Does More Information Lead to More Financing? Local Information Shocks and Bank Credit*

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ABSTRACT

It is widely argued that increased information should lead to more financing for firms, but there is relatively little direct evidence on this question. We analyze information shocks generated by exchange-rate-induced movements of Peruvian firms across a regulatory threshold that influences information generation by banks. Firms that cross the threshold experience both reduced information asymmetries and a changed regulatory status, and the combined impact results in more bank financing. Neighboring firms subject to a pure decrease in information asymmetries, by contrast, receive less bank financing, and the overall effect across all firms is that more information leads to less credit from banks.

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Do information frictions impede the financing of small businesses? Some economists and policymakers have argued that information asymmetries between creditors and borrowers can lead to the under-provision of financing and credit rationing of small firms. This suggests that small businesses may chronically under-invest, a condition potentially requiring remediation by special government programs or subsidies. A counter-argument, however, is that asymmetric information has no impact on the funding of small firm or may even lead to excessive financing. If this counter-claim is correct, then the financing of small firms does not require any particular policy attention. Distinguishing between these arguments requires clear evidence. Theories of asymmetric information, however, are not always straightforward to test. In this paper we empirically assess the extent to which small firms in the emerging market of Peru are subject to information-driven credit rationing.

There is some prior empirical work that has found that rationing is an important feature of credit markets, particularly for small firms. Much of this research has emphasized the role of bank-firm relationships in overcoming adverse selection and promoting lending (Petersen and Rajan (1994), Elsas and Krahnen (1998) and Lehmann and Neuberger (2001)). Other studies have argued that asymmetric information increases collateral requirements (Jiménez, Salas and Saurina (2006) and Berger et al. (2011)), which may restrict the borrowing ability of firms with few hard assets. A countervailing literature, however, has claimed that credit rationing has little empirical importance (Berger and Udell (1992), Cressy (1996) and Caling and Lundberg (2005)). The chief difficulty in distinguishing between these contrasting findings is that exogenous information shocks are not easy to find. As a result, it has proven challenging to identify changes in the degree of credit rationing that are clearly information-driven. This is a general problem in testing the implications of information models of financing. From an empirical perspective, therefore, it is very much an open question whether adverse selection driven by asymmetric information reduces financing.

Moreover, from a theoretical perspective it is not clear that it should. In deeply influential work Stiglitz and Weiss (1981) claim that when creditors cannot observe firm risk characteristics, it is the worse quality borrowers that are most attracted to outside financing. Knowing this, lenders withdraw from the market and provide less financing than would be optimal in the absence of asymmetric information. De Meza and Webb (1987), by contrast, develop a model in which information asymmetries lead to over-provision of financing. The intuition for their result is that weak firms will secure financing by mimicking better firms. Banks are aware of this but in equilibrium the better firms essentially cross-subsidize the worse ones, and the competitive banking sector breaks even. The primary difference between the Stiglitz and Weiss (1981) and De Meza and Webb (1987) models is that the former assume that observably identical firms differ in their risk, while the latter assume that they differ in their average returns. It is not clear on a priori theoretical grounds which assumption is more reasonable, so distinguishing between the models is best done through empirical testing.

In this paper we provide an empirical framework to assess the impact of asymmetric information on financing through a study of small and medium sized firms in Peru in the period of 2001-2010. Peruvian banking regulators apply a set of different rules to loans to firms with total debt that exceeds a certain threshold. Firms above this threshold (set at $20,000 up to 2003 and $30,000 thereafter) are designated as “Commercial” (COM) and those below it are referred to as “Micro-enterprises” (MES). A crucial distinction between firms in the two categories is that banks lending to COM firms, unlike those lending to MES firms, are required to collect quantitative information about them in the form of financial statements. A shift in status for a firm from MES to COM status thus results in a move to significantly more intense information collection by its bank. This shift is therefore typically accompanied by an intensive bank review of this firm and an assessment of its business environment.

The decision to grant a firm COM status should be generally seen as negotiated by the firm and its bank, a result of an endogenous bargaining process. It is the case, however, that some exogenous factors influence this negotiation. In particular, most Peruvian firms borrow in the local currency (the Nuevo Sol, called Sol hereafter), while, for historical reasons, the thresholds were defined in U.S. dollars during the sample period. As a result, among the class of MES firms with Sol loan balances that are below but close to the threshold, there is a group that may be pushed above the threshold by Sol-U.S. dollar exchange rate movements in the subsequent months. These exchange rate movements will cause some firms to be forced across the threshold and into COM status while other, very similar, firms will fall just short of the threshold and remain MES. We make use of this regulatory threshold and currency movements that are clearly exogenous from the perspective of any firm to implement a regression discontinuity design contrasting future outcomes for firms that end up just above and just below the threshold.

We first show that firms with exchange-rate-adjusted balances above the threshold are indeed more likely to be assigned COM status. The relationship is subject to some noise (due, for example, to shifts in the loan balance over the course of the month), but we find a large discontinuous jump in the probability of COM status for firms with exchange-rate-adjusted balances just above this threshold, which allows us to implement a "fuzzy" regression discontinuity design. We also provide evidence in support of the argument that the assignment to COM status is quasi-random. First, we show that the distribution of exchange-rate-adjusted balances is continuous around the threshold in the sense of McCrary (2008); the data do not exhibit a pattern of bunching in which many firms are just above or just below the threshold which might be indicative of manipulation.(Such manipulation is implausible in any case due to the role of the currency markets in determining firms' exchange-rate-adjusted balances.) Second, we find that observable firm characteristics such as age, loan performance and number of banking relationships are all continuous around the threshold, again suggesting that firms above and below the threshold are fundamentally alike, aside from the probability of assignment to COM status.

