Slippery Slope or Wake-up Call? Negative Credit Rating Shocks for Consumers*

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ABSTRACT

What is the impact of an exogenous negative credit rating shock for consumers? Exploiting banking regulations in Peru and making use of currency movements, we show that consumers who face a credit rating downgrade due to bad luck experience a reduction in financing for two years. Consumers respond proactively to the negative shock, making efforts to pay down their most troubled loans. Despite this, consumers who experience the shock end up with very negative medium-term outcomes; they are more likely to exit the loan market and to have loans become subject to judicial collection action. This spiral of negative consequences arising from a completely uninformative shock suggests the benefits of imposing limited credit histories or other forgiveness policies on formal credit reporting systems.

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Consumer credit scores are a critical tool used by financial institutions to inform their lending to individuals. Credit ratings are not, however, under the complete control of consumers and may be affected by externally driven negative shocks. In this paper we consider two primary questions. First, do borrowers who experience rating downgrades that are generated purely by bad luck experience reduced access to credit? Second, what actions do borrowers take to respond to exogenous ratings shocks? Using a broad panel data sample on consumers in Peru, we show that rating downgrades lead to less financing for two years. In response to these shocks, consumers move to pay down their most troubled loans in an attempt to improve their financial profile. These efforts, however, are insufficient to insulate borrowers from the serious medium-term impact of a downgrade, which include the transition of some of their loans into deep delinquency and eventual complete exit from the credit market.

Understanding how individual borrowers respond to financial adversity has implications for lenders designing and pricing loan contracts, for investors holding consumer debt, for regulators implementing policies and, of course, for the consumers themselves. It is empirically challenging, however, to study a consumer's response to a negative shock.[1] Even though external events like recessions clearly have an important impact on consumers, the consequences of macroeconomic shifts differ across individuals, for reasons that are at least partially endogenous, and that also obviously have an effect on more than a single consumer. In this paper we present a quasi-experiment that uses a regression discontinuity design exploiting exchange rate movements to isolate and analyze the impact of negative financial

[1] This theme is discussed in the literature on the broad 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).

access shocks experienced by individual consumer borrowers. This allows us to study their response to the shocks and to trace the medium-term implications for the consumers. Our results allow us to portray both the nature of consumers' dynamic responses to these negative shocks as well as the limits to their resilience.

Credit scores should be expected to have a meaningful impact on lending decisions. Our first research question is whether consumers experience negative credit access consequences from downgrades generated by clearly exogenous events. There are reasons to think that banks would penalize these unlucky borrowers. It may be 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.

Our second question relates to the response of consumers to exogenously-generated negative credit rating events with the potential for hindering their ability to borrow. There are two natural hypotheses. The first is that the restricted access to capital for the consumer reduces her financial flexibility and leaves her unable to make adjustments when faced with future shocks. This leads to further deterioration in the consumer's credit performance and reputation; in essence, a downgrade leads a consumer down a slippery slope to potentially even more serious negative credit outcomes in the future. A second hypothesis is that, confronted by a negative bank response, a consumer may make special efforts to repair her credit situation. The consumer may become more cautious about her credit decisions. This shift in attitude and focus can eventually lead to better outcomes for the consumer. In essence, the deterioration in her relationships with banks will have served as a wake-up call to the consumer to repair her credit situation.

Assessing the impact of exogenous credit shocks on banks and 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.[2] First, Peruvian banking regulations require that banks provide to a central credit registry a quantitative risk assessment of each client. 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.

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

[2] 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.

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 degradation in his good credit ratings, as required by the regulator, leading to an overall rating record that appears very weak. The other borrower with the delinquent loan just below 20% of his 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 begin by showing that our exchange-rate-adjusted balances clearly predict whether a borrower's actual loan balance will shift to over 20% of his 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 from the perspective of any given consumer. We 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 two years following the shock, relative to below-threshold borrowers. Further, these consumers are less likely to initiate new banking relationships and are subject to reduction in their unused credit line balance. These results suggest that the rating shock, with its damaging effect on the credit rating of the consumer, has a meaningful negative impact on lending to the borrower, despite the fact that it arose from exogenous currency movements. Even though banks have access to all the information necessary for unravelling the source of the downgrade, there is nonetheless a substantial impact on lending. That is, the answer to our first question is that unlucky borrowers are punished with negative credit consequences for a fairly long period of time.

Our second question is to consider the medium-term impact of the shock on the consumer's actions. We offer several findings to address this issue. 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 both the next year and two 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. This effect may be driven by behavioral factors; a negative rating shock may focus an individual borrower's limited attention on improving his financial condition by raising the salience of his current credit status (Hirshleifer and Teoh 2003 and Lee and Malmendier 2011).

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. Further, we find that the negative rating change reduces the probability that consumers will initiate new entrepreneurial ventures in the year and two years following the shock. 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.

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 2015). Our findings complement this research, by showing the relevance of credit ratings for a variety of consumer outcomes. Our work is also linked to studies of the implications of income shocks for consumption and financing (Agarwal, Liu and Souleles 2007, Bertrand and Morse 2009 and Agarwal and Qian 2014). Recent research has also focused on the effects of changes in regulations and market liquidity on the supply of consumer credit (Assunção, Benmelech and Silva 2014 and Benmelech, Meisenzahl and

Ramcharan 2015). Our analysis differs from previous work in its focus on the consequences of individual negative financial shocks to consumers for both their choices and medium-term outcomes.

