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Consumer Default, Credit Reporting, and Borrowing Constraints

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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 itself accounts for 25% to 65% of their observed decline in borrowing at various horizons over the following several years.

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 (Mian and Sufi (2010, 2011), Hall (2011), Eggertsson and Krugman (2012), Mian, Rao, and Sufi (2013), and Guerrieri and Lorenzoni (2016)). 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 to credit access. 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

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credit downgrade due simply to bad luck are subjected to an extended period of reduced financial access.

We next apply our methodology to a set of borrowers who have had their loans downgraded to the lowest level by all of 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% to 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 may itself be a key mechanism substantially reducing future borrowing, irrespective of expansionary central bank policies or other macroeconomic stimuli such as those implemented in the United States 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 2001 to 2011 sample period, 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 one borrower may have a poorly performing loan pushed across the 20% threshold purely by exchange rate movements, while another borrower with a similar loan profile but a somewhat different currency exposure may remain below the threshold. We implement a regression discontinuity design that compares borrowers with banking relationships whose exchange-rate-adjusted balances (i.e., previous month's balances adjusted by changes in the current month's exchange rate) are just above 20% to borrowers with relationships whose exchange-rate-adjusted balances are just below 20%. A borrower with a delinquent loan that crosses the 20% threshold will experience a downgrade that is imposed by regulation, leading to an overall rating record that appears very weak. Another borrower with a delinquent loan just below 20% of her total loan portfolio will not

[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.

experience these consequences, due simply to specific movements in the currency market.

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 show 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 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.

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 balances 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.

Banks have access to all of the information necessary for unraveling the quasi-random source of the downgrade, but it nonetheless has a meaningful negative impact on lending to the borrower. This relates to findings in other settings that rating events with no information content can have an impact on financial outcomes when regulations are linked to credit ratings (Kisgen and Strahan (2010), Ellul, Jotikasthira, and Lundblad (2011), and Bongaerts, Cremers, and Goetzmann (2012)). We provide new evidence that the impact of these purely regulatory effects may not be immediate but nonetheless may be sustained over a long period of time, as we document a decrease in financing that manifests two years after the rating shock and remains present during the third year.

We further 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 who receive 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. The rating shock appears to lead consumers down a slippery slope toward very negative outcomes, despite 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.

In our final analysis, we decompose 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 postrecession recovery.

In addition to informing the debate about the determinants of consumer recovery cycles, our study of negative credit events and lending also relates to the 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, 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 future (Jagtiani and Li (2013)), but it may be argued that this reflects the underlying strained conditions that led to the bankruptcy rather than the actual 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 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 postbankruptcy 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 recessions, our results have implications for policy makers 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 downturn when the consumption of borrowers is already limited due to weakened household balance sheets (Baker (2014) and Stroebel and Vavra (2016)).

It is well understood that public credit registries broadly enhance access to finance (Jappelli and Pagano (2002) and Djankov, McLiesh, and Shleifer (2007)). Our findings highlight one of the potential costs of these registries, which is their effect in seriously restricting credit access following recessions and thereby potentially hampering recoveries. This feature of registries is likely an example of an unintended consequence of a financial regulation that causes a negative byproduct in pursuit of other important policy aims (Linck, Netter, and Yang (2009), Laeven and Levine (2009), and Battalio and Schultz (2011)). Our results suggest a potential remedy: it may be worth considering policies that link the regulated length of consumer-retained credit histories to the state of the macroeconomy.

The rest of the paper is organized as follows. Section I details the Peruvian banking data that we analyze. Section II outlines our empirical specification. We describe the results in Section III. Finally, Section IV concludes.

I. Data

We analyze monthly consumer bank loan data from Peru over the period 2001 to 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 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 or 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 sample period, 72% of the loan balances of the banks' 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 provisions that vary according to the risk classification, ranging from 1% for normal loans to 100% for loss loans.

[2] Our data cover the formal sector and exclude informal lending, which is not insignificant in Peru (World Bank (2016), accessed November 29, 2016).

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

II. Empirical Specification

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*.[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 borrower's payment history.[5] The rule of twenty thus 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 up just less than 20% of the borrower's overall balance, and if this loan transitions to just above 20% of the borrower's balance, the rule of twenty would require that all of the borrower's other lenders adjust their risk classifications upward. Loan balances are endogenous, but the use of two currencies in Peruvian banking that we describe 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 through 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 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, thus raising the required loss provision of the sol lender 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 risk adjustment. In this sense, the first consumer experiences an exogenous exchange-rate-driven shock to her risk classification.

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

[5] There is a stream of work that shows the importance of consumer credit scores in predicting loan defaults (Agarwal, Skiba, and Tobacman (2009)) and in determining access to finance (Keys et al. (2010)) and payment behavior (Mayer, Piskorski, and Tchistyi (2013) and Liberman (2016)). These themes are also discussed in the broad literature on consumer credit (Campbell (2006), Karlan and Zinman (2009), Melzer (2011), Morse (2011), and Carrell and Zinman (2014)). Consumer account-level financial data are used in Gross and Souleles (2002), Agarwal and Qian (2014), and Gelman et al. (2014).

[6] In common with the balance sheet literature (e.g., Calvo, Izquierdo, and Mejia (2004), Céspedes, Chang, and Velasco (2004), and Aguiar (2005)), 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.

As this example suggests, for currency movements to have an effect on the relative sizes of 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 on consumers with the following characteristics: the consumer must borrow from multiple banks and in multiple currencies, all of the consumer's 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 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, 236,811 consumer-bank-month observations meet these criteria. Table I provides summary statistics for these observations.