In addition to the requirement of additional information supply in the form of financial statements, firms with COM status differ in other respects from MES firms. From a regulatory standpoint, the consequences for the bank of more lending to a firm are quite different depending on whether a client is COM or MES. Specifically, new lending that causes a client to exceed the COM threshold has few implications for the bank of an existing COM firm, but the bank of an existing MES firm would incur significant new information gathering costs if it caused its client to breach the threshold and enter COM status. It is also the case that banks are granted more discretion in assigning the delinquency status of COM firms, which may make lending to COM firms more attractive. These differences suggest that banks should be more willing to lend to COM firms for regulatory reasons, irrespective of any information differences.

We label the firms close to the threshold "focal firms". We show that focal firms with exchange-rate-adjusted balances just above the threshold subsequently receive significantly more new financing from their banks in the subsequent twelve months. We also find that they are more likely to receive new forms of financing such as credit card cash advances. These results are consistent with Stiglitz and Weiss (1981), but they may also be driven by the regulatory differences between COM and MES firms.

To uncover the pure information effect on financing, we turn our attention away from the focal firms and towards their "network neighbors," which we define to be all businesses within 100 meters of a focal firm that share a bank with the focal firm. A focal firm's shift to COM status leads its bank to be provided with far more detailed financial information about the focal firm. We show that multiple measures of firm performance are highly correlated for firms within 100m of each other, even controlling for conditions in broader neighborhoods. As a result, a focal firm's transition into COM status now provides the bank with clearer information about its neighbors as well. The neighbor firms, however, do not experience a shift in regulatory status. For the neighbor firms, a focal firm's shift to COM generates a pure information shock.

We estimate the impact of this information shock by comparing outcomes for neighbors of focal firms just above and just below the threshold. These neighbor firms should be quite alike, aside from the fact that some experience an increase in local information supplied to their bank and others do not. We find that the neighbors of focal firms just above the cutoff subsequently receive approximately 5.4-9.3% less new financing (scaled by the existing loan balance) in the subsequent twelve months. In other words, firms whose banks receive more information about their area later receive less new funding. This negative effect contrasts with the positive impact of information on the focal firms themselves. Taken together, the focal firms and neighbor firms receive 4.8-8.2% less financing. In other words, the main impact of more information is to reduce the provision of bank loans.

Consistent with the argument that it is an information channel that drives the reduction in financing, we find that the effects are strongest for neighbor firms in the same industry as the focal firm. Nonetheless, there is a (smaller) negative effect even for neighbor firms in a different industry. We do not find that neighbor firms subject to an information shock are able to substitute for the lost funding with financing from new banks. In fact, these neighbor firms actually receive less financing from other banks in the subsequent twelve months relative to those that do not receive an information shock. Other banks may recognize that a withdrawal of funding from its current bank after an information shock produces rather negative signals about a firm's prospects. In other words, there may be significant informational capture of firms by their current banks (Sharpe (1990), Rajan (1992) and von Thadden (2004)).

Does the focal firm's transition to COM result in an information advantage for the bank about the neighbor firms? We provide evidence on this question by showing that in the medium-term more of the neighbor firms exit the financial system, while those that continue to be financed by the bank exhibit improved performance. This is clearly consistent with the argument that the bank is now able to identify the weaker risks, and these firms are denied funding, while (previously unobservably) better prospects continue to be financed.

We study a large sample of heterogeneous small businesses in an emerging market, an empirical context in which information issues may be expected to be of first-order importance. Our main finding is that more information leads to the provision of less financing, not more. Information production may therefore not be an unmixed blessing for borrowers and our analysis thus raises questions about the benefits to firms arising from the work of information intermediaries such as banks, venture capitalists and credit rating agencies. Our results also suggest that small businesses may actually receive too much financing, rather than too little, as is generally argued. Our findings indicate the need for a more complex understanding of the role of information frictions in influencing the supply of financing.

I Theoretical Background

Consider a firm that is seeking bank finance to fund a project. Suppose the firm's manager is better informed about the firm than potential lenders. What is the effect of this asymmetric information on the quantity of financing provided by the bank? In this section we analyze the contrasting predictions of three influential theoretical papers that explore this question. Stiglitz and Weiss (1981) and Myers and Majluf (1984) emphasize the possibility that asymmetric information will lead to under-provision of financing and underinvestment. De Meza and Webb (1987), by contrast, argue that asymmetric information will be associated with a surfeit of financing and overinvestment.

These different predictions are driven by the varying assumptions of the models. The central distinction between the models of Stiglitz and Weiss (1981) and De Meza and Webb (1987) is with respect to the form of firm heterogeneity. In both models, firm owners have private information and face competitive banking markets, but in Stiglitz and Weiss (1981) all firms have the same mean expected returns and differ in their risk, while in De Meza and Webb (1987) firm have different expected returns. As a result, in Stiglitz and Weiss (1981), if a loan with a given interest rate is attractive to a certain firm, then it is also attractive to all *lower* quality (higher risk) firms as well; high risks are drawn to debt financing because they shift the downside risk to the bank and capture a share of any good outcomes. As the interest charged is increased, only lower quality firms will seek loans. Suppose that all the projects are NPV-positive. If a bank offers financing at a rate which would attract the best firms, then it may well lose money on these loans, as all the worse quality firms would also be attracted by these terms. As a result, banks may not offer loans at higher rates, which leads to under-financing in equilibrium.