We find that consumers are penalized by banks for bad luck, and that they respond to negative credit risk shocks in a surprisingly constructive way, but that their efforts are insufficient to overcome the very damaging impact of the shocks to their medium-term financial status. The spiral of negative consequences that we find for borrowers who are simply subject to some ill fortune buffeting their credit ratings illustrates the seriously harmful potential effects of credit reporting systems for some consumers. While the use of consumer risk ratings can help enhance financial access in both developed markets and in emerging economies, and while any reporting system will make some errors, it is nonetheless troubling that the consumers in our study hit by an exogenous and uninformative negative shock are significantly more likely to end up in grave financial distress. Despite their best efforts and struggles to improve their financial situation, these borrowers have an increased probability of being ensnared in delinquency and ejected from the borrowing market. Our findings highlight some of the costs of formal credit reporting systems for consumers and thus suggest the value of instituting policies requiring that reporting institutions limit the length of their retained credit histories and institute other forgiveness policies.

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, US dollars) in which the loan has been granted.[3] 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 loan, on a five-point integer scale from normal (a score of 0) to loss (a score of 4). 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 provisions that vary according to the risk classification, ranging from 1% for normal loans

[3]Consumer account-level financial data has been used in Gross and Souleles 2002, Agarwal and Qian 2014 and Gelman, Kariv, Shapiro, Silverman and Tadelis 2014.

to 100% for loss loans.

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 borrower 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.*[4] 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 payment history of the borrower. 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 relatively high risk classification that makes up just less than 20% of the borrower's overall balance and this loan experiences a transition 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

[4]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).

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.

A consumer with one loan in Soles and a second loan in U.S. dollars will experience shifts in his loan balances that are generated by exogenous exchange rate movements. Consider, for example, a consumer with 19% of his total debt balance in a U.S. dollar loan with a high risk classification and 81% of his 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 his 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 and risk ratings of a consumer's various relationships be very different. We therefore focus our study 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 of its lending in one currency. Finally, the rule of twenty mandates that all loans must reflect the *worst* classification of any 20% or larger loan, so only relatively risky loans will have an impact on the classification 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 this database, there are 236,811 consumer-bank-month observations that meet these criteria. Summary statistics are given in Table I. The robustness of our results to other samples is discussed in Section G.

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. In some specifications we estimate local linear regressions. 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.

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 Crossing the Twenty Percent Threshold

As described in Section II above, 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 II (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 II. We also estimate equation (1) using OLS and an indicator for above threshold exchange-rate-adjusted balances in various narrow windows around 20%. As shown in columns fourth through sixth of Table II, the coefficients from these estimates range from 0.176 to 0.299, with t-statistics from 8.61 to 26.39. In the seventh column of Table II we detail the results from a local linear estimate of equation (1), making use of the Imbens and Kalyanaraman (2012) optimal bandwidth. We find a coefficient of 0.191 (t-statistic=13.37). 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.

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 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 consumer borrows, the loan-weighted mean debt rating classification, the log of the amount of highly delinquent debt subject to judicial collection and the fraction of debt that is subject to judicial collection. As shown in Table III, none of these variables exhibits a discontinuity at the threshold. Figure 2 provides further evidence that these variables are all indistinguishable for just above- and just below-threshold relationships. The presentation of this figure follows that of Figure 1.

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.

C Crossing the Threshold and Borrower Risk Classifications

Peruvian banking regulations require an alignment of debt classifications for a given borrower, and specifically state that the risk classification on relationships making up more than 20% of the overall loan balance should be reflected in all classifications. In this section we consider to what extent this regulation 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 IV, 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 IV, 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. The estimated coefficients are uniformly both small in magnitude and statistically insignificant. These relatively safe loans have no impact on the risk ratings of other loans and are not considered in the subsequent analysis.

D Financing Conditions for Shocked Borrowers

We showed in Table IV 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? This change is unlikely to bring any new information to the borrower's other lenders: the information in the credit registry on loan balances and exchange rates is available to all the consumer's banks. The difference between above- and below-threshold borrowers is due purely to exogenous currency movements, that is, bad luck. Will it have an impact on a borrower's access to finance?

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 V, 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 a negative and significant (t-statistic=-2.82) decline in total consumer financing in the second year. Total loan balances drop by more than 30% in the second year. The shock to the rating classification appears to take place approximately over the course of a year and the reduction in total financing then occurs in the following year.

Consistent with this interpretation, 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 a significant reduction (t-statistic=-1.69) in new consumer financing in the second year after the shock, as detailed in the second panel of Table V.

Above-threshold borrowers also initiate significantly fewer new banking relationships in the two years after the shock (t-statistic=-1.74), though there is no significant effect in the first year, as shown in the third panel of Table V. The estimated impact on new banking relationships in the second year following the shock is -0.069 for above threshold consumer, which is large compared to the sample average of 0.62 new relationships. In the fourth panel of Table V we show that above-threshold consumers experience a reduction in the the log of their unused credit line balance (relative to the initial balance) of approximately 19 percent in the two 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 is quite consistent: no meaningful impact in the year following the shock and a large and significant effect is observed two years after the currency movement induced transition across the threshold. The results in Table V make clear that a negative credit rating shock due to exogenous currency movements leads to restricted credit provision for borrowers for two years: consumers are punished for bad luck. As discussed earlier, this may arise from banks' concerns that not all observers will be able to disentangle the cause of the delinquency, or the banks themselves may not expend effort understanding the shifts in credit ratings and instead apply uniform penalties to all those with poor records.

