)
Complete default	-4.318^{***}	-4.040^{***}	-3.634^{***}
	(-145.78)	(-129.51)	(-102.41)
Year-month F.E.	Yes	Yes	Yes
R^2	0.06	0.04	0.03
Sample size	6.8M	6M	5.1M
N. clusters (clients)	101562	94042	87422
	Exit Consumer Loan Market		
through period:	*t+12*	*t+24*	*t+36*
	(III.4)	(III.5)	(III.6)
Complete default	0.490^{***}	0.476^{***}	0.427^{***}
	(117.04)	(109.17)	(88.81)
Year-month F.E.	Yes	Yes	Yes
R^2	0.03	0.02	0.02
Sample size	6.8M	6M	5.1M
N. clusters (clients)	101562	94042	87422
	Has Judicial Debt Balance at some point		
through period:	*t+12*	*t+24*	*t+36*
	(III.7)	(III.8)	(III.9)
Complete default	0.040^{***}	0.041^{***}	0.042^{***}
	(19.15)	(17.89)	(15.89)
Year-month F.E.	Yes	Yes	Yes
R^2	0.00	0.00	0.00
Sample size	6.8M	6M	5.1M
N. clusters (clients)	101562	94042	87422

***, **,* significant at the 1%, 5% and 10% level. t-statistics shown in parentheses are clustered by client.

Table IV: Exchange-rate Adjusted Share and Crossing the 20% Threshold

This table reports estimates of equation (1) on observations at the client-bank-month level of the sample described in Table I. Above threshold is a dummy equal to one when the exchange rate adjusted share is greater than or equal to 20%. For estimation, models reported in columns 1-6 employ OLS whereas the model in the seventh column employs nonparametric local linear regressions with the optimal bandwidth of Imbens and Kalyanaraman (2012). The models in the fourth, fifth, and sixth column restrict the sample only to a narrow window in which the running variable, the exchange rate adjusted share of debt, takes values that are within 1%, 0.5%, and 1.5% of the value of 20%, respectively. All OLS models employ robust standard errors clustered at the level of each client.

	Dependent Variable (1/0): **Share of this Bank is Above 20% of Debt Balance**						
Estimation:	OLS						Nonparametric
Running variable window width:	Full	Full	Full	1%	0.5%	1.5%	
	(IV.1)	(IV.2)	(IV.3)	(IV.4)	(IV.5)	(IV.6)	(IV.7)
Above threshold	0.127***	0.350***	0.131***	0.233***	0.176***	0.299***	0.191***
	(6.73)	(39.22)	(5.90)	(16.51)	(8.61)	(26.39)	(13.37)
Polynomial degree	7	3	10				
Year-month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	No
R^2	0.58	0.58	0.58	0.09	0.09	0.12	
Sample size	236811	236811	236811	5481	2709	8176	236811
N. clusters (clients)	54961	54961	54961	3524	2044	4725	

***, **,* significant at the 1%, 5% and 10% level. t-statistics clustered by client are shown in parentheses.

Table V: Characteristics Around the Threshold

This table reports estimates of equation (2) on observations at the client-bank-month level of the sample described in Table I for variables measured contemporaneously with the exchange rate adjusted balance. The specification is as in the first model of Table IV. All variables are defined in Table I.

	Dependent Variables:			
	Log of Debt Balance	**Number of Banks**	**Loan-Weighted Average Classification**	**Log of Judicial Debt**
	(V.1)	(V.2)	(V.3)	(V.4)
Above threshold	0.021	0.011	0.031	0.061
	(0.46)	(0.30)	(1.59)	(0.75)
Year-month F.E.	Yes	Yes	Yes	Yes
R^2	0.11	0.09	0.74	0.08
Sample size	236811	236811	236811	236811
N. clusters (clients)	54961	54961	54961	54961
	Judicial Debt/ Debt	**Log of Debt and Lines**	**Age in System**	**Client Sex**
	(V.5)	(V.6)	(V.7)	(V.8)
Above threshold	0.002	0.022	−0.199	−0.022
	(0.32)	(0.46)	(−0.34)	(−0.64)
Year-month F.E.	Yes	Yes	Yes	Yes
R^2	0.12	0.11	0.66	0.01
Sample size	236811	236811	236811	87693
N. clusters (clients)	54961	54961	54961	20516
	Log Number of Business Neighbors	**Fraction of B. Neighbors in Mining**	**Fraction of B. Neighbors in Oil Related**	
	(V.9)	(V.10)	(V.11)	
Above threshold	0.050	−0.000	0.000	
	(0.52)	(−0.82)	(0.37)	
Year-month F.E.	Yes	Yes	Yes	
R^2	0.03	0.01	0.01	
Sample size	77250	77250	77250	
N. clusters (clients)	18883	18883	18883	

***, **,* significant at the 1%, 5% and 10% level. t-statistics clustered by client are shown in parentheses.

Table VI: Impact on Changes in Average Classifications across Initial Classification Differences

This table reports estimates of equation (2) on observations at the client-bank-month level. The specification is as in the first model of Table IV. Panel A uses the sample defined in Table I. Panel B uses a placebo sample: the consumer borrows from multiple banks, borrows in multiple currencies, all her loans in one currency come from one bank, and the loan of the observation studied is not substantially more risky than the loan-weighted average classification of her other loans, i.e., its riskiness is less than two rating classes greater. The dependent variable is the change of the loan-weighted mean classification of the loans of the client in month $t+k$ with respect to month t, where k takes the value of different leads.