In the De Meza and Webb (1987) model, however, if a loan with a given interest rate is attractive to a certain firm, then it is also attractive to all *higher* quality (higher mean) firms. The higher quality firms have a higher probability of a good outcome and a possible payoff to the firm after its debt payments have been made. If the equilibrium interest rate is set such that only positive (or zero) NPV projects are funded, then banks will make profits. In a competitive banking market, the equilibrium interest rate must therefore be lower, such that the marginal project is negative NPV and average bank profits are zero. That implies that some negative NPV projects are funded — there is overinvestment.

Myers and Majluf (1984) and De Meza and Webb (1987) differ on the locus of uncertainty. In Myers and Majluf (1984), firm owners have private information about the value of their existing assets. High quality firms are reluctant to accept financing on terms that undervalue their existing assets and thereby cross-subsidize low quality firms. As a result, high quality firms may not seek outside funding for their new positive NPV projects, which leads to under-financing. In De Meza and Webb (1987) model, there is no asymmetric information about the value of the firm's existing assets; all firm owners have the same amount of cash that they fully invest in the new project. Payoffs come only from this new project. As a result, high quality firms do not worry about the undervaluation of their existing assets, and they are more willing to invest in their project than low quality firms. The mechanism by which concern about undervalued assets hinders the demand for financing therefore does not operate in De Meza and Webb (1987).

The three models all offer compelling and coherent descriptions of the possible impact of asymmetric information on the provision of financing. It is not clear from an a prior theoretical standpoint if asymmetric information should lead to more or less financing. Evaluating the predictions of these models thus requires empirical tests.

II Data

We analyze monthly business bank loan data from Peru over the period 2001-2010. 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*) database. The data describe for each Peruvian financial institution the monthly loan balances of every business borrower. We draw from two data sets. Firms are assigned to a category, and an associated data set, based on the amount of their borrowing. The first is the Small and Medium Enterprise (MES) data set that is designed to report loan balances for all firms with a total borrowing across the entire financial system of less than \$20,000 (changed to \$30,000 in 2003). We describe this cutoff as the MES threshold. The second is the COM data set for firms with a total loan balance above the MES threshold. In Section A below, we discuss in some detail the rules for assigning firms to either category, and the implications of this assignment for firms and banks. We are primarily interested in firms in the MES data set, with a particular focus on those that transition to COM status. There are 18 million firm-bank-month observations in this joint MES and COM database, never analyzed before.

In addition to supplying loan balances, the data specify the currency in which each loan is denominated (either Peruvian Soles, denoted by S/., or U.S. dollars). Over the term of the sample period, 77% of the loan balances of MES firms are in Soles, with this fraction increasing over time. By 2010, 90% of the loan balances of MES firms are in Soles. Much of our analysis will consider the amount of new financing received by a firm. The RCD database provides information on loan balances, and does not identify new loans. We therefore adopt the classification rule that any exchange-rate-adjusted increase in the loan balance of more than 5% is treated as a new loan. For a firm that receives a new loan, we view the entire new balance as a new loan. Our results are robust to using cutoffs other than 5%.

We also have geocoded location information for firms in the six largest cities of Peru (Lima, Callao, Arequipa, Chiclayo, Huancayo and Trujillo). Locations are provided in the form of eight digit longitudes and latitudes, and are precise to an accuracy of +/- 7.5 meters. This precision enables us to undertake a microgeographical analysis of the effects of information on bank funding.

A MES versus COM

The central distinctions between the banking regulations applicable to MES and COM firms is that once firms enter the COM category, their lenders are required to collect formal financial statements from them.[1] That is, the transition to COM results in the provision of quantitative information to lenders. Why don't banks require financial statements from MES borrowers as well? Generating these documents is costly for small borrowers, and collecting and evaluating them is costly for banks.

It is also the case that along with the formal requirement for the provision of financial statements, banks will often send representatives to meet with firms that transition to COM. These representatives are typically assigned responsibility for specific geographic areas. In some cases, these bank representatives will also canvass neighboring firms for their views of the company. In general, a shift to COM status leads to significantly more information gathering by the bank, a process that includes an intensified consideration of the firm's local market conditions.

COM and MES firms also differ in certain other aspects of their regulatory regimes.

[1]Source: SBS Resolution 808-2003, among others.

Most importantly, delinquency is assessed differently for COM and MES firms, and banks are required to make different loss provisions for delinquent COM and MES firms. Our analysis will also consider the possible impact of these regulatory differences.

III Empirical Specification

We are interested in the effect of an exogenous information shock on a firm's financing outcomes. Following the formal rules of the Peruvian banking regulation, firms with a total loan balance above the threshold should be subject to COM regulations. Banks and firms likely agree to the COM transition for unobserved reasons, so a regression of financing characteristics on an indicator for COM status would likely be subject to endogeneity concerns. The formal eligibility threshold can, however, be used in a regression discontinuity design to measure the causal impact of a transition to COM status. Banks are required to assign firms with total balances above the threshold to COM. The threshold level in Soles will not be known until the end of the period, at which point the official exchange rate is announced. The firm's end of month balance in Soles may also not be known, particularly if the firm has U.S. dollar debt. This suggests that there may be some noise in the assignment of firms to COM status. Nonetheless, a bank may observe a firm's previous period balance and the current Sol per Dollar exchange rate R_t to assess whether the firm is likely to exceed the eligibility threshold. Consider the set of firms with MES status in period $t-1$. A firm i in month t with an exchange-rate-adjusted month $t-1$ balance that exceeds the month t exchange-rate-adjusted cutoff should be likely to be assigned to COM:

$$Commercial\ Status_{i,t} = \alpha + \beta(Exchange\,rate\,adjusted\,Balance_{i,t} > Cutoff_t) + \epsilon_{i,t} \quad (1)$$

$$= \alpha + \beta(USD\,balance_{i,t-1} * R_t + Soles\,balance_{i,t-1} > (DollarCutoff_t)R_t) + \epsilon_{i,t}$$

where $Commercial\ Status_{i,t}$ is an indicator variable for whether firm i is assigned to the COM database for the first time, $Cutoff_t$ is the the month t Commercial cutoff measured in Soles and $\epsilon_{i,t}$ is an error term. Equation (1) can be estimated via local linear regression (Hahn, Todd and Van der Klaauw, 2001).

The bank may also use other unobserved variables to assign a firm to COM status, but we will not exploit this potentially endogenous information in our design. The bank may also have information about within-month balances that we cannot exploit given our end-of-month database. In this sense, equation (1) describes a "fuzzy" regression discontinuity design, in which we are testing for a discontinuous jump in the probability of COM status assignment, but this jump need not be equal to one. In essence, we are testing if firms that are pushed across the eligibility threshold by exchange rate movements are substantially more likely to be given COM status.

We first consider whether the flow of information generated by entry into COM has an impact on the financing of the focal firm that makes the transition. This suggests the following specification:

$$Financing\, outcome_{i,t+12} = \gamma + \delta(Exchange\, rate\, adjusted\, Balance_{i,t} > Cutoff_t) + \nu_{i,t}, \quad (2)$$

where $\nu_{i,t}$ is an error term. We estimate equation (2) using local linear regression techniques.

Yet our primary interest is in the impact of the focal firm's transition on the funding of *neighboring* firms. As described in Section A, focal firms that enter COM status receive both an information and a regulatory shock. Neighbor firms, by contrast, receive a pure information shock. To measure the impact of this information shock, we match each focal firm that may potentially be subject to a transition to the set of neighbor firms within 100 meters of its location that share a bank with the focal firm. The focal firm is designated the "local focal firm" for each of its neighbors. We consider a focal firm to be potentially subject to a transition if its exchange-rate-adjusted balance is within some window of the cutoff in period t. We then contrast financing outcomes T months in the future for neighbors of focal firms that cross the threshold with the corresponding outcomes for neighbors of focal firms that do not cross the threshold. Specifically, we estimate:

$$Neighbor\ Firm\ Financing\ Outcome_{i,t+T} \quad (3)$$

$$= \zeta + \lambda(Local\, Focal\, Firm\, Exchange\, rate\, adjusted\, Balance_{i,t} > Cutoff_t) + controls_{i,t} + u_{i,t},$$

where $controls_{i,t}$ is a set of neighbor firm controls include location, time and industry fixed effects and $u_{i,t}$ is an error term. The smallest administrative subdivision of Peru is a district, of which there are 1,834. Given Peru's population of 29.4 million, this gives an average size of just over 16,000 people per district, or roughly twice the population of a typical U.S. ZIP code. We include fixed effects at the district-year-month interaction level to control for a rich set of time and location unobservables. We estimate equation (3) using ordinary least squares (OLS), analyzing the differences between the neighbors of focal firms that are on opposing sides of the threshold, for samples in which the focal firms are all within tight windows of the cutoff.

IV Results

A Transition to Commercial Status

A.1 Loan Balances and Commercial Status

As described in Section II.A above, Peruvian firms are assigned to either MES or COM status, and this categorization is formally governed by the total outstanding loan balance, expressed in dollars, held by the firm in the financial system. We begin by analyzing the relationship between loan balances and COM/MES status. Does the loan balance threshold determine the firm classification in practice?

We adopt the approach described in Section III and analyze the effect on a firm's COM status of exchange rate shocks to both the threshold and the firm's balance in the previous month. This approach does not make use of within-month balance changes (which we do not observe) or other endogenous variables that may govern the bank's decision to grant a firm COM designation, so we do not expect to perfectly predict this outcome. By exploiting the impact of currency shifts, however, we can contrast firms that fall on either side of the threshold for exogenous reasons.

The first question is whether differences between above- and below-threshold firms are indeed quasi-random, as presumed by the regression discontinuity design. While this cannot be proven incontrovertibly, there are three arguments that suggest it is likely to be the case. The first is that exchange rate changes are hard to forecast and exogenous from the perspective of any given firm, so it seems quite likely that this introduces an element of random noise into the exchange-rate adjusted loan balance (Lee (2008)). The second point is to consider the distribution of exchange-rate adjusted loan balances. A significant discontinuity in this distribution at the threshold showing, for example, substantially more firms below the threshold than above, might indicate that the exchange-rated adjusted loan balances are being manipulated. Figure 1 shows the exchange rate adjusted loan balance (with the threshold normalized to zero) for loans within 2,500 Soles of the boundary. As the figure makes clear, there is no significant discontinuity at zero. A formal McCrary test comparing the relative log heights of the estimated probability densities at zero yields a coefficient of -0.058 and a t-statistic of -0.82. There is no evidence of a jump in the frequency of firms with exchange-rated adjusted balances just above or below the cutoffs. While banks and firms may purposely choose initial loan balances above or below the threshold, Figure 1 demonstrates that exchange rate movements generate enough local noise to ensure that exchange-rate-adjusted balances are quasi-randomly distributed around the cutoff. It is for this reason that our analysis focuses on exchange-rate-adjusted balances rather than the balances themselves.