D.1 Financing Results- Supply or Demand Effects?

Table V shows that negative risk rating shocks lead to reduced provision of consumer financing. One question is whether these effects 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 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 his 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 his banks, or subtle cues that may indicate a change in the consumer's relationships with his 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. It is clear, however, that the consumer's demand for loans will not be affected by slight differences in currency-adjusted loan amounts: we are observing a supply shock to lending.

E 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 plausible 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. The consumer can borrow less, and therefore loses financial flexibility. Without the cushion of strong banking relationships and 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 his banking relationships and credit supply have become potentially endangered, the consumer takes steps to improve his position. The consumer's caution and focus on his 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 VI, 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. In the second column of the first panel of Table VI we show that they are also 17.1 percentage points more likely (t-statistic=2.70) to fully pay down at least one judicial status loan in the two years 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 VI, 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) and two years (t-statistic=2.14) after the shock.

We also consider the consumer's actions on his 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, he may move to reduce his credit card balance to zero to indicate to banks that he 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 VI. There is no impact two 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 an effort to ameliorate their relationships with banks and their overall credit record. These borrowers work out their most delinquent loans and have them removed from their records, thereby significantly improving their credit profile.

There is also some evidence that the borrowers reduce their credit card balances to zero. 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 V. Consumers respond quickly 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.

F Medium-term Broader Impacts

If, as shown in Table VI, 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 VII, 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 V, 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 that eventually results in the consumer being forced out of the formal lending market. Despite the evidence in Table VI 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.

To provide some insight on the mechanism driving these very negative outcomes, 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 VII, 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 VII.

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 large upswing in judicial loans may reflect a lack of financial flexibility on the part of the shocked clients. Their inability to open new banking relationships, as described in Table V, may hinder their access to new capital that could be used to keep some of their most delinquent accounts current.

The increased probability of loan market exit and transition to judicial status for shocked consumers contrasts with the results in Table VI 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 VII 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 his 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. We find that shocked consumers are 1.5 percentage points less likely

(t-statistic=-1.67) to acquire a business tax ID at a horizon of one year and 2.5 percentage points less likely (t-statistic=-1.98) to acquire a business tax ID at a two year horizon. Overall, only 4.3% percent of consumers acquire a business tax ID after one year and only 8.6% acquire a business tax ID at the two year horizon, so the estimated magnitudes are relatively large. There is an insignificant effect three years after the shock. Overall, there is evidence that a negative credit rating shock discourages entrepreneurship. The graphical counterparts of the results on medium-term broader impacts are provided in Figure 7.

Taken together, the results in Tables VI and VII 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.

G 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 third- or tenth-degree polynomials yields similar results with essentially identical implications for statistical inference; our findings are robust to these alternative estimation techniques.

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 IV). 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 medium-term 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 described in Table II. The reduced form 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.

IV Conclusion

We analyze the impact of negative credit rating shocks to consumers on their access to finance, and we study the reaction of the consumers themselves to these shocks. Using a regression discontinuity design that exploits credit rating alignment regulations in Peru and makes use of variation arising from currency movements, we show that consumers who experience a credit rating downgrade due simply to bad luck experience reduced consumer loan balances and receive fewer new consumer loans in the two years following the shock. They also initiate fewer new banking relationships. We find evidence that consumers respond to the shock by proactively improving their credit profile by paying off their most delinquent loans and reducing their credit card debt to a zero balance. In this sense, the negative credit rating shock appears to serve as a wake-up call to consumers. Unfortunately, despite these actions, consumers subject to the shock experience several serious negative medium-term outcomes: increased probability of consumer loan market exit, higher likelihood of loans entering extreme delinquency such that they are subject to judicial collection and decreased probability of starting a new entrepreneurial venture. Overall, the negative credit rating shock, caused purely by exogenous factors, initiates a downward spiral in financial consequences.

Credit ratings are one of the most important assets possessed by individual consumers. Our results show not only that ratings matter, but that random shocks to ratings can have an impact on financial access for several years. We find that consumers are attentive to maintaining their ratings, but that downgrades outside their control lead to medium-term negative consequences that borrowers cannot evade. In an important sense, the destinies of consumer borrowers do not lie entirely in their own hands.

References

Agarwal, Sumit, Souphala Chomsisengphet, Neale Mahoney, and Johannes Stroebel. 2015. Regulating consumer financial products: Evidence from credit cards. *The Quarterly Journal of Economics* 130: 111–164.

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.

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

Benmelech, Efraim, Ralf R. Meisenzahl and Rodney Ramcharan. 2015. The real effects of liquidity during the financial crisis: Evidence from automobiles. Working Paper, Northwestern University.

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.

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.

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

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.

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.

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

Liberman, Andres. 2015. The value of a good credit reputation: Evidence from credit card renegotiations. Forthcoming, *Journal of Financial Economics*.

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.

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

Table I: Summary Statistics

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.