Consider a consumer who meets 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 consumer's overall debt. If the exchange-rate-adjusted balance on the loan is more than 20% of the exchange-rate-adjusted overall debt, the loan is likely subject to the rule of twenty:

$$\begin{aligned}
&ShareAboveTwenty(1/0)_{i,t}\\
&\quad = \alpha + \beta(ExchangeRateAdjustedShare_{i,t} \geq 20\%)\\
&\qquad + F(ExchangeRateAdjustedShare_{i,t}) + Controls + \epsilon_{i,t}\\
&\quad = \alpha + \beta\left(\frac{(DollarBalance_{i,t-1} * R_t + SolBalance_{i,t-1})}{\sum_{i=1}^{N}(DollarBalance_{i,t-1} * R_t + SolBalance_{i,t-1})} \geq 20\%\right)\\
&\qquad + F\left(\frac{(DollarBalance_{i,t-1} * R_t + SolBalance_{i,t-1})}{\sum_{i=1}^{N}(DollarBalance_{i,t-1} * R_t + SolBalance_{i,t-1})}\right) + Controls + \epsilon_{i,t},
\end{aligned} \tag{1}$$

where F is a flexible function of the exchange-rate-adjusted share, typically a polynomial, and the equation is estimated via OLS. The controls include 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 previous month's balances will make it likely that the loan is subject to the rule of twenty. In

Table I

Summary Statistics: Study Sample

This table presents summary statistics based on the 236,811 client-bank-month observations of the sample selected for the study: the consumer borrows from multiple banks and in multiple currencies, all of the consumer's 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 the consumer's other loans. The exchange rate is in Peruvian soles per U.S. dollar and is given at the monthly frequency. The bank share of lending is expressed at the client-bank-month level and is defined as the ratio of the 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 is the amount of 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 is the sum 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 total debt balance shares for 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 and is 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, that is, loss; this variable is calculated for the current month or for the previous 12 months.

Variable	Mean	Median	Std. Dev.	1st Percentile	99th Percentile
Exchange rate (Peruvian 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	7,659	3,570	18,939	254	59,832
Amount of new consumer loan financing $t + 12$	6,420	2,350	17,530	0	60,789
Amount of new consumer loan financing $t + 24$	13,250	5,389	31,363	0	119,929
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	8,685	0.00	2,4691
Judicial debt/debt	0.05	0.00	0.19	0.00	0.97
Amount of credit card debt	331	0	2208	0	8,322
Entered complete default (current month)	0.02	0.00	0.14	0.00	1.00
Entered complete default (previous 12 months)	0.07	0.00	0.26	0.00	1.00

this sense, we implement a fuzzy regression discontinuity design. We cluster t-statistics by each individual consumer. For ease of reference, we 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 the rule of twenty into account. To what extent does this undermine the regression discontinuity design? As long as the control of borrowers or banks is less than absolutely total, 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

$$\begin{aligned} ClientOutcome_{i,t+12} = \gamma + \delta(&ExchangeRateAdjustedShare_{i,t} \geq 20\%) \\ &+ G(ExchangeRateAdjustedShare_{i,t}) + Controls + \nu_{i,t}, \end{aligned} \tag{2}$$

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

III. Results

A. *Complete Default and Credit Outcomes: 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 event in which all of her banks assign her the highest credit rating of loss. This occurrence, which we refer to as "complete default," is unambiguously unfavorable for the consumer.

What are the implications of complete default for 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. Table II provides summary statistics. In Table III, we show results from performing regressions on these data to provide descriptive (not causal) evidence on the observed correlations between complete default and future credit access.

In the first panel of Table III, we show that consumers who experience complete default have significantly lower future loan balances over the next three years. This finding is consistent with the long-lasting negative effects of bankruptcy on credit access in the United States documented by Jagtiani and Li (2013). Moreover, consumers subjected to complete default are also much more likely to exit the financial system, as shown in the second panel of Table III, and complete default is linked to a higher probability that the consumer will have debt that is subject to judicial collection, as shown in the third panel of Table III.

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

Table II
Summary Statistics: Random Sample

This table presents 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 total debt balance shares for 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 and is 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, that is, loss; this variable is calculated for the current month or for the previous 12 months.

Variable	Mean	Median	Std. Dev.	1st Percentile	99th Percentile
Debt balance	6,477	2,393	13,682	0	57301
Loan-weighted average classification	0.29	0.00	0.77	0.00	3.67
Judicial debt	34.95	0.00	1,181.88	0.00	0.00
Judicial debt/debt	0.00	0.00	0.05	0.00	0.00
Entered complete default (current month)	0.004	0.00	0.065	0.00	0.00
Entered complete default (previous 12 months)	0.019	0.00	0.138	0.00	1.00

B. Shocks to Risk Classifications

B.1. Crossing the 20% Threshold

In Section II, we describe our empirical approach and the 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 suffer an exogenous change in their risk classifications can be attributed to the credit rating decline and not to 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 and higher (riskier) loan classifications, are more likely to have debt subject to judicial collection, and are more likely to enter complete default. These differences are not surprising, as our empirical design requires that the study sample 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 affect 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-20% relationships using measures of consumers' previous-month balances and exchange rate shocks.

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 in the log of total consumer loan 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 $t+36$. ***, **, and * indicate significant at the 1%, 5%, and 10% level. t-statistics shown in parentheses are clustered by client.

Dependent Variable:	While Remaining Banked, Change in the Log of Total Consumer Loan Balance		
	through $t+12$ (1)	*through* $t+24$ (2)	*through* $t+36$ (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)	101,562	94,042	87,422
Dependent Variable:	**Exit Consumer Loan Market**		
	through $t+12$ (4)	*through* $t+24$ (5)	*through* $t+36$ (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)	101,1562	94,042	87,422
Dependent Variable:	**Has Judicial Debt Balance at Some Point**		
	through $t+12$ (7)	*through* $t+24$ (8)	*through* $t+36$ (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)	101,562	94,042	87,422

This approach mitigates endogeneity considerations, but it comes at the cost of not using current information about a consumer's loan balances. Accordingly, our first tests examine whether this proxy is an effective predictor of above-20% relationships.

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

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) to (6) employ OLS whereas the model in column (7) employs nonparametric local linear regressions with the optimal bandwidth of Imbens and Kalyanaraman (2012). The models in columns (4) to (6) restrict the sample to only 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 client level. ***, **, and * indicate significant at the 1%, 5%, and 10% level. t-statistics clustered by client are shown in parentheses.