As a final test, we analyze the distribution of observable firm characteristics around the threshold. We present results for four variables. The first is the firm's age in the financial system, as measured by the number of months since its first appearance in the RCD. The second is the number of bank relationships enjoyed by the firm. The third is the worst classification of any loan held by the firm; the Peruvian banking regulation mandates that all financial institutions report on the delinquency status of each loan, on a five-point scale from normal (a score of 0) to loss (a score of 4). The final characteristic is the amount of troubled debt, defined to be any debt with a classification of below normal. As shown in Figure 2, none of these variables exhibits a discontinuity at the cutoff. That is, above- and below-threshold firms have quite similar ages, numbers of bank relationships, loan classifications and levels of troubled loans.

Next we must consider whether exchange rate shocks that push MES firms with Sol loans across the COM eligibility threshold actually cause these firms to be given COM status. We address this issue by estimating equation (1) regressing COM status on the exchange rate adjusted balance. The results from this regression are shown in the first column of Table I. The local linear estimator shows that there is a discrete jump of 12.5 percentage points (t-statistic=24.9) in the probability of COM status precisely at the formal eligibility threshold. This result demonstrates that even when a firm is pushed across the threshold by an exogenous exchange rate shock, the formal cutoffs continue to have a substantial effect on classification. This is a fuzzy regression discontinuity design in which we do not observe all the information the banks uses to classify firms. Nonetheless, it is clear that exchange rate driven shocks have a strong impact in pushing some firms across the threshold and leading them to enter COM status while other, very similar, firms remain below the threshold and maintain their MES classification.

Columns 2-4 of Table I display results from estimating equation (1) in which we use OLS to regress COM status on an indicator for an above-threshold exchange rate adjusted balance in varying narrow windows around zero. The results are shown for windows of +/-2000, 1500 and 2500 Soles, in columns 2-4 respectively. (To give a sense of magnitudes, the average above-threshold level during the sample period was 0.032 and its standard deviation was 0.176 for the whole database; in the narrow window of 2500 Soles, the average above-threshold level was 0.426 and its standard deviation was 0.494). These results only make use of firms very close to the threshold to estimate the discontinuity. The results are somewhat smaller than for the local linear estimator, with coefficients ranging from 6.9 to 8.7 percentage points, and the estimated coefficients are significant (the t-statistics range from 6.74 to 11.09). Column 5 of Table I shows the similar result from an OLS polynomial specification, with the polynomial of order seven. This result is depicted graphically in Figure 3

B Focal Firm Financing

The analysis in Table I establishes that firms that are pushed across the COM threshold by exchange rate movements are indeed significantly more likely to be granted COM status. We now consider the impact of COM status on the amount of financing received by a firm. Specifically, we estimate equation (2) and regress the log of the new financing received by the firm in the next year on an indicator for whether a firm has an exchange-rate-adjusted balance above the classification threshold. The local linear estimator using the optimal bandwidth of Imbens and Kalyanaraman (2009) yields a coefficient of 0.36 (t-statistic=3.22) on the above threshold indicator, as displayed in the first row of the first column Table II. This indicates that firms that achieve COM status due to exchange rate movements receive 43.0% more new financing in the following year than otherwise very similar firms whose exchange-rate-adjusted balances fall just below the COM threshold. The results displayed in the second and third rows of the first column show that this effect is robust to the choice of other bandwidths. In other words, COM status appears to have a large causal effect on subsequent financing.

The second column of Table II describes local linear regressions of the log of new financing scaled by the log of the existing debt balance on an indicator for an above threshold exchange-rate-adjusted loan balance. These specifications again show that firms that achieve COM status subsequently receive significantly more financing.

Does COM status lead not only to larger amounts of financing but also to new forms of credit? Credit cards have been shown to be an important source of financing for young firms in the U.S. (Han, Fraser and Storey (2009)). Does COM status lead to more credit card lending for Peruvian companies? To analyze this question, we consider whether a firm receives its first cash advance via a credit card in the twelve month period after the focal month. We regress a dummy variable for first credit card cash advance on an indicator for an above threshold exchange-rate-adjusted balance. The local linear specification using the optimal bandwidth, as shown in the first row of the first column of III, yields a coefficient of 0.024 (t-statistic=4.28). This is very large relative to the sample mean of 0.021 for the first credit cash advance in the following month. The estimated coefficients using other bandwidths are of comparable magnitude, as shown in the second and third rows of the first columns of Table III. These results indicate that COM firms are much more likely to be granted access to credit card cash advance financing. Results for credit card usage that does not include cash advances, shown in the second column of III, are quite similar. COM status is associated with both more credit overall and different types of financing.

C Information versus Regulations: Descriptive Regressions

The results described thus far appear to be consistent with the arguments of Stiglitz and Weiss (1981): firms that are exogenously pushed by exchange-rate movements across the threshold into COM status receive an information shock as their banks shift to the intensive information gathering processes required for COM firms. As a result information asymmetries are reduced, and more financing is supplied.