Variable	Mean	Median	Std.Dev.	1st pctile.	99th 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

Table II: 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%	
	(II.1)	(II.2)	(II.3)	(II.4)	(II.5)	(II.6)	(II.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 III: 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 II. All variables are defined in Table I.

	Dependent Variables:				
	Log of Debt Balance	**Number of Banks**	**Loan-Weighted Average Classification**	**Log of Judicial Debt**	**Judicial Debt / Debt**
	(III.1)	(III.2)	(III.3)	(III.4)	(III.5)
Above threshold	0.021	0.011	0.031	0.061	0.002
	(0.46)	(0.30)	(1.59)	(0.75)	(0.32)
Year-month F.E.	Yes	Yes	Yes	Yes	Yes
R^2	0.11	0.09	0.74	0.08	0.12
Sample size	236811	236811	236811	236811	236811
N. clusters (clients)	54961	54961	54961	54961	54961

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

Table IV: 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 II. 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 V: 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 II. The change of log of total consumer loans balance and the change of log of unused credit line balance are calculated in $t+12$ or $t+24$ with respect to month t.

	Dependent Variables:	
	While Remaining Banked, Change of Log of Total Consumer Loans Balance	
	t+12	*t+24*
	(V.1)	(V.2)
Above threshold	0.002	−0.386***
	(0.02)	(−2.82)
Year-month F.E.	Yes	Yes
R^2	0.03	0.03
Sample size	233962	228931
N. clusters (clients)	53786	51683
	Log Amount of New Consumer Loan Financing	
	through t+12	*through t+24*
	(V.3)	(V.4)
Above threshold	−0.215	−0.301*
	(−1.19)	(−1.69)
Year-month F.E.	Yes	Yes
R^2	0.01	0.02
Sample size	233962	228931
N. clusters (clients)	53786	51683
	Number of New Banking Relationships	
	through t+12	*through t+24*
	(V.5)	(V.6)
Above threshold	−0.025	−0.069*
	(−0.95)	(−1.74)
Year-month F.E.	Yes	Yes
R^2	0.05	0.05
Sample size	233962	228931
N. clusters (clients)	53786	51683
	Change of Log of Unused Credit Line Balance	
	t+12	*t+24*
	(VI.7)	(VI.8)
Above threshold	−0.125	−0.208*
	(−1.29)	(−1.71)
Year-month F.E.	Yes	Yes
R^2	0.11	0.13
Sample size	233962	228931
N. clusters (clients)	53786	51683

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

Table VI: 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 II. 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 $t+12$ or $t+24$.

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

***, **,* significant at the 1%, 5% and 10% level.

t-statistics shown in parentheses are clustered by client.

Table VII: Medium-term Broader Impact

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 II. 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*
	(VII.1)	(VII.2)	(VII.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*
	(VII.4)	(VII.5)	(VII.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*
	(VII.7)	(VII.8)	(VII.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*
	(VII.10)	(VII.11)	(VII.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*
	(VII.13)	(VII.14)	(VII.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.

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 II. The running variable is normalized to zero by taking the difference with respect to 20%.