Dependent Variable: **Change of Loan-Weighted Average Classification with respect to month t**

Panel A: *Difference of classification* ≥ 2

	t+1	*t+2*	*t+3*	*t+4*	*t+5*	*t+6*	*t+7*
Above threshold	0.063***	0.089***	0.055	0.090**	0.082*	0.042	0.043
	(2.97)	(2.93)	(1.46)	(2.03)	(1.66)	(0.76)	(0.75)
Year-month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.04	0.06	0.07	0.08	0.09	0.09	0.10
Sample size	207379	189672	175069	162874	152800	144569	137112
N. clusters (clients)	49408	46221	43444	40610	38148	36277	34532

	t+8	*t+9*	*t+10*	*t+11*	*t+12*	*t+24*	*t+36*
Above threshold	0.096	0.065	0.065	0.080	0.058	−0.054	0.037
	(1.59)	(1.04)	(0.97)	(1.15)	(0.81)	(−0.62)	(0.52)
Year-month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.10	0.11	0.12	0.13	0.13	0.17	0.23
Sample size	130969	125729	121196	117461	113870	94112	85506
N. clusters (clients)	33177	31954	30768	29933	28899	23716	21363

Panel B: *Difference of classification* < 2

	t+1	*t+2*	*t+3*	*t+4*	*t+5*	*t+6*	*t+7*
Above threshold	0.003	0.000	−0.005	−0.002	−0.003	−0.006	−0.007
	(0.96)	(0.04)	(−0.92)	(−0.31)	(−0.47)	(−0.88)	(−0.92)
Year-month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.00	0.00	0.01	0.01	0.01	0.01	0.01
Sample size	3296444	3126185	3000400	2896007	2800870	2720057	2646278
N. clusters (clients)	221887	214295	208325	203906	199369	195492	191788

	t+8	*t+9*	*t+10*	*t+11*	*t+12*	*t+24*	*t+36*
Above threshold	−0.004	−0.006	0.001	−0.001	−0.011	−0.014	−0.007
	(−0.51)	(−0.71)	(0.08)	(−0.11)	(−1.14)	(−1.24)	(−0.50)
Year-month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.00
Sample size	2581025	2520524	2470702	2421603	2373940	2013784	1798147
N. clusters (clients)	188724	185567	182608	179971	176580	151446	134404

***, **,* significant at the 1%, 5% and 10% level. t-statistics shown in parentheses are clustered by client.

Table VII: Impact on Financing

This table reports estimates of equation (2) for financing variables on observations at the client-bank-month level of the sample described in Table I. The specification is as in the first model of Table IV. The change of log of total consumer loans balance and the change of log of unused credit line balance are calculated in $t+12$, $t+24$ or $t+36$ with respect to month t.

	Dependent Variables:		
	While Remaining Banked, Change of Log of Total Consumer Loans Balance		
	t+12	*t+24*	*t+36*
	(VII.1)	(VII.2)	(VII.3)
Above threshold	0.002	-0.386^{***}	-0.466^{***}
	(0.02)	(-2.82)	(-2.87)
Year-month F.E.	Yes	Yes	Yes
R^2	0.03	0.03	0.03
Sample size	233962	228931	223760
N. clusters (clients)	53786	51683	49843
	Log Amount of New Consumer Loan Financing		
	through t+12	*through t+24*	*t+36*
	(VII.4)	(VII.5)	(VII.6)
Above threshold	-0.215	-0.301^{*}	-0.341^{*}
	(-1.19)	(-1.69)	(-1.93)
Year-month F.E.	Yes	Yes	Yes
R^2	0.01	0.02	0.02
Sample size	233962	228931	223760
N. clusters (clients)	53786	51683	49843
	Number of New Banking Relationships		
	through t+12	*through t+24*	*t+36*
	(VII.7)	(VII.8)	(VII.9)
Above threshold	-0.025	-0.069^{*}	-0.144^{***}
	(-0.95)	(-1.74)	(-2.85)
Year-month F.E.	Yes	Yes	Yes
R^2	0.05	0.05	0.04
Sample size	233962	228931	223760
N. clusters (clients)	53786	51683	49843
	Change of Log of Unused Credit Line Balance		
	t+12	*t+24*	*t+36*
	(VIII.10)	(VIII.11)	(VII.12)
Above threshold	-0.125	-0.208^{*}	-0.259^{*}
	(-1.29)	(-1.71)	(-1.77)
Year-month F.E.	Yes	Yes	Yes
R^2	0.11	0.13	0.11
Sample size	233962	228931	223760
N. clusters (clients)	53786	51683	49843

***, **,* significant at the 1%, 5% and 10% level. t-statistics shown in parentheses are clustered by client.

Table VIII: Impact on Client Actions Regarding Existing Debt

This table reports estimates of equation (2) for variables modeling consumer actions on observations at the client-bank-month level of the baseline sample described in Table I. The specification is as in the first model of Table IV. The first and second panels of the table restrict the baseline sample only to clients with an existing judicial-status loan at time t. The third panel restricts the baseline sample only to clients with positive credit card debt at time t that remained banked at time $t+12$, $t+24$ or $t+36$.

	Dependent Variables: **Completely Pays Down at Least One Judicial-Status Loan**		
	through t+12	*through t+24*	*through t+36*
	(VIII.1)	(VIII.2)	(VIII.3)
Above threshold	0.124**	0.171***	0.201***
	(2.33)	(2.70)	(2.93)
Year-month F.E.	Yes	Yes	Yes
R^2	0.04	0.05	0.07
Sample size	17243	17178	16878
N. clusters (clients)	2850	2844	2830
	Completely Pays Down at Least One Judicial-Status Loan and Receives New Debt from the Same Bank		
	through t+12	*through t+24*	*through t+36*
	(VIII.4)	(VIII.5)	(VIII.6)
Above threshold	0.073**	0.091**	0.101**
	(2.19)	(2.14)	(2.17)
Year-month F.E.	Yes	Yes	Yes
R^2	0.02	0.02	0.02
Sample size	17243	17178	16878
N. clusters (clients)	2850	2844	2830
	While Remaining Banked, Has Credit Card Balance equal to Zero		
	t+12	*t+24*	*t+36*
	(VIII.7)	(VIII.8)	(VIII.9)
Above threshold	0.125*	0.029	0.063
	(1.70)	(0.35)	(0.69)
Year-month F.E.	Yes	Yes	Yes
R^2	0.01	0.01	0.01
Sample size	21209	16572	13032
N. clusters (clients)	9473	7312	5769

***, **,* significant at the 1%, 5% and 10% level. t-statistics shown in parentheses are clustered by client.

Table IX: Broader Impacts

This table reports estimates of equation (2) for medium-term broader outcomes on observations at the client-bank-month level of the sample described in Table I. The specification is as in the first model of Table IV. Exit consumer loan market is based on future sustained lack of activity in outstanding debt and unused credit line balances. Judicial status is assessed for each of the loans of the clients to model the dependent variables in the second, third and fourth panels. Obtains a Tax ID for business purposes is modeled using the Peruvian tax authority registry.