It is the case, however, that a shift to COM status results in more than a pure information shock. There are presumably significant costs to a bank in establishing COM review procedures, which is why banks are much more likely to shift small firms to COM status only when required to do so by SBS regulations. There are thus two significant differences between COM and MES firms. First, the bank collects more information about COM firms. Second, the transition costs for a COM firm have already been paid by the bank. Suppose, for example, that COM status did not result in any additional information for the bank, but simply led to greater compliance costs. Even if this were true, we still might expect COM firms to receive greater future financing because they have already crossed the regulatory threshold, so the compliance costs have already been paid. For MES firms, an increase in future financing may be unattractive to the bank because it may lead to a costly transition and increase in compliance costs. For COM firms, these costs are already sunk.

In other words, MES firms may face a bank that is reluctant to extend them credit that leads to their breaching the COM threshold. This may place a ceiling on future lending to MES firms that is not present for COM firms. To provide a general sense of the importance of this potential ceiling, we consider two descriptive regressions linking COM status to future new financing. In the first, we regress the log of the firm's debt balance in the following month on an indicator for COM status this month, year-month fixed effects and fixed effects for the current month's debt balance in Soles. In other words, we contrast the next month's debt balance for COM and MES firms that currently have the same amount of debt. The result that COM firms have 3.0% (t-statistic=4.34) more debt next month is described in the first column of Table IV, Panel A. This regression does not describe a causal relationship, for in addition to the regulatory and informational differences between COM and MES firms, there are likely be other unobserved differences as well. Nonetheless, it does indicate that COM firms tend to have larger loan balance increases than similar MES firms. Is this driven specifically by a barrier at the MES cutoff? In the second column of Table IV, Panel A we display the results from regressing an indicator for whether next month's loan balance exceeds the MES cutoff on an indicator for COM status this month, year-month fixed effects and fixed effects for the current month's debt balance. The coefficient on the current month COM status indicator is highly significant (coefficient=0.004 and t-statistic=15.73). Moreover, it is quite large in magnitude: it is 10% of the sample mean of the indicator for next month's loan balance exceeding the COM cutoff. In other words, firms that currently have COM status are dramatically more likely to have a loan balance exceeding the cutoff next month. Due to the presence of possible omitted variables the results of Table IV are not meant to be definitive, but they do suggest that MES firms may face barriers to borrowing amounts that would lead them to breach the COM threshold. It is then possible that any observed differences in future financing between focal firms that cross the cutoff for exchange rate reasons and those that do not may be driven by regulatory, rather than informational, considerations.

Are there firms that are subjected to a shock that is more clearly only informational in character? A firm's transition to COM status results in more information for the bank about the firm itself, and it may also therefore provide more information about the firm's neighbors. To examine whether this is true, we select a random sample of 300,000 firms chosen at random points in time, and we calculate the change in their worst debt classification across all banking relationships over the following twelve months for these selected firms. We also calculate the average twelve month change in worst debt classification for all local firms within 100 meters of the selected firms. To what extent is a firm's change in debt classification correlated with the changes experienced by its near neighbors? In the first column of Table IV, Panel B we display the results from regressing the firm's change in debt classification on the average change of its neighbors, including district-year-month fixed effects as controls. The local average classification change is significantly correlated with that of the selected firm (coefficient=0.028 and t-statistic=3.99). (The final sample is smaller than 300,000 because some firms are selected late in the sample so that a twelve month future does not exist or the firms themselves simply do not exist twelve months later). The inclusion of district-year-month fixed effects controls for any general economic changes in the district (or city or country). The significant correlation we find shows that outcomes for firms in very local areas are highly related, even controlling for changes in broader areas like districts.

We conduct an analogous test for the probability that the selected firm exits the financial system within twelve months. (We describe a firm as having exited from the financial system if it has a zero loan balance with all banks). As shown in column of Table IV, Panel B, the frequency of local exits is highly correlated with that of the selected firm (coefficient=0.063 and t-statistic=6.43). In other words, information about local conditions and the performance of nearby firms may be very useful in assessing the performance of a given company.

As we discussed in Section II.A, a firm's shift to COM status results in significantly more local information collection by its bank. The descriptive results in this section suggest that this additional information should serve to also reduce information asymmetries about the bank's other local borrowers. A shift to COM provides a bank with a deeper insight into local conditions and thereby supplies it with helpful information about all local firms. As the bank becomes more knowledgeable about the local business environment and trends, its informational disadvantage relative to borrowers should be expected to decrease.

D Neighbor Firm Financing

For focal firms, the shift to COM status is also accompanied by a change in regulatory conditions, as we discussed in Section IV.B. For neighboring firms, however, the shift of a focal firm to COM status generates a pure information shock: the bank now knows more about neighboring firms even though their regulatory classification is unchanged.

To examine the impact of this information shock on neighboring firms, we identify for each focal firm all the MES firms within 100 meters of its location. We then contrast the outcomes for neighbors of focal firms whose exchange-rate adjusted balances fall just above and just below the COM cutoff. We argued above that focal firms just above and below the threshold are quite alike, and it is also the case that the neighbors of these firms are likewise fundamentally similar. The main distinction between the two sets of neighbors is that the neighbors of above threshold focal firms are significantly more likely to receive an information shock, as above threshold focal firms are more likely to achieve COM status.