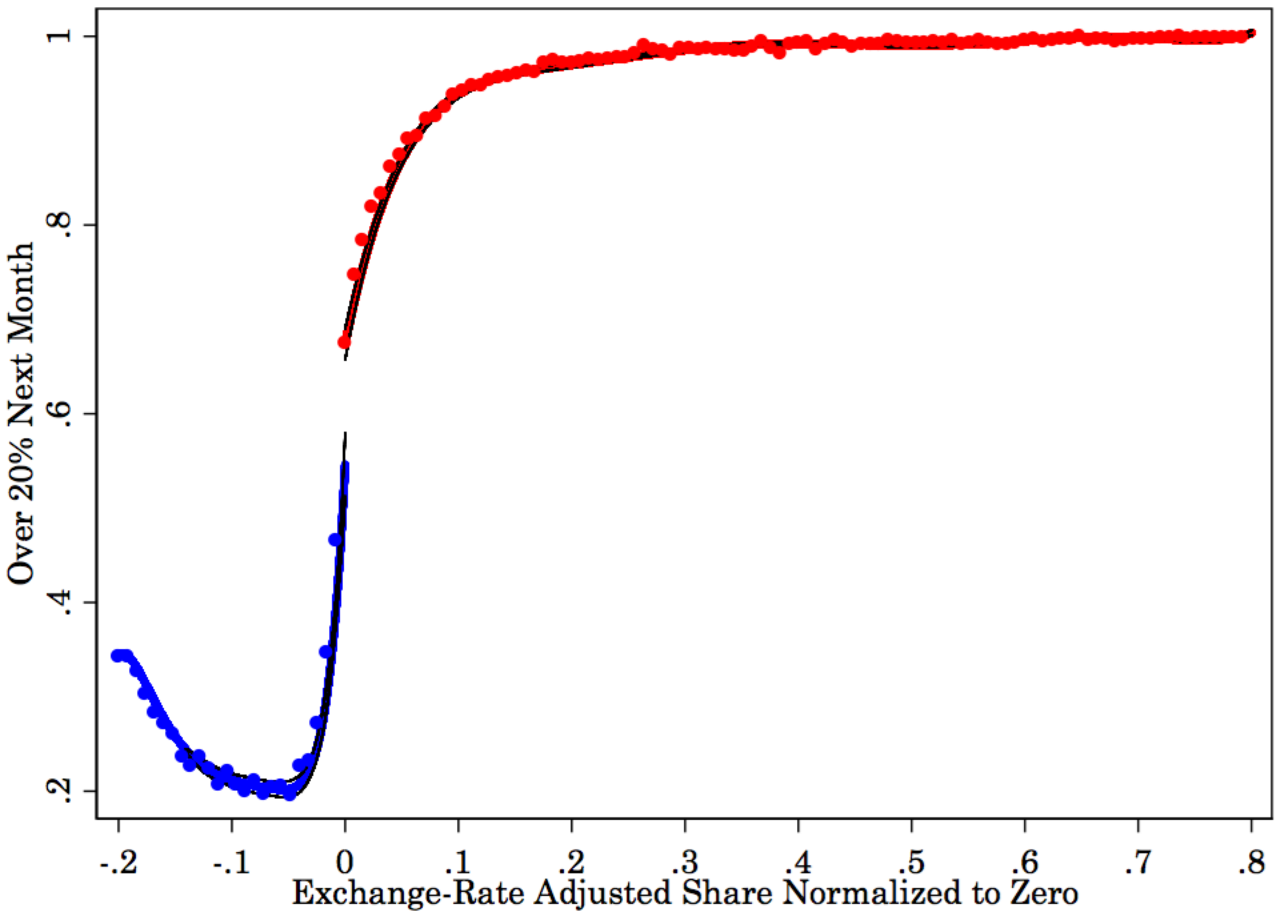

Figure 2: Characteristics Around the Threshold

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

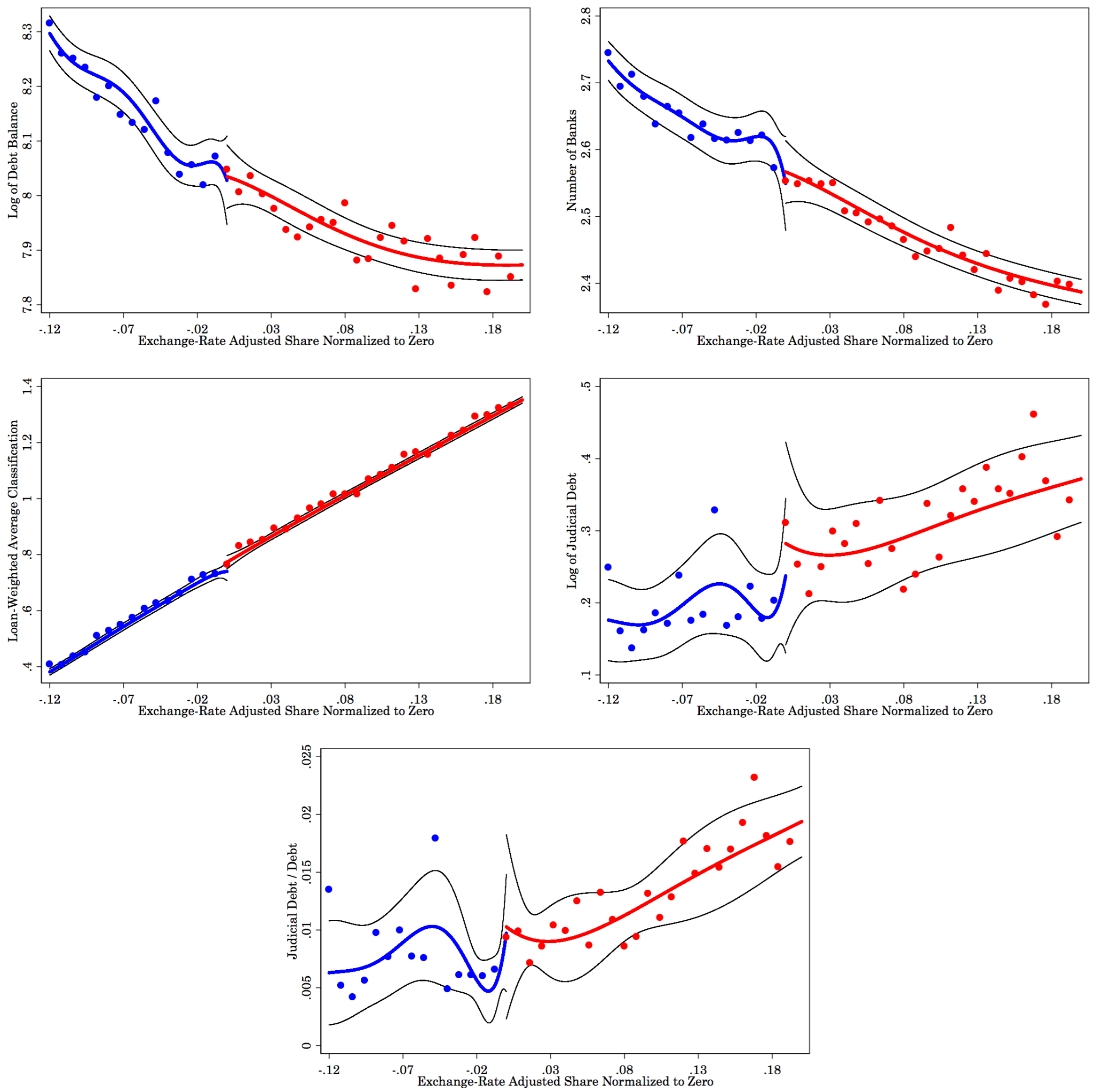

Figure 3: Densities of the Exchange-rate-adjusted Share Around the Threshold

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.