Dependent Variable:	Share of this Bank Is Above 20% of Debt Balance						
	OLS						Nonparametric
Running Variable Window Width:	Full (1)	Full (2)	Full (3)	1% (4)	0.5% (5)	1.5% (6)	(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	236,811	236,811	236,811	5,481	2,709	8,176	236,811
N clusters (clients)	54,961	54,961	54,961	3,524	2,044	4,725	

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 shown in the first column of Table IV (t-statistics are clustered by consumer and year-month fixed effects are included). This is clear evidence that exchange rate shocks can discontinuously push relationships into the above-20% category. We also find significant jumps in specifications using third- and tenth-degree polynomials, as shown in the second and third columns of Table IV. As columns (4) through (7) of Table IV show, we also estimate equation (1) using OLS and an indicator for above-threshold exchange-rate-adjusted balances in 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 estimates, all of the methods indicate 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 plots the estimates for the seventh-degree polynomial model. The lines represent fitted polynomials above and below the threshold as well as the

[7] See the Internet Appendix, available in the online version of the article on the *Journal of Finance* website, for robustness to other samples and specifications.

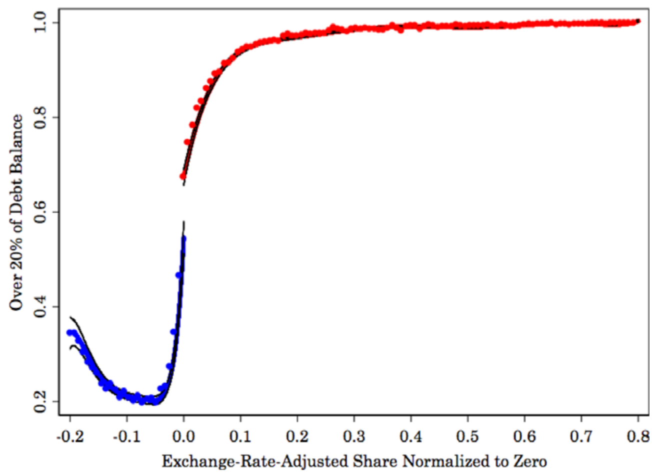

Figure 1. Exchange-rate-adjusted share and crossing the 20% threshold. This graph displays the regression discontinuity model characterizing the impact of the exchange-rate-adjusted share of debt balance on whether the bank's share crosses the 20% threshold in month t, analogous to the first model of Table IV. The running variable is normalized to zero by taking the difference with respect to 20%. (Color figure can be viewed at wileyonlinelibrary.com)

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 0.8% buckets in the exchange-rate-adjusted share. For clarity of presentation, the figure presents the regression results and bucket averages without year-month fixed effects (with minimal effect on the estimated coefficients).

B.2. Local Characteristics and Distribution around the Threshold

Our estimation technique uses currency movements to introduce 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 or below 20% are somehow different. We address this question by considering the distributions of loan characteristics for above- and below-threshold borrowers.

Our study focuses on consumer lending, ratings, and delinquency. As a consequence, we consider the following variables: log of bank debt, number of banks from which the consumer borrows, loan-weighted mean debt rating classification, log of the amount of highly delinquent debt subject to judicial collection, fraction of debt that is subject to judicial collection, log of total debt plus lines of credit, number of years in the RCD, and client sex. Although all of our borrowers are consumers without business IDs, we also consider some characteristics of the businesses located within 500m of each client when available: log of the number of such businesses, fraction involved in mining (Peru's number one export), and fraction involved in oil-related firms (Peru's number one import). As

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

Dependent Variables:	Log of Debt Balance (1)	Number of Banks (2)	Loan-Weighted Average Classification (3)	Log of Judicial Debt (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	236,811	236,811	236,811	236,811
N clusters (clients)	54,961	54,961	54,961	54,961

Dependent Variables:	Judicial Debt/Debt (5)	Log of Debt and Lines (6)	Age in System (7)	Client Sex (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	236,811	236,811	236,811	87,693
N clusters (clients)	54,961	54,961	54,961	20,516

Dependent Variables:	Log Number of Business Neighbors (9)	Fraction of Business Neighbors in Mining (10)	Fraction of Business Neighbors in Oil Related (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	77,250	77,250	77,250
N clusters (clients)	18,883	18,883	18,883

Table V shows, none of these variables exhibit a discontinuity at the threshold. Figure 2 provides visual evidence that these variables do not exhibit jumps at thresholds.

As further evidence on the possible manipulation of exchange-rate-adjusted balances on the part of banks or borrowers (which seems highly implausible 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. This test yields a coefficient of 0.014 (t-statistic = 0.78). This result is depicted in Figure 3 and indicates no evidence of strategic manipulation of the exchange-rate-adjusted balances around 20%. Along with the null

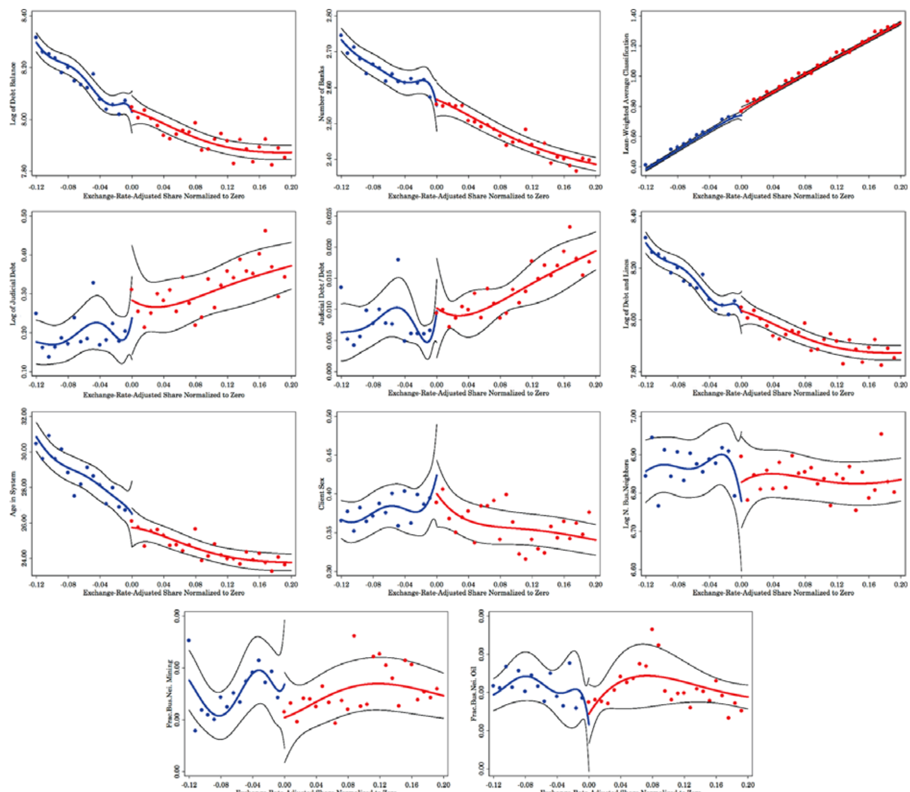

Figure 2. Characteristics around the threshold. This graph displays the regression discontinuity results analogous to the models in Table V. (Color figure can be viewed at wileyonlinelibrary.com)

findings on local characteristics, these results indicate that variation between above- and below-threshold relationships is plausibly quasi-random.