To assess the impact of the information shock on the neighboring firms we estimate equation (3), using a window of $[-2,000\,S/., +2,000\,S/.]$. For each neighbor firm we regress the log of new financing in the subsequent twelve months over the existing loan balance on an indicator for whether its associated focal firm has an exchange-rate-adjusted balance above the cutoff, age fixed effects, industry fixed effects, bank fixed effects, a control for the number of local focal firms and district-year-month interaction fixed effects. We report robust standard errors clustered by district. The result, detailed in the first column of Table V, is that the neighbors of above threshold firms receive 9.3% less financing (t-statistic=-3.79). More information, in the form of a local information shock due to the transition of a focal firm to COM status, results in less financing for its neighbor firms.

In Table II we showed that focal firms themselves received more financing after a transition to COM status, and argued that this may be due to either informational or regulatory effects. Here we find that neighboring firms subjected to pure information shock due to the transition of a focal firm receive less financing. What is the effect of the shock on all the local firms, focal and neighboring firms combined? For this sample, as shown in the second column of Table V, the net impact of the information shock is to reduce financing by 8.2% (t-statistic=-3.62). It is clear that the overall impact of more information is to reduce the supply of financing. This is strong evidence in favor of De Meza and Webb's (1987) theory. We find that asymmetric information leads to an over-supply of financing, not credit rationing. The analysis below will also consider some of the other implications of this theory for firm exits and subsequent performance.

The results are not dependent on the specific window used with respect to the threshold. As shown in the third through sixth columns of Table V, the finding that more information leads to less financing is robust across a number of specifications. Given this general robustness, our subsequent analysis will focus on the neighbors of focal firms with exchange-rate-adjusted balances in the window of $[-2,000\ S/., +2,000\ S/.]$

D.1 Industry Effects

The local information shock generated by the transition of a focal firm into COM status is likely to be more important and relevant for neighboring firms in the same industry. While general local economic conditions are informative about all neighboring firms, the bank is likely to learn more about local firms in the same line of business as the focal firm.

Firms in the database are assigned industry classifications by the Peruvian tax authority SUNAT. These industry designations are similar to four digit NAICS codes. To test the prediction that the information shock matters more for neighbors in the same industry as the focal firm, we regress the log of new financing over the existing loan balance on an indicator for whether its associated focal firm has exchange-rate-adjusted balance above the cutoff, an indicator for neighboring firms in the same industry as the focal firm, the interaction between these two indicators and the previous set of controls. The result, displayed in the first column of Table VI shows that the coefficient on the interaction is -0.157 (t-statistic=-4.39). Neighboring firms in the same industry as the focal firm experience a dramatically larger reduction in financing if the focal transitions to COM status. The information shock is indeed larger for firms in the same industry. The information effect, though, is not purely confined to firms in the same industry. Excluding these firms, as shown in the second column of Table VI, still leads to a negative and significant coefficient on the above threshold indicator (coefficient=-0.054 and t-statistic=-1.94).

D.2 Substitution of Financing and New Forms of Credit

Are neighbor firms that receive an information shock that leads to less financing able to access substitute funding from banks other than those they share with the focal firm? We regress the log of new financing from other banks on the above threshold indicator and the usual controls. As detailed in the first column of Table VII, the coefficient on the above threshold indicator is negative and significant (coefficient=-0.132 and t-statistic=-6.62). There is no evidence of substitute financing- in fact, the information shock is associated with reduced financing from other banks. Scaling the new debt by the existing debt level gives a similar result, as shown in the second column of Table VII. These findings are consistent with the intuition of Sharpe (1990), Rajan (1992) and von Thadden (2004) that increased information for the current bank can lead to a form of borrower capture that can discourage lending by other banks.

Are the neighbor firms that are affected by information shocks able to initiate new banking relationships? We regress the number of new banking relationships in the 12 months following the shock on the above threshold indicator and the standard controls. The result, documented in the third column of Table VII, is an insignificant coefficient on the above threshold indicator. Taken together, the findings in Table VII indicate that when a bank receives increased information about a firm this leads to a reduction in that firm's borrowing from other banks. There is clearly no evidence of substitute financing being supplied.

E Do Transitions to COM Generate Local Information Shocks?

Focal firms that transition to COM supply more information to their banks in the form of financial statements. The results in Table V clearly establish that a focal firm's exchange-rate-generated transition to COM leads to a reduction in new financing for its neighbors. We interpret this result to show that information shocks reduce the supply of capital, and in support of this interpretation we show in Table IV that information about focal firms is likely to be highly informative about the conditions of their neighbors. Nonetheless, it is reasonable to ask if the quasi-random transition of focal firms to COM may have effects on the supply of capital to their neighbors that are not solely information-driven.

For example, it may be argued that banks allocate fixed amounts to local areas (perhaps due to capital allocation strategies across branches). In this case, the increased lending to focal firms that become COM that is documented in Table II may naturally lead to a reduction in lending to neighbor firms for reasons that are unrelated to information; it may simply be due to the fixed local supply of capital.

We think this is unlikely to be a correct description of the mechanisms at work, as the results in the second, fourth and sixth columns of Table V all show that the focal firm's transition to COM results in the bank's reducing its lending to all firms in the local area, on average, even when including the focal firm itself. That is, it is not that the bank is conserving its local capital and simply shifting more of it to the focal firm. The bank is reducing its total lending in the local area. A related argument is that the bank perhaps reduces its lending to the neighbors for reasons related to competition; as the bank lends more to the focal bank, perhaps it makes less sense to fund its local competitors. This hypothesis is also difficult to reconcile with the fact that total lending is declining. While the bank may elect to cut financing to some neighbors for this reason, it is not at all clear that it should actually reduce its total lending to neighbors by more than its increased lending to the focal firm. In fact, the main result in Table V is that overall local lending (including both the focal and neighbor firms) is reduced, and this finding is in tension with both the argument that there is fixed local lending and the hypothesis related to competitive effects.