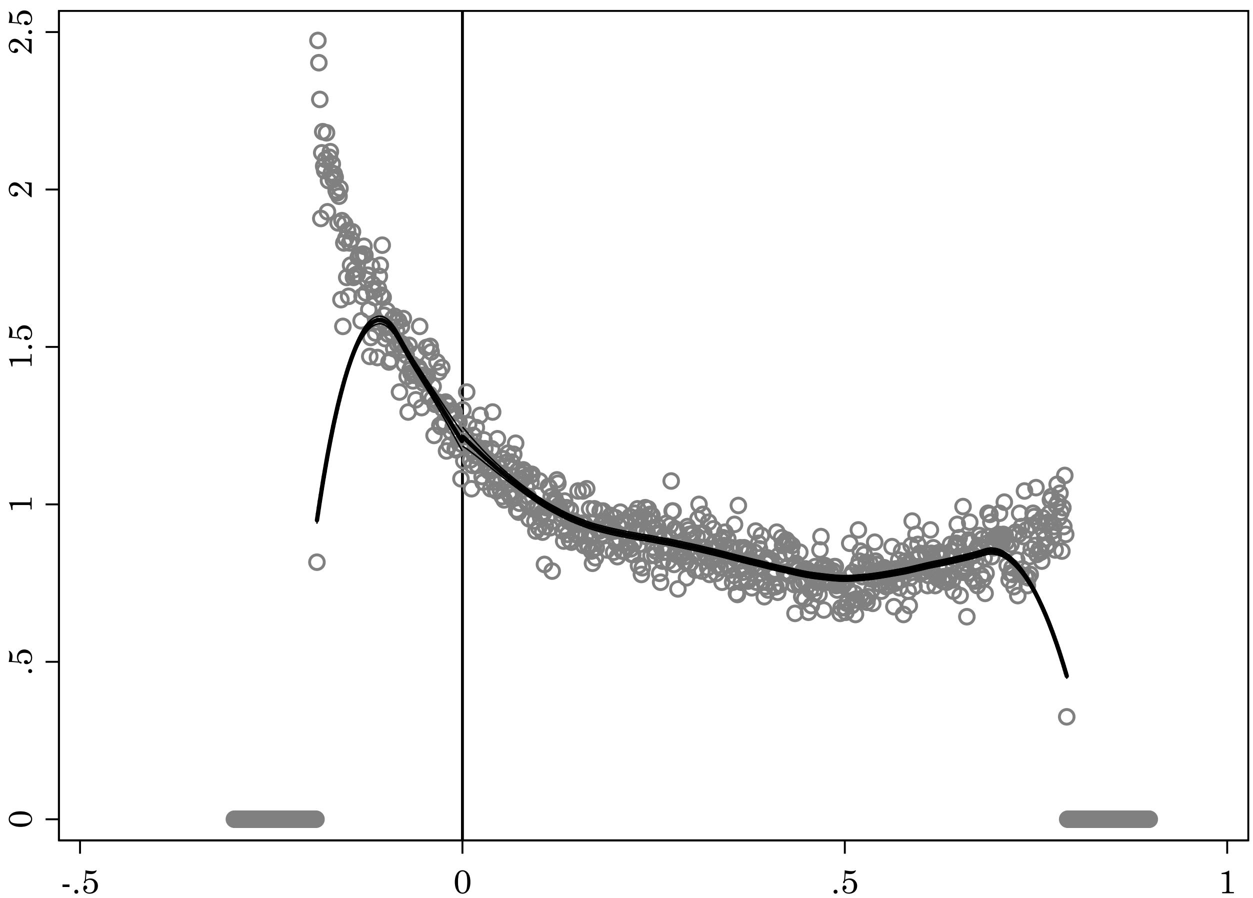

Figure 4: Impact on Change in Classifications

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

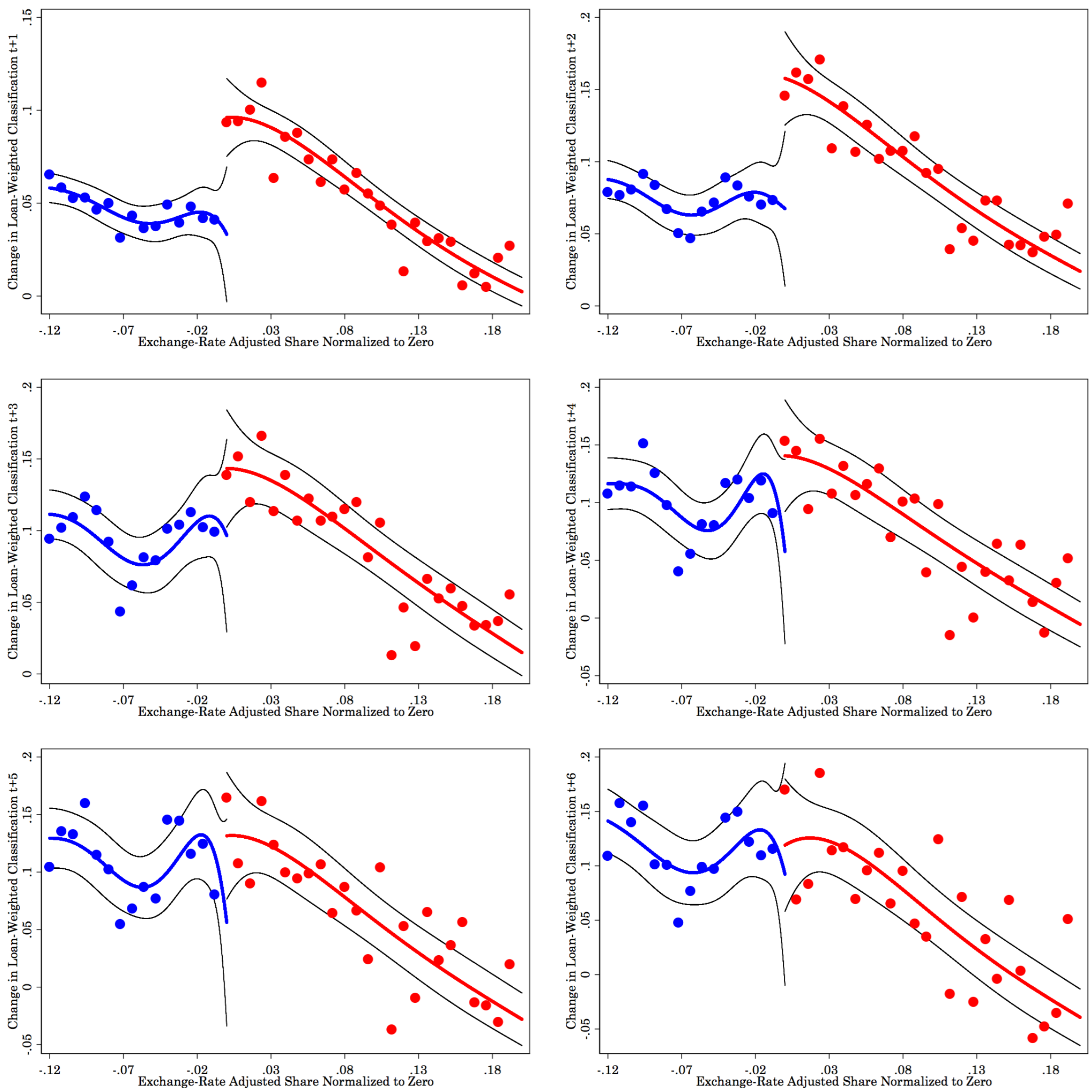