	Dependent Variables:		
	Exit Consumer Loan Market		
	through t+12	*through t+24*	*through t+36*
	(IX.1)	(IX.2)	(IX.3)
Above threshold	−0.001	0.021*	0.037**
	(−0.16)	(1.72)	(2.41)
Year-month F.E.	Yes	Yes	Yes
R^2	0.02	0.03	0.03
Sample size	233962	228931	223760
N. clusters (clients)	53786	51683	49843
	Has Judicial Debt Balance at some point		
	through t+12	*through t+24*	*through t+36*
	(IX.4)	(IX.5)	(IX.6)
Above threshold	0.012	0.027	0.043**
	(0.80)	(1.60)	(2.57)
Year-month F.E.	Yes	Yes	Yes
R^2	0.08	0.10	0.11
Sample size	183490	142766	113130
N. clusters (clients)	41260	30925	24206
	Incurs Judicial Status for a Loan that Was Not in Judicial Status		
	through t+12	*through t+24*	*through t+36*
	(IX.7)	(IX.8)	(IX.9)
Above threshold	0.003	0.012	0.018**
	(0.42)	(1.44)	(2.03)
Year-month F.E.	Yes	Yes	Yes
R^2	0.01	0.01	0.01
Sample size	233962	228931	223760
N. clusters (clients)	53786	51683	49843
	Initially With a Judicial Status Loan, Incurs Judicial Status for Another Loan that Was Not in Judicial Status		
	through t+12	*through t+24*	*through t+36*
	(IX.10)	(IX.11)	(IX.12)
Above threshold	0.055*	0.089**	0.100**
	(1.85)	(2.11)	(2.17)
Year-month F.E.	Yes	Yes	Yes
R^2	0.02	0.03	0.03
Sample size	17243	17178	16878
N. clusters (clients)	2850	2844	2830
	Obtains a Tax ID for Business Purposes		
	through t+12	*through t+24*	*through t+36*
	(IX.13)	(IX.14)	(IX.15)
Above threshold	−0.015*	−0.025**	−0.016
	(−1.67)	(−1.98)	(−1.08)
Year-month F.E.	Yes	Yes	Yes
R^2	0.00	0.00	0.00
Sample size	236811	236811	236811
N. clusters (clients)	54961	54961	54961

***, **,* significant at the 1%, 5% and 10% level. t-statistics shown in parentheses are clustered by client.

Table X: Complete Default and Credit Outcomes– Study Sample Narrow Window

This table reports estimates of regressions of financing and broader outcome variables on complete default using observations from the study sample of borrowers with exchange-rate-adjusted shares within ten percentage points of the rule of the twenty cutoff. Observations are at the client-bank-month level. The change of log of total consumer loans balance is calculated in $t+12$, $t+24$ or $t+36$ with respect to month t. Exit consumer loan market is based on future sustained lack of activity in outstanding debt and unused credit line balances through months $t+12$, $t+24$ or $t+36$.

	Dependent Variables:		
	While Remaining Banked, Change of Log of Total Consumer Loans Balance		
through period:	*t+12*	*t+24*	*t+36*
	(X.1)	(X.2)	(X.3)
Complete default	-1.042^{***}	-0.496^{***}	-1.016^{***}
	(-7.69)	(-3.19)	(-5.66)
Year-month F.E.	Yes	Yes	Yes
R^2	0.02	0.02	0.02
Sample size	55690	55058	54066
N. clusters (clients)	18380	18069	17591
	Exit Consumer Loan Market		
through period:	*t+12*	*t+24*	*t+36*
	(X.4)	(X.5)	(X.6)
Complete default	0.048^{***}	0.038^{**}	0.063^{***}
	(4.08)	(2.56)	(3.64)
Year-month F.E.	Yes	Yes	Yes
R^2	0.02	0.03	0.03
Sample size	55690	55058	54066
N. clusters (clients)	18380	18069	17591
	Has Judicial Debt Balance at some point		
through period:	*t+12*	*t+24*	*t+36*
	(X.7)	(X.8)	(X.9)
Complete default	0.063^{***}	0.056^{***}	0.054^{***}
	(4.44)	(3.89)	(3.68)
Year-month F.E.	Yes	Yes	Yes
R^2	0.01	0.01	0.01
Sample size	55690	55058	54066
N. clusters (clients)	18380	18069	17591

***, **,* significant at the 1%, 5% and 10% level. t-statistics shown in parentheses are clustered by client.

Table XI: Decomposing the Impact of Complete Default on Credit Outcomes

This table reports estimates of regressions of financing and broader outcome variables on complete default, the expected exogenous change in classification and their interaction using observations from the study sample of borrowers with exchange-rate-adjusted shares within ten percentage points of the rule of the twenty cutoff. Observations are at the client-bank-month level. The change of log of total consumer loans balance is calculated in $t+12$, $t+24$ or $t+36$ with respect to month t. Exit consumer loan market is based on future sustained lack of activity in outstanding debt and unused credit line balances through months $t+12$, $t+24$ or $t+36$.