B.3. Crossing the Threshold and Borrower Risk Classifications

In this section, we consider the extent to which 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) using the change in the mean borrower risk classification as the dependent variable, and a seventh-degree polynomial model. The first panel of Table VI shows 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

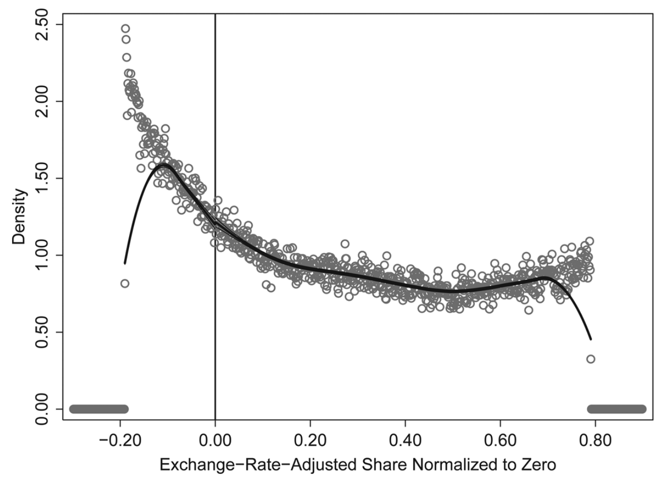

Figure 3. Densities of the exchange-rate-adjusted share around the threshold. This graph displays the density of the exchange-rate-adjusted share of debt for the sample studied. This running variable is normalized to zero by taking the difference with respect to 20%. The McCrary (2008) test comparing 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. The thick line represents the density estimate and the surrounding thin lines depict the 95% confidence interval.

out. The mean average rating class 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 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.

Above we argue that loan relationships with relatively low (safe) risk classifications should not be expected to affect 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 consider the sample of relatively safe loans (with a rating less than two 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.

The credit rating shocks we describe arise due to Peruvian banking regulations. Borrowers in the United States may experience similar effects from slight movements in their credit scores around the fixed eligibility thresholds

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 and in multiple currencies, all of the consumer's 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, that is, its riskiness is less than two rating classes greater. The dependent variable is the change in 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. ***, **, and * indicate significant at the 1%, 5%, and 10% level. t-statistics shown in parentheses are clustered by client.

Dependent Variables:	Change in the 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	207,379	189,672	175,069	162,874	152,800	144,569	137,112
N clusters (clients)	49,408	46,221	43,444	40,610	38,148	36,277	34,532
	$t+8$	$t+9$	$t+10$	$t+11$	$t+12$	$t+24$	$t+36$
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	130,969	125,729	121,196	117,461	113,870	94,112	85,506
N clusters (clients)	33,177	31,954	30,768	29,933	28,899	23,716	21,363

(*Continued*)

Table VI—*Continued*

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	3,296,444	3,126,185	3,000,400	2,896,007	2,800,870	2,720,057	2,646,278
N clusters (clients)	221,887	214,295	208,325	203,906	199,369	195,492	191,788

	$t+8$	$t+9$	$t+10$	$t+11$	$t+12$	$t+24$	$t+36$
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	2,581,025	2,520,524	2,470,702	2,421,603	2,373,940	2,013,784	1,798,147
N clusters (clients)	188,724	185,567	182,608	179,971	176,580	151,446	134,404

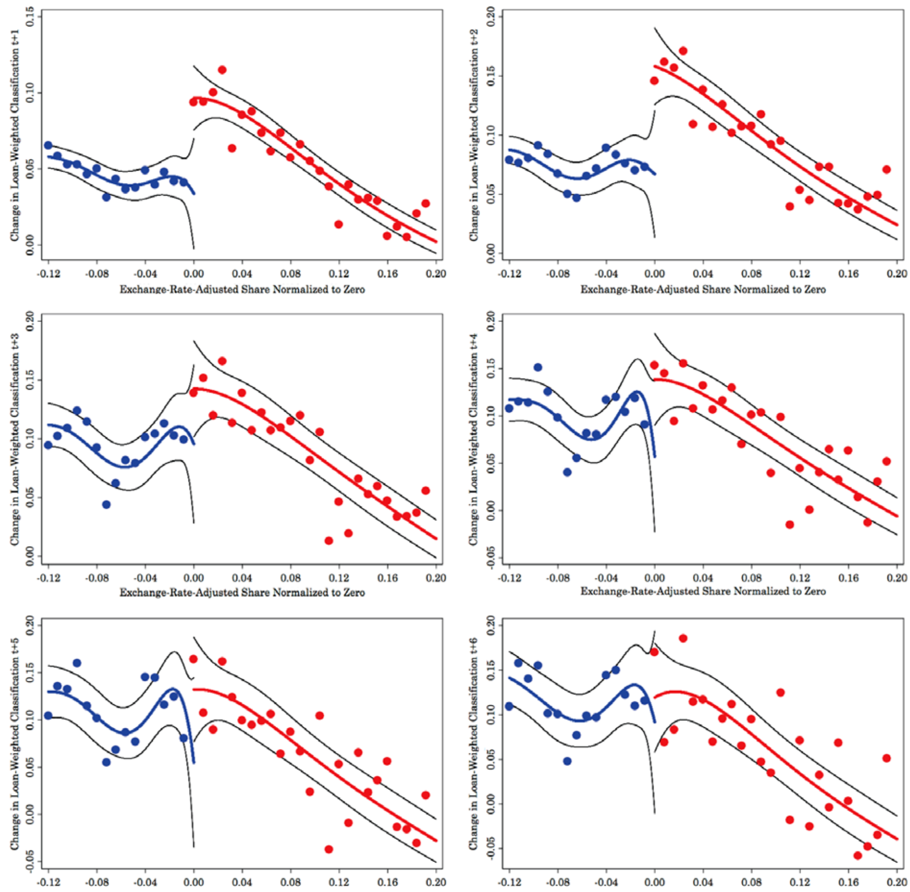

Figure 4. Impact on the change in classifications. This graph displays the regression discontinuity results analogous to the models in Panel A of Table VI for months $t + 1$ through $t + 6$. (Color figure can be viewed at wileyonlinelibrary.com)