Figure 5: Impact on Financing

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

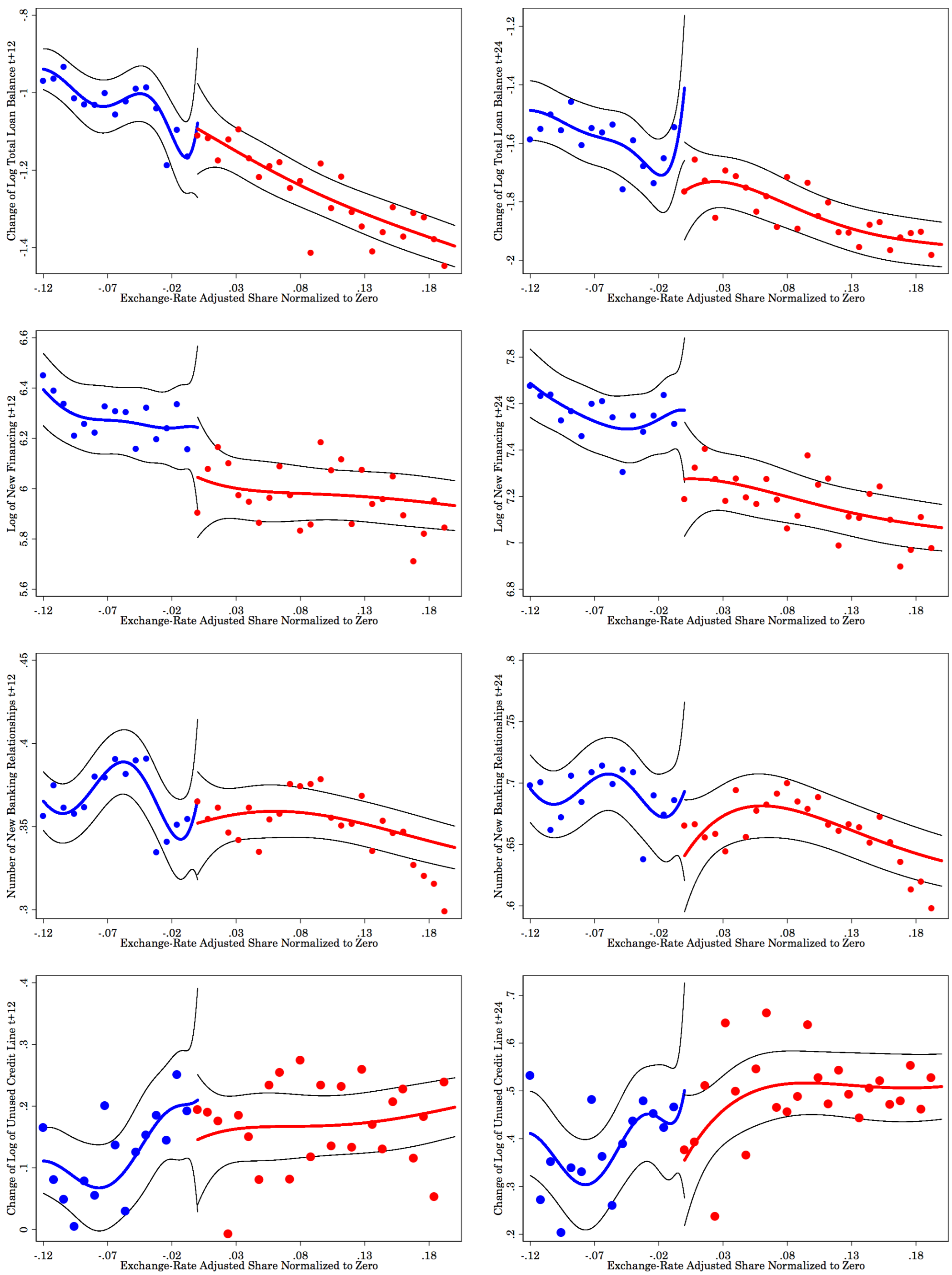

Figure 6: Impact on Client Actions Regarding Existing Debt