	Dependent Variables:		
	While Remaining Banked, Change of Log of Total Consumer Loans Balance		
through period:	*t+12*	*t+24*	*t+36*
	(XI.1)	(XI.2)	(XI.3)
Exp. exog. change in classif. × Complete default	0.311***	0.296***	0.295**
	(3.42)	(2.66)	(2.26)
Complete default	−1.425***	−0.852***	−1.373***
	(−7.88)	(−4.31)	(−5.79)
Expected exogenous change in classification	−0.049***	−0.083***	−0.078***
	(−3.47)	(−3.90)	(−2.93)
Year-month F.E.	Yes	Yes	Yes
R^2	0.02	0.02	0.02
Sample size	55690	55058	54066
N. clusters (clients)	18380	18069	17591
	Exit Consumer Loan Market		
through period:	*t+12*	*t+24*	*t+36*
	(XI.4)	(XI.5)	(XI.6)
Exp. exog. change in classif. × Complete default	−0.006	−0.012	−0.021*
	(−0.70)	(−1.06)	(−1.68)
Complete default	0.054***	0.051***	0.089***
	(3.43)	(2.64)	(3.76)
Expected exogenous change in classification	0.001	0.005***	0.005**
	(1.16)	(2.86)	(2.05)
Year-month F.E.	Yes	Yes	Yes
R^2	0.02	0.03	0.03
Sample size	55690	55058	54066
N. clusters (clients)	18380	18069	17591
	Has Judicial Debt Balance at some point		
through period:	*t+12*	*t+24*	*t+36*
	(XI.7)	(XI.8)	(XI.9)
Exp. exog. change in classif. × Complete default	−0.019*	−0.016	−0.018
	(−1.78)	(−1.47)	(−1.64)
Complete default	0.084***	0.074***	0.074***
	(4.56)	(3.92)	(3.85)
Expected exogenous change in classification	0.007***	0.007***	0.008***
	(3.01)	(2.89)	(2.95)
Year-month F.E.	Yes	Yes	Yes
R^2	0.01	0.01	0.02
Sample size	55690	55058	54066
N. clusters (clients)	18380	18069	17591

***, **,* significant at the 1%, 5% and 10% level. t-statistics shown in parentheses are clustered by client.

Figure 1: Exchange-rate Adjusted Share and Crossing the 20% Threshold

This graph displays the regression discontinuity model characterizing the impact of the exchange-rate adjusted share of debt balance on whether the bank's share crosses the 20% threshold in month *t* analogous to the first model of Table IV. The running variable is normalized to zero by taking the difference with respect to 20%.

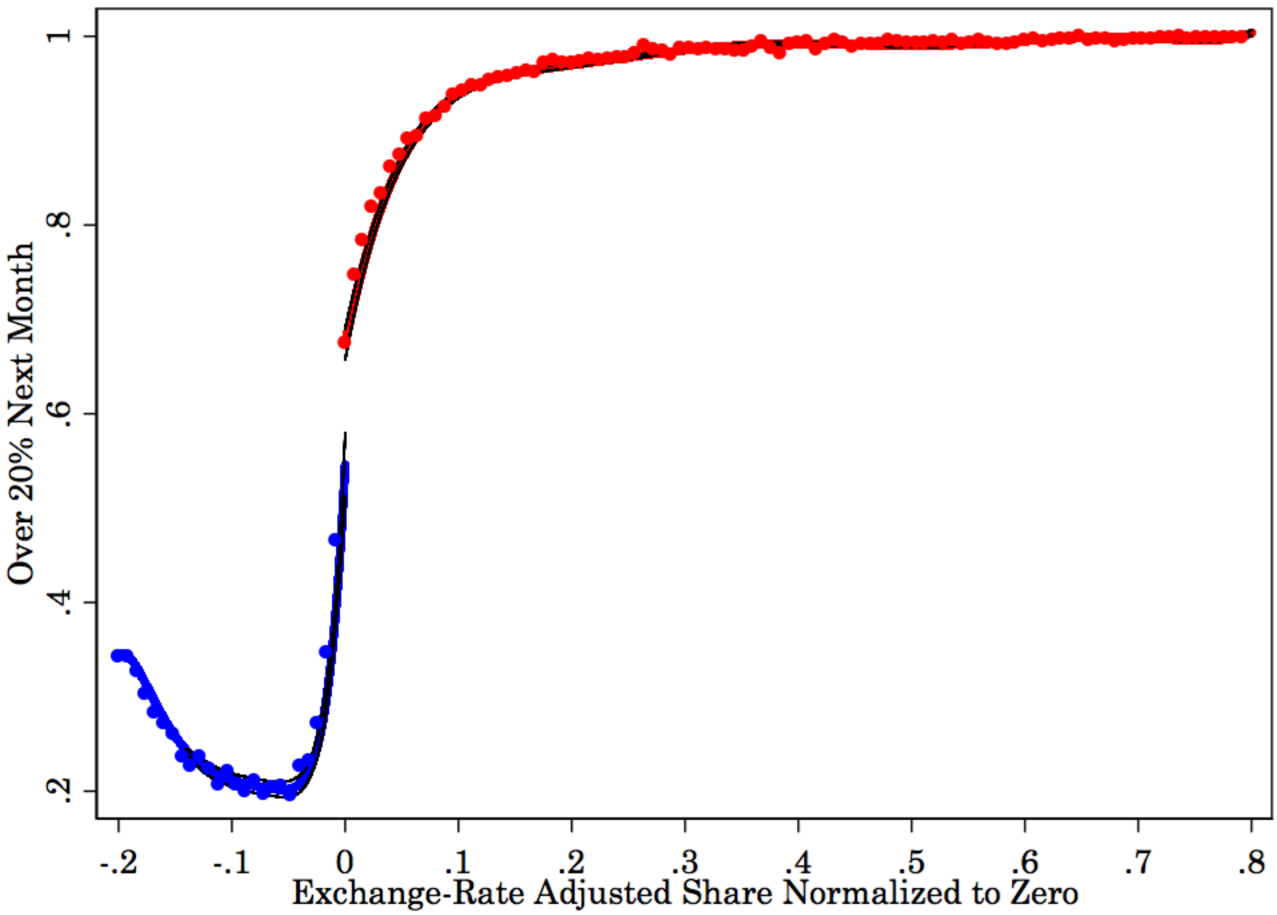


Figure 2: Characteristics Around the Threshold

This graph displays the regression discontinuity results analogous to the models in Table V.