used for mortgage issuance by both government-sponsored entities and private lenders (Keys et al. (2010)). Noise or minor reporting variations can lead borrowers to have scores just below these thresholds and thus experience different treatment of their loans. Falling slightly below a threshold is in many ways analogous to experiencing a credit rating shock. Our analysis of credit rating shocks thus has implications for borrowers in other markets with fixed credit score cutoffs.

B.4. Financing Conditions for Shocked Borrowers

We show 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 classification for a period of at least five months. What are the broader implications of this negative risk classification shock for a borrower?

To address this question, we estimate (2) using the log of the balance of total consumer loan financing as the dependent variable. We find that, as shown 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, however, do 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% by 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.

These results provide clear evidence that credit rating downgrades lead to the consumer deleveraging that is emphasized by Eggertsson and Krugman (2012), Guerrieri and Lorenzoni (2016), Hall (2011), Mian, Rao, and Sufi (2013), and Mian and Sufi (2010, 2011) in their accounts of the slow post-2008 recovery. Our results suggest that after a recession in which many consumers experience 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 significant changes 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 shown 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 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 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 due to a regulatory event with no information content (Kisgen and Strahan (2010), Ellul, Jotikasthira, and Lundblad (2011), and Bongaerts, Cremers, and Goetzmann (2012)). 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. A bank may also worry that outside

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 in the log of total consumer loan balance and the change in the log of unused credit line balance are calculated in $t + 12$, $t + 24$, or $t + 36$ with respect to month t. ***, **, and * indicate significant at the 1%, 5%, and 10% level. t-statistics shown in parentheses are clustered by client.

Dependent Variable:	While Remaining Banked, Change in the Log of Total Consumer Loan Balance		
	through $t + 12$ (1)	*through* $t + 24$ (2)	*through* $t + 36$ (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	233,962	228,931	223,760
N clusters (clients)	53,786	51,683	49,843
Dependent Variable:	**Log Amount of New Consumer Loan Financing**		
	through $t + 12$ (4)	*through* $t + 24$ (5)	*through* $t + 36$ (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	233,962	228,931	223,760
N clusters (clients)	53,786	51,683	49,843
Dependent Variable:	**Number of New Banking Relationships**		
	through $t + 12$ (7)	*through* $t + 24$ (8)	*through* $t + 36$ (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	233,962	228,931	223,760
N clusters (clients)	53,786	51,683	49,843
Dependent Variable:	**Change in the Log of Unused Credit Line Balance**		
	through $t + 12$ (10)	*through* $t + 24$ (11)	*through* $t + 36$ (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	233,962	228,931	223,760
N clusters (clients)	53,786	51,683	49,843

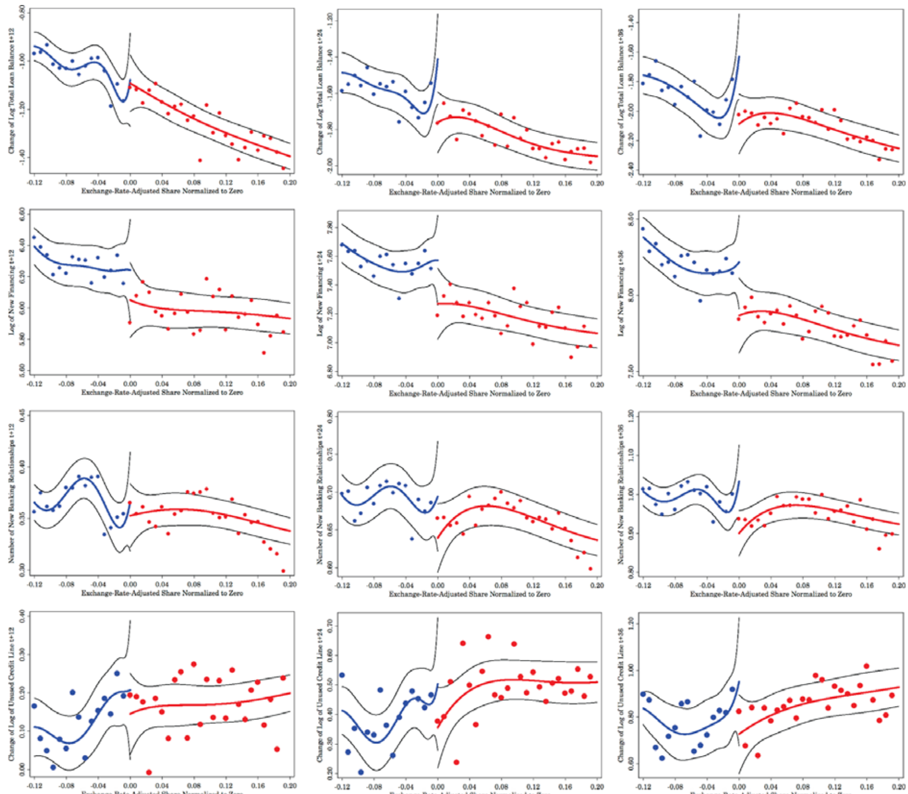

Figure 5. Impact on financing. This graph displays the regression discontinuity results analogous to the models in Table VII. (Color figure can be viewed at wileyonlinelibrary.com)

observers (including other borrowers) may misinterpret any leniency granted to unlucky borrowers as weakness on the part of the bank. Or it may be the case 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 that penalize borrowers with low ratings in all cases.[8]

Financing Results: Supply or Demand Effects? A question that arises is whether the effects in Table VII are driven by reduced demand for or supply of credit. It seems highly implausible 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 expected impact of these shocks is on the lending environment and the supply of loans.