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

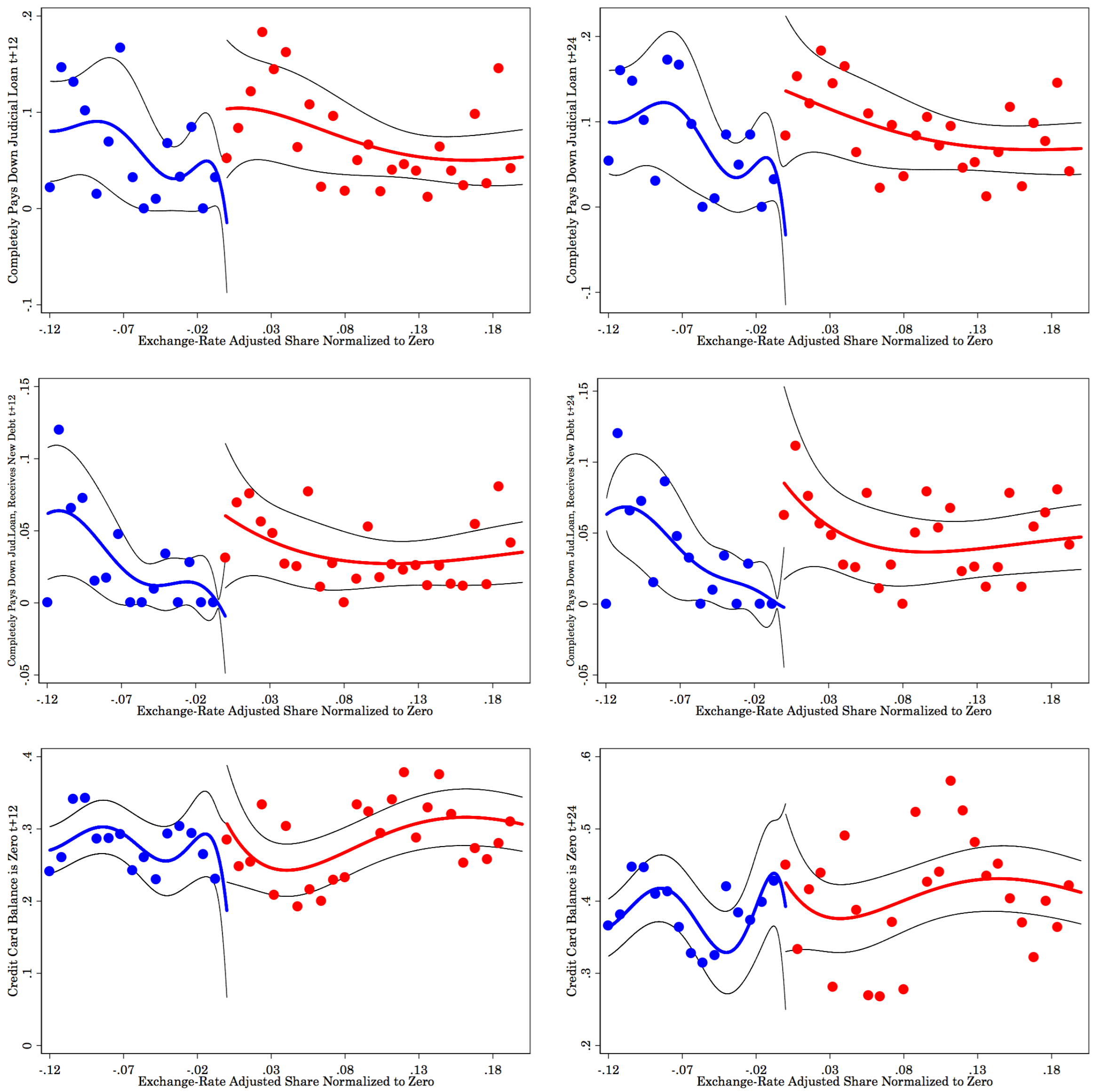

Figure 7: Medium-term Broader Impact

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