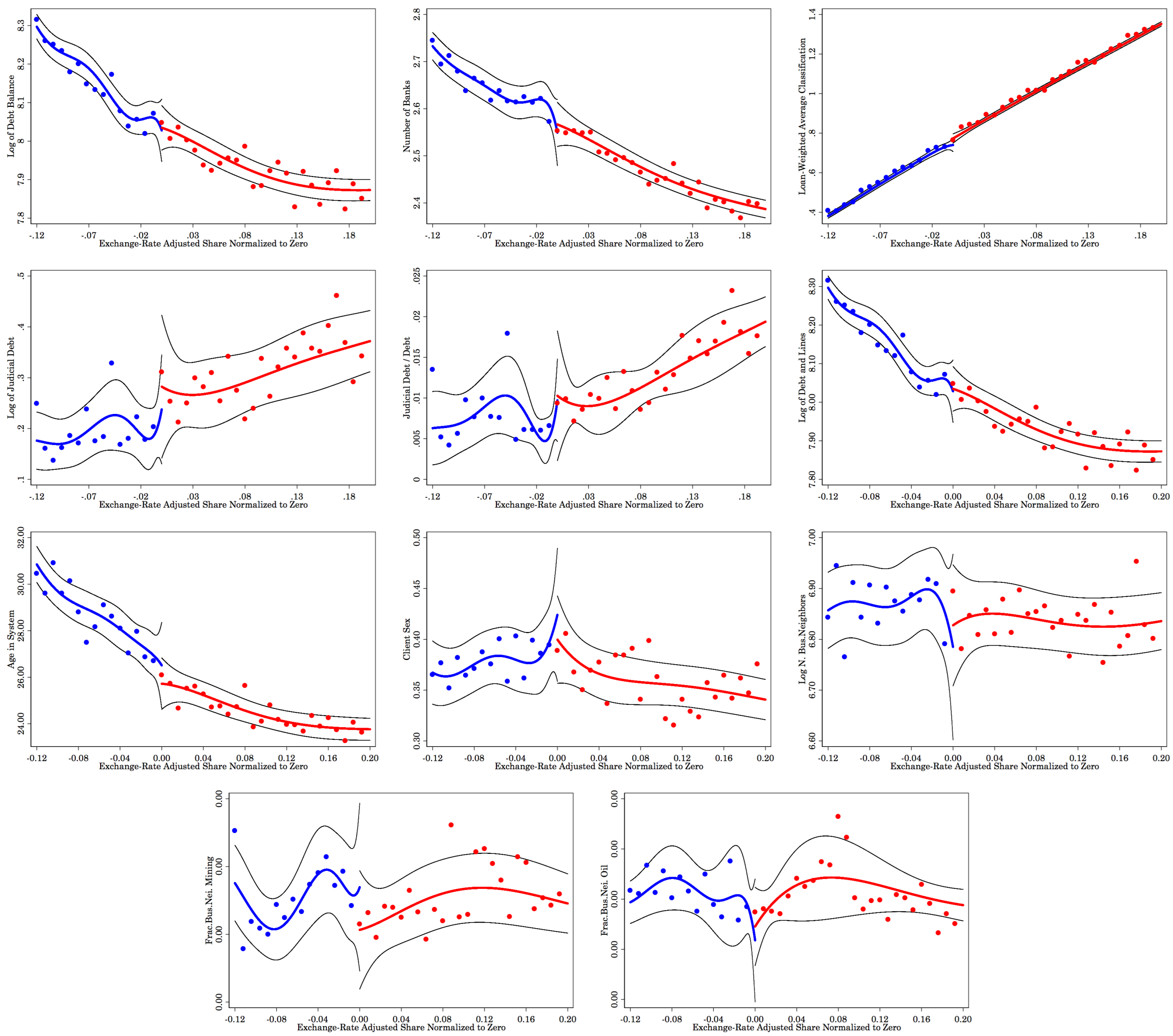


Figure 3: Densities of the Exchange-rate-adjusted Share Around the Threshold

This graph displays the density of the exchange-rate adjusted share of debt for the sample studied. This running variable is normalized to zero by taking the difference with respect to 20%. The McCrary test comparing the relative log heights of the estimated probability densities at the threshold yields a coefficient of 0.014 and a t-statistic of 0.78.