[8] We focus on the impact of credit downgrades on future consumer borrowing. Other studies emphasize 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 (2017)) on the supply of consumer credit.

Another question that arises 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 examine 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 shift in supply or whether it is simply a perceived shift in supply.

Financing Results: Mechanism. What is the mechanism linking a current-period quasi-random downgrade to the long-term reduction in financing that we document in Table VII? We argue that our results provide evidence that consumer credit histories matter: the recording of negative information has a sustained adverse impact on lending. Banks have access to consolidated credit reports (*Reportes Crediticios Consolidados*) documenting the credit histories of all borrowers (SBS resolution 11356-2008). Consumer rating histories are thus observable to banks, and our findings are consistent with the argument that negative credit reports have a meaningful effect on lending decisions for several years even if they supply no new information.

Given that banking regulations in Peru require larger loss provisions for loans with higher risk classifications, an alternative hypothesis is that the decrease in financing after a credit downgrade that we observe 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 decrease in 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, while 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.

Might the reduced financing after a downgrade reflect the influence of the Basel II risk-weighting scheme that was adopted by Peru in 2010? Perhaps loans to downgraded consumers carry a higher risk weight that makes further lending to them unattractive. We think Basel II risk-weighting is unlikely to explain our results for two reasons. First, the primary determinant of a loan's risk weight is whether it is defined as compliant. For consumers, however, compliance is defined at the relationship/transaction level, not at the borrower level

(SBS resolution 14354-2009). As a result, compliant relationships subjected to a risk classification downgrade due to the rule of twenty will not enter into noncompliance. Risk weights may potentially shift with provisions, but, as noted above, the impact of the downgrade on provisions is quite short-lived. Second, exit from noncompliance occurs after 12 months of timely payments. Given that the downgrade does not cause noncompliance and the impact of noncompliance disappears after a year, it is unlikely that Basel II risk-weighting rules can explain the pattern of downgraded consumers' financing, which exhibits no impact in the first year and a sizable reduction in lending after years two and three. As further evidence on this point, Tables IAI and IAII of the Internet Appendix show that, after a shock, consumers are not more likely to subsequently shift their borrowing to more solvent or liquid lenders, as might be expected if Basel II risk-weighting considerations were motivating banks (and especially insolvent or illiquid banks) to avoid extending credit to downgraded borrowers.

The time pattern of reduced financing we observe and the availability of credit histories to banks both support the idea that rating shocks have a long-run negative impact on credit access due to damage to a consumer's reputation rather than through loss provisioning or risk-weighting effects.

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 causes a loss of financial flexibility, leading the consumer down a slippery slope and initiating a series of negative outcomes. The second hypothesis is that a negative rating shock serves as a wake-up call that encourages the consumer to improve her position, potentially leading to better medium-term outcomes.

To test these contrasting hypotheses, we examine the impact of a negative rating shock on the consumer's actions. Specifically, we consider the way consumers manage their most delinquent accounts, that is, those that are subject to judicial collection. We thus restrict attention to the consumers in our sample who have loans that have been consigned to the judicial collection category. In column (1) 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 address this concern, we limit attention to 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

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 to clients with an existing judicial-status loan at time t. The third panel restricts the baseline sample to clients with positive credit card debt at time t that remained banked at time $t + 12$, $t + 24$, or $t + 36$. ***, **, and * indicate significant at the 1%, 5%, and 10% level. t-statistics shown in parentheses are clustered by client.

Dependent Variable:	Completely Pays Down at Least One Judicial-Status Loan		
	through $t + 12$	*through* $t + 24$	*through* $t + 36$
	(1)	(2)	(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	17,243	17,178	16,878
N clusters (clients)	2,850	2,844	2,830
Dependent Variable:	Completely Pays Down at Least One Judicial-Status Loan and Receives New Debt from the Same Bank		
	through $t + 12$	*through* $t + 24$	*through* $t + 36$
	(4)	(5)	(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	17,243	17,178	16,878
N clusters (clients)	2,850	2,844	2,830
Dependent Variable:	While Remaining Banked, Has Credit Card Balance Equal to Zero		
	through $t + 12$	*though* $t + 24$	*through* $t + 36$
	(7)	(8)	(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	21,209	16,572	13,032
N clusters (clients)	9,473	7,312	5,769

borrowers whose loans had to be discharged without payment. 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.

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 signal to banks that she can behave responsibly. For consumers who remain in the banking system, we regress an

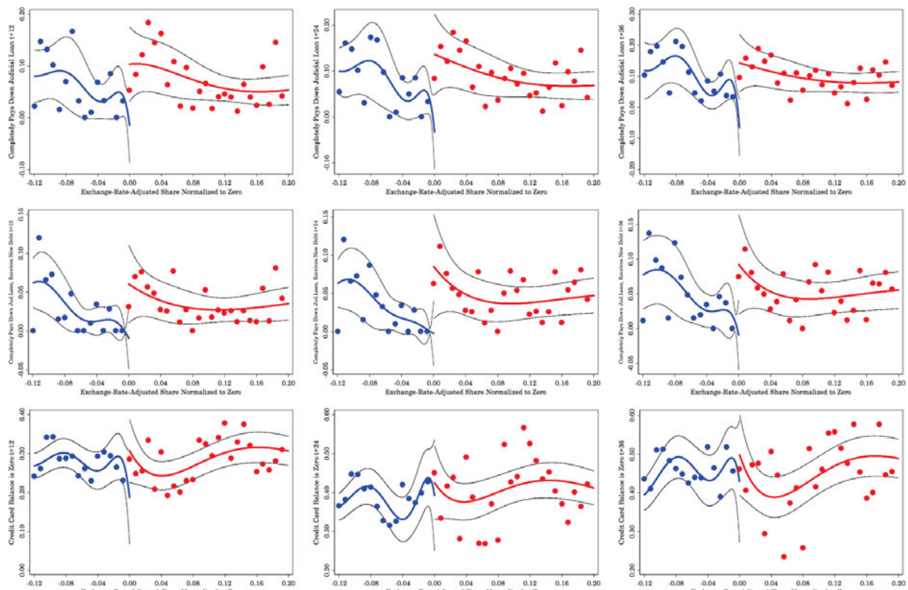

Figure 6. Impact on client actions regarding existing debt. This graph displays the regression discontinuity results analogous to the models in Table VIII. (Color figure can be viewed at wileyonlinelibrary.com)

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. Figure 6 displays these results.