It is useful, however, to seek direct evidence that more information is generated about the neighbors of focal firms that transition to COM. One way to explore this issue is to note that in the De Meza and Webb (1987) model granting banks additional information about borrowers allows them to distinguish those firms that are better risks from within a class of previously observably identical companies. The net effect is that an information shock should lead to a winnowing of the set of borrowers: the weaker borrowers should no longer receive financing and only the firms with better underlying qualities will continue to be funded by the bank. If these qualities are revealed over time, then these firms should also exhibit better outcomes in the medium-term. Subsequent to this winnowing out of weaker firms, better outcomes should be observed for the firms that continue to be financed. Table V shows that banks reduce average financing in the 12 month period after an information shock, so improvements in the performance of survivors should be observed over a subsequent period.

We pursue this analysis by contrasting medium-term outcomes for neighbors of focal firms pushed across the COM threshold by exchange rate changes with outcomes for neighbors of focal firms whose exchange-rate-adjusted balances fall just short of the threshold. Specifically, we first consider changes in the neighbor firms' worst debt classification over the subsequent 36 months. That is, we estimate (3) using the change in worst debt classification as the dependent variable in a sample that includes all the neighbors of focal firms falling within a window of 2,000 Soles of the threshold.

If the exchange-rate-generated transition to COM of the focal firm leads to more information about neighbor firms, then we should expect to see banks engaging in more successful sorting of these neighbor firms. As argued above, firms that continue to receive financing after an information shock should have better subsequent performance. The results displayed in the first column of Table VIII support this interpretation. Neighbors of focal firms with above-threshold exchange-rate-adjusted balances experience a significant 0.021

decline (t-statistic=-2.49) in worst debt classification, which we label as firm classification, over the subsequent 36 months (recall that lower debt classifications are assigned to healthier firms). This sample only includes the the firms that are still in the financial system and receiving loans. This result therefore shows that the neighbors of above-threshold firms that continue to receive bank financing experience relative performance improvements. This is evidence that banks can more successfully sort the neighbors of firms that transition to COM.

In the second column of Table VIII we detail the results from regressing the change in the classification of the neighbor firm's loan with the bank it shares with the focal firm (rather than its worst classification loan, which was analyzed in the first column) on an indicator for above-threshold focal firms. This sample only includes neighbor firms that continue to receive loans from the bank they share with the focal firm. We again find that neighbors of above-threshold focal firms experience a decline in classification (that is, an improvement in performance): the coefficient is -0.013 and the t-stat=-2.89. These results together suggest that that neighbors of focal firms that transition to COM do indeed experience an information shock.

As another measure of medium-term outcomes, we consider whether firms exit the financial system and no longer receive loans from any bank. For each neighbor firm we regress a dummy for financial system exit in the subsequent 36 months on the above threshold indicator and the standard controls. The result is described in the third column of Table VIII. As predicted by De Meza and Webb (1987), firms that receive an information shock are more likely to exit the financial system (coefficient=0.009, t-statistic=3.09). That is, greater information provision to a firm's bank makes it more likely that the firm will subsequently receive no financing at all.

The results in Table VIII show that information shocks to neighbor firms increase the probability of their exiting from the financial system, but, conditional on their continuing to receive financing, they tend to have better outcomes than their peers that did not receive a shock. These results are consistent with the basic predictions of the De Meza and Webb (1987) model for the impact of a reduction in asymmetric information. The findings in this section thus serve to document a clear pattern of improved sorting by banks of observably similar neighbor firms after the transition of a focal firm to COM status. This pattern is precisely what would be expected after the bank becomes better informed, and the evidence in Table VIII thus provides strong support for the argument that the transition to COM leads to a local information shock.

V Conclusion

We study the impact of information shocks on the supply of bank financing to Peruvian firms in the period 2001-2010. Banks of firms with total loan balances above a certain U.S. dollar threshold were required by banking regulation to collect formal financial statements from their clients; these firms were designated to have a Commercial status and were governed by different regulations. Exploiting currency movements and implementing a regression discontinuity analysis, we contrast outcomes for firms with exchange-rate-adjusted balances just above and below the threshold. We label the companies close to the threshold as focal firms, and we find that focal firms pushed into Commercial (COM) status by exchange rate movements subsequently receive substantially more financing. This may be due to either the information shock they receive or the differential regulatory regime to which they are now subject.

By contrast, the very close geographic neighbors that share a bank with focal firms that transition receive a pure information shock — the bank receives more data about their area, but their regulatory status is unchanged. Neighbor firms receive less financing after an information shock, and the impact of more information on neighbor and focal firms taken together is clearly negative. Consistent with the argument that transitions to COM yield more information for the bank about local firms, we find that after such transitions the bank displays a clear pattern of improved firm sorting and winnowing. Specifically, more neighbor firms subsequently receive no financing from any bank at all, and we show that those firms that do continue to receive funding after a shock tend to exhibit stronger future performance.

Overall, our results suggest that for a large sample of heterogeneous small firms in an emerging market, more information leads to less financing. Information asymmetries thus lead to over-financing of these small businesses, rather than the under-financing that is the focus of much policy attention. A new understanding of the positive and negative outcomes of information production in banking markets is likely to have substantial welfare implications.

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Table I: Exchange-rate adjusted Distance to Threshold and Transitioning to Commercial Status

This table reports the impact of total debt status on