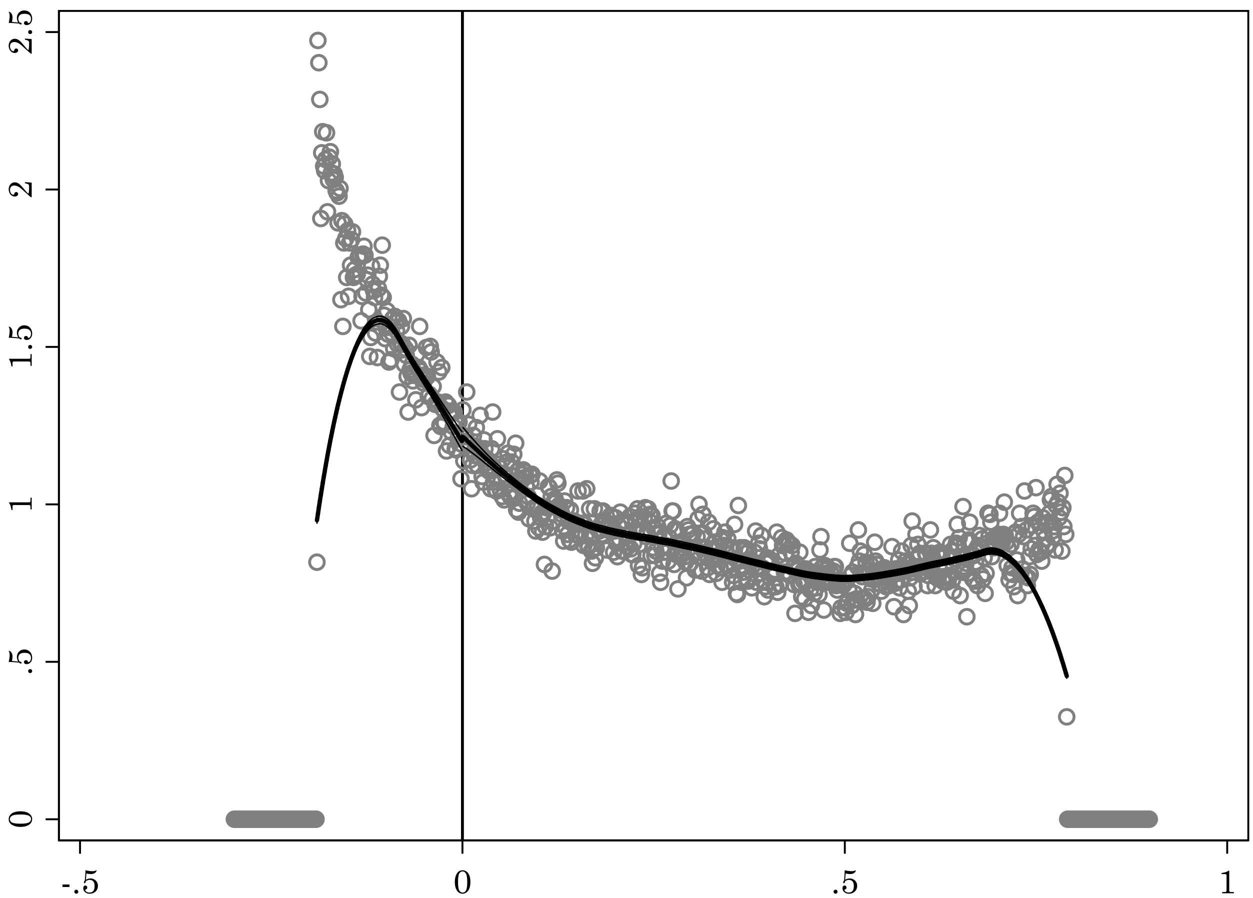


Figure 4: Impact on Change in Classifications

This graph displays the regression discontinuity results analogous to the models in Panel A of Table VI for months *t+1* through *t+6*.

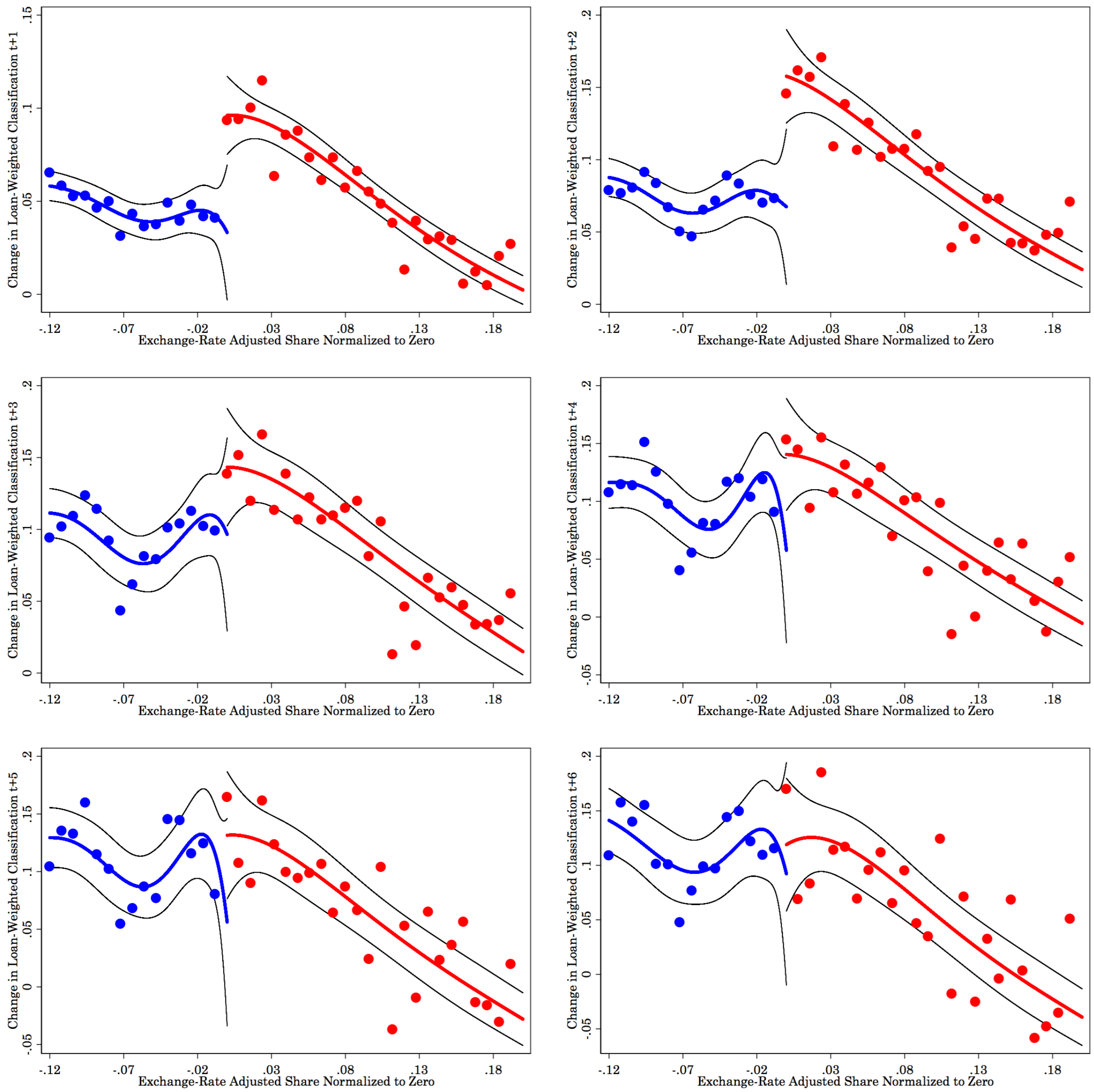


Figure 5: Impact on Financing

This graph displays the regression discontinuity results analogous to the models in Table VII.