We interpret these findings as showing that the above-threshold borrowers who receive an exogenous credit rating shock make efforts to improve their 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. 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 Table VIII shows, 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. To do so, 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 exit the consumer loan market completely.

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 end all consumer banking relationships. This result relates closely to an important assumption in models of the equilibrium effects of personal bankruptcy law (Athreya (2002), Chatterjee et al. (2007), and Livshits, MacGee, and Tertilt (2007)) as well as studies of asset pricing and portfolio choice when households can default (Alvarez and Jermann (2000, 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 of time. We show that this assumption is empirically verified: irrespective of a consumer's current economic circumstances, a credit downgrade (such as that associated with entrance into formal bankruptcy) does lead to exclusion from the credit market, though we find that the impact may not be immediate.

To provide some insight into 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 2.7 percentage points (t-statistic = 1.94) more likely to have a judicial status loan in the third year after the shock. This may be compared with the 13% average probability of having a judicial debt balance. Shocked consumers are not only more likely to have judicial status loans in the third year, but also are more likely (t-statistic = 2.03) to have loans transition into judicial from nonjudicial status, as shown 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 above result raises the question of whether credit downgrades directly reduce further lending or whether downgrades lead to increased judicial collection, which in turn causes reduced credit access. That is, do downgrades have a direct or indirect impact on financing? To shed some light onto this question, we regress future financing on the rating shock for the sample of consumers who never experience any judicial debt collection over the sample period. This is a selected sample: those borrowers who experience a shock and do not have

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

Dependent Variable:	Exit Consumer Loan Market		
	through $t + 12$ (1)	*through* $t + 24$ (2)	*through* $t + 36$ (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	233,962	228,931	223,760
N clusters (clients)	53,786	51,683	49,843
Dependent Variable:	**Has Judicial Debt Balance at Some Point**		
	through $t + 12$ (4)	*through* $t + 24$ (5)	*through* $t + 36$ (6)
Above threshold	0.012	0.022	0.027*
	(0.95)	(1.63)	(1.94)
Year-month F.E.	Yes	Yes	Yes
R^2	0.06	0.06	0.06
Sample size	233,962	228,931	223,760
N clusters (clients)	53,786	51,683	49,843
Dependent Variable:	**Incurs Judicial Status for a Loan that Was Not in Judicial Status**		
	through $t + 12$ (7)	*through* $t + 24$ (8)	*through* $t + 36$ (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	233,962	228,931	223,760
N clusters (clients)	53,786	51,683	49,843
Dependent Variable:	**Initially with a Judicial Status Loan, Incurs Judicial Status for Another Loan that Was Not in Judicial Status**		
	through $t + 12$ (10)	*through* $t + 24$ (11)	*through* $t + 36$ (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

(*Continued*)

Table IX—*Continued*

Dependent Variable:	Initially with a Judicial Status Loan, Incurs Judicial Status for Another Loan that Was Not in Judicial Status		
	through $t + 12$ (10)	*through* $t + 24$ (11)	*through* $t + 36$ (12)
Sample size	17,243	17,178	16,878
N clusters (clients)	2,850	2,844	2,830

Dependent Variable:	Obtains a Tax ID for Business Purposes		
	through $t + 12$ (13)	*through* $t + 24$ (14)	*through* $t + 36$ (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	236,811	236,811	236,811
N clusters (clients)	54,961	54,961	54,961

a loan enter judicial status are likely to be of particularly high quality, so the impact of the shock on their borrowing may be muted. Nonetheless, the results, provided in Table IAIII of the Internet Appendix, show that, even for this set of borrowers, we find a negative impact of the shock on future financing that is very similar to that documented in Table VII. This finding suggests that even if the shock does not cause judicial collection, it still leads to reduced financing. We cannot rule out the possibility that credit downgrades have an impact on unobservable borrower characteristics that in turn cause the decrease in lending, but it is clear that the restricted future credit access that we observe is not driven purely by increased entry into judicial collection.

The increased probability of transition to judicial status for shocked consumers in the second and third panels of Table IX 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 nonjudicial status loan transition into judicial status at horizons of one, two, and three years after the shock. While shocked consumers are more likely to pay down existing judicial status loans, they are also more likely to have different loans newly enter the judicial category.

The shock may influence not only consumer lending to the borrower but also 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 Peru. We analyze the impact