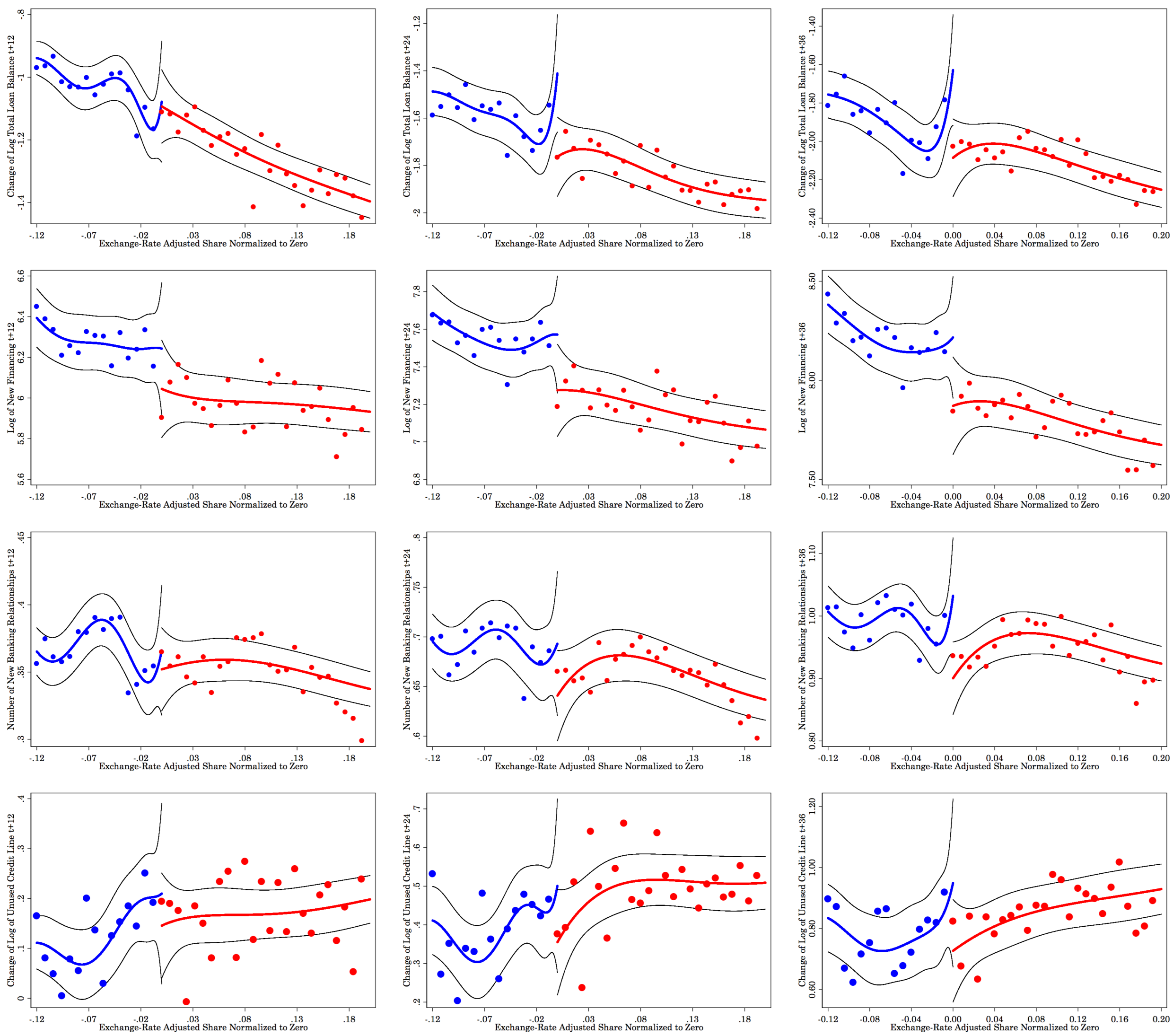


Figure 6: Impact on Client Actions Regarding Existing Debt

This graph displays the regression discontinuity results analogous to the models in Table VIII.

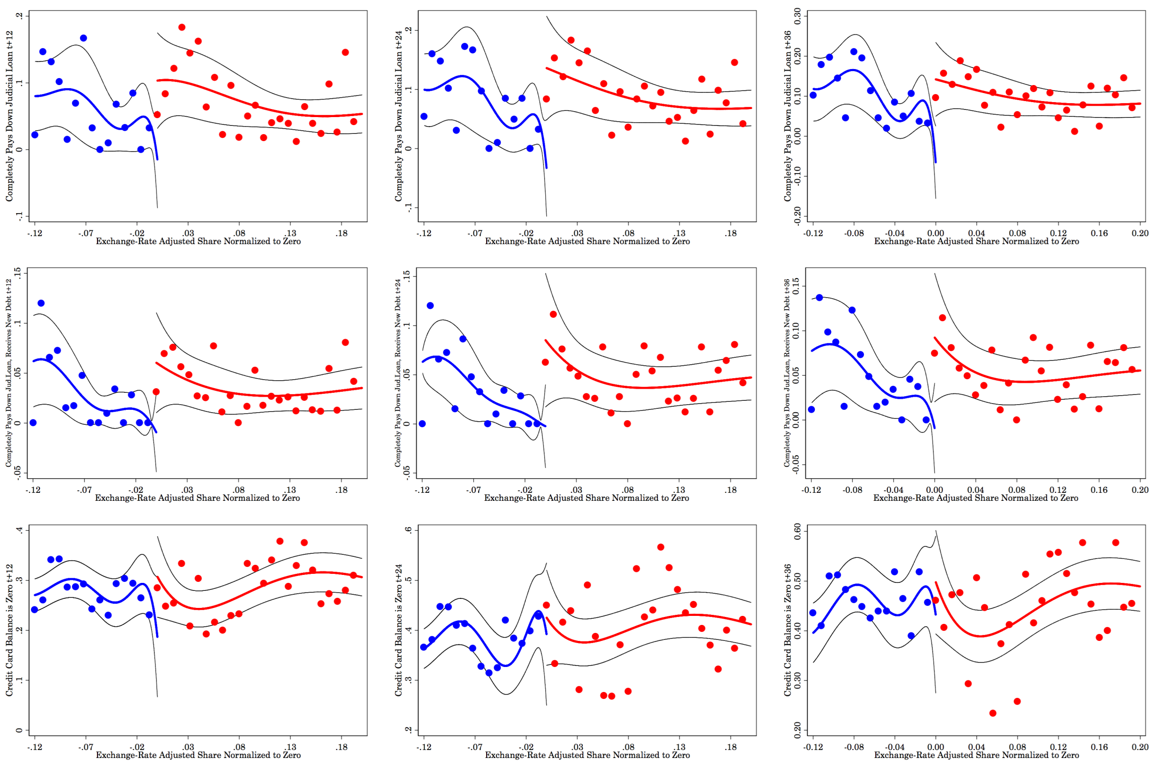
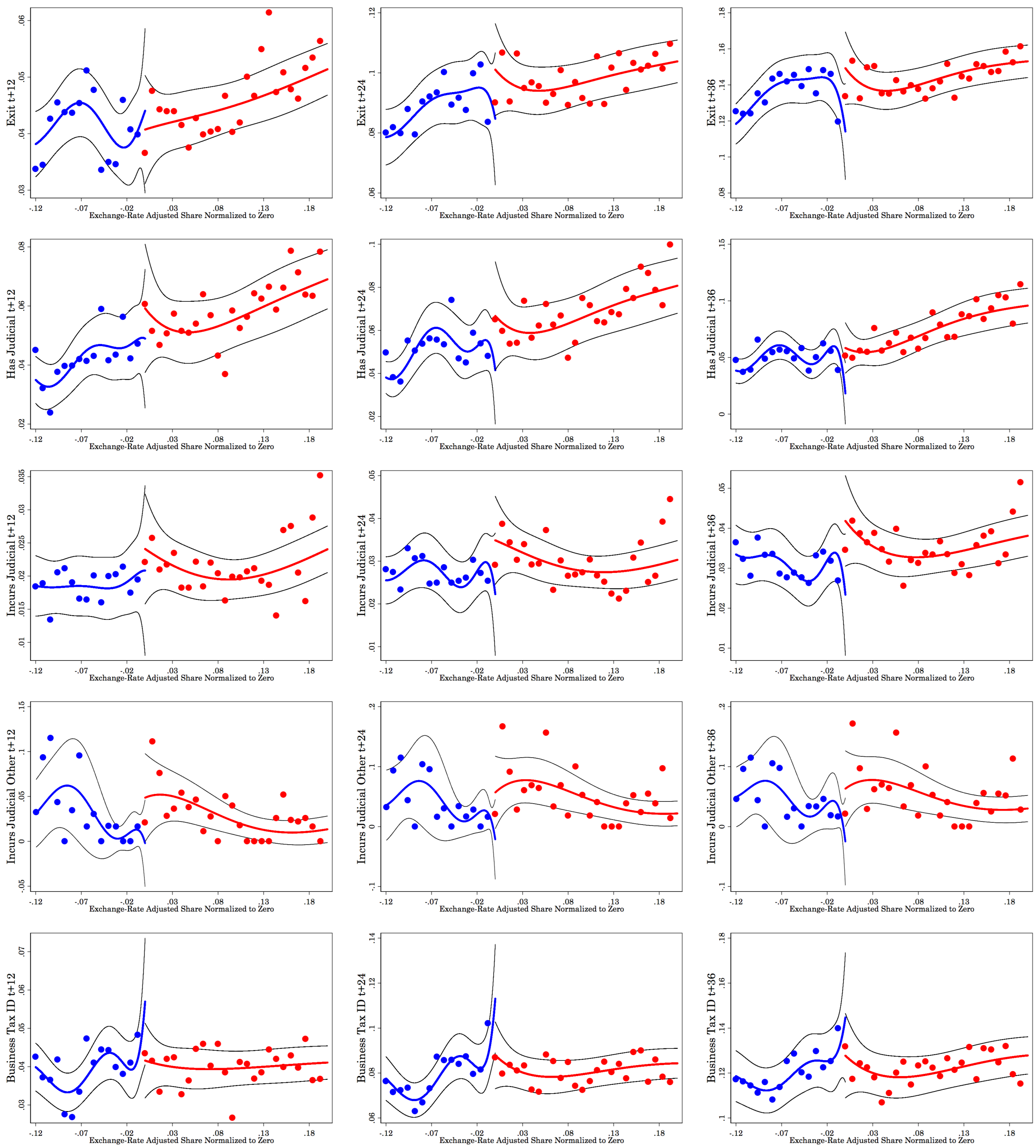


Figure 7: Broader Impacts

This graph displays the regression discontinuity results analogous to the models in Table IX.



Supplementary Appendix

A1 Robustness

In this section we discuss the robustness of our central findings to different specifications and samples. The main specification presented in the paper is the seventh-degree polynomial model. Estimating equations (1) and (2) using tenth-degree polynomials yields similar results; our main findings are robust to this alternative estimation technique.

There are several possible variations on the sample selected. The empirical strategy of the paper requires that we focus on consumers who borrow from multiple banks in multiple currencies. In our base sample we do not restrict the number of banks (as long as it is at least two) from which consumer may borrow, and we require that her borrowing from at least one bank exhaust one of the currencies of the loans (to ensure that bank shares will be affected by currency movements). Restricting the sample to consumers who borrow from precisely two banks yields very comparable findings. Widening the sample by including all borrowers from multiple banks who borrow in multiple currencies and insisting only that they do not borrow from any given bank in multiple currencies (a looser restriction than the currency-exhausting requirement in our main sample) also has little impact on our findings.

In the sample used in the paper, we divide loans into relatively high- and low-risk by identifying whether a given loan is two ratings classes higher than a consumer's loan-weighted average across her other debt. According to the rule of twenty, only high risk loans with risk ratings above other loans may have an impact on the ratings of those other loans (and we show this in the top and bottom panels of Table VI). Amongst loans with risk ratings above those of the weighted average rating of a consumer's other loans, the mean difference is 1.83 ratings classes. If we divide loans into high and low risk according to whether they exceed this mean difference in risk ratings, the results in the paper are unchanged.

Another approach is to estimate the impact of having a large (above 20%) high risk loan on financing, client actions and broad outcomes using the above threshold indicator as an instrumental variable. Given that above threshold serves as the sole instrumental variable, the estimated coefficients on having a large high risk loan in that specification are simply scalings of the estimated coefficients on above threshold that we present, with the scaling determined by the first stage regression in Table IV. The regressions that we detail allow for a clearer description of the rating shock, tracing its influence over multiple time periods. We argue that it is the shock generated by crossing the threshold, rather than simply the presence of a large risky loan, that is the primary economic object of interest, and for that reason we present results focused on the above threshold variable.