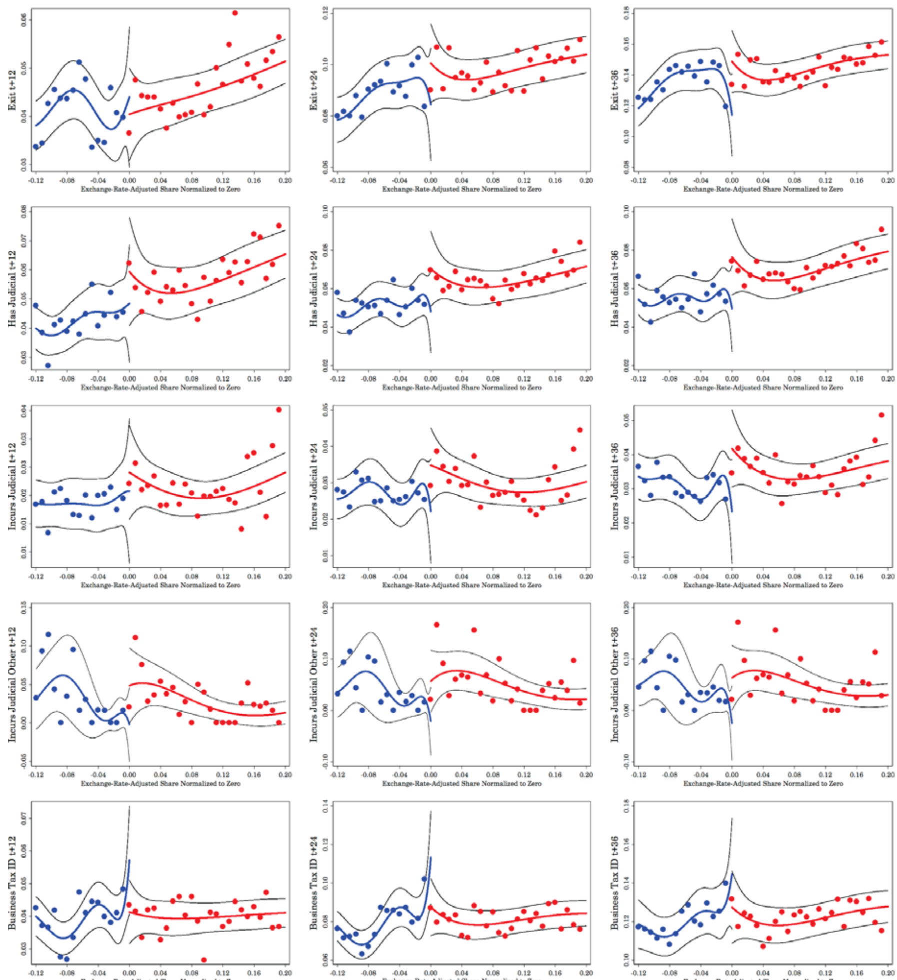

Figure 7. Broader impacts. This graph displays the regression discontinuity results analogous to the models in Table IX. (Color figure can be viewed at wileyonlinelibrary.com)

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, although the effect is insignificant three years after the shock. Figure 7 provides the graphical counterparts of the results on broader impacts.

C. Complete Default, Rating Shocks, and Credit Outcomes

The results presented in Section III.A document that complete default is clearly followed by reduced credit access. Complete default is often triggered 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 III.B we show that negative rating changes alone can lead to unfavorable medium-term financial outcomes even in the absence of any real shock. In this section, we employ the approach developed in Section III.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 and the credit rating downgrade. The second group of borrowers will only suffer from the credit rating change. The difference 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.

To exploit the ability of 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 consider differences between above- and below-threshold borrowers with exchange-rate-adjusted shares within 10 percentage points of the rule-of-twenty cutoff. The first issue to consider is whether complete default has a similar effect in both the random sample and this sample, so we begin the analysis by repeating the regressions described in Table III for the present sample. As shown in Table X, 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 an increased likelihood that the borrower will have debt that is subject to judicial collection.

We next 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 employ 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 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 column (1) of the first panel of Table XI, we report the results from a regression of the change in the log of the total loan balance in one year on the expected exogenous change in classification, an indicator for complete default,

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 10 percentage points of the rule-of-twenty cutoff. Observations are at the client-bank-month level. The change in the log of total consumer loan 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 $t+36$. ***, **, and * indicate significant at the 1%, 5%, and 10% level. t-statistics shown in parentheses are clustered by client.

Dependent Variable:	While Remaining Banked, Change in the Log of Total Consumer Loan Balance		
	through $t+12$ (1)	*through* $t+24$ (2)	*through* $t+36$ (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	55,690	55,058	54,066
N clusters (clients)	18,380	18,069	17,591
Dependent Variable:	Exit Consumer Loan Market		
	through $t+12$ (4)	*through* $t+24$ (5)	*through* $t+36$ (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	55,690	55,058	54,066
N clusters (clients)	18,380	18,069	17,591
Dependent Variable:	Has Judicial Debt Balance at Some Point		
	through $t+12$ (7)	*through* $t+24$ (8)	*through* $t+36$ (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	55,690	55,058	54,066
N clusters (clients)	18,380	18,069	17,591

their interaction, and year-month fixed effects. The key coefficient of interest is that on the interaction term, which describes the extent to which the outcomes are different for borrowers who experience 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

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 10 percentage points of the rule-of-twenty cutoff. Observations are at the client-bank-month level. The change in the log of total consumer loan 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 $t+36$. ***, **, and * indicate significant at the 1%, 5%, and 10% level. t-statistics shown in parentheses are clustered by client.

Dependent Variable:	While Remaining Banked, Change in the Log of Total Consumer Loan Balance		
	through $t+12$ (1)	*through* $t+24$ (2)	*through* $t+36$ (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	55,690	55,058	54,066
N clusters (clients)	18,380	18,069	17,591
Dependent Variable:	**Exit Consumer Loan Market**		
	through $t+12$ (4)	*through* $t+24$ (5)	*through* $t+36$ (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	55,690	55,058	54,066
N clusters (clients)	18,380	18,069	17,591
Dependent Variable:	**Has Judicial Debt Balance at Some Point**		
	through $t+12$ (7)	*through* $t+24$ (8)	*through* $t+36$ (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)

(*Continued*)

Table XI—*Continued*

Dependent Variable:	Has Judicial Debt Balance at Some Point		
	through $t+12$ (7)	*through* $t+24$ (8)	*through* $t+36$ (9)
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	55,690	55,058	54,066
N clusters (clients)	18,380	18,069	17,591

that the impact of complete default on future lending is smaller for those who are driven into complete default 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 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 $1 - \exp(0.311 \times 3.262 - 1.425 - 0.049 \times 3.262) = 43.5\%$. Comparing this result with the 75.9% overall reduction, we estimate that 57.3% of the one-year decline in the future loan balance is due exclusively to the credit downgrade. As displayed in columns (2) and (3) of the first panel of Table XI, the interaction is positive and significant in the two- 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 of 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 finding suggests that a substantial fraction of the postrecession consumer deleveraging that is the focus of Eggertsson and Krugman (2012), Guerrieri and Lorenzoni (2016), Hall (2011), Mian, Rao, and Sufi (2013), and Mian and Sufi (2010, 2011) arises purely from features of the credit reporting system that are independent of monetary or fiscal stimulus policies.

The analogous regressions for exit from the consumer loan market are reported in the second panel of Table XI. The interaction is insignificant at the one- and two-year horizons, but is negative and significant at the three-year horizon (t-statistic $= -1.68$). At this 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 judicial collection are reported in the third panel of Table XI. For this 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.[9]

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 following 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 over 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 employs 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 three years following the shock. We further find 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 and we show that the impact of a credit downgrade itself accounts for 25% to 65% of the 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

[9] The analysis in Table XI is conducted over a window of 10 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 threshold 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.

available to policy makers following a recession. Credit reporting systems bring many benefits but may have unattractive unintended effects. 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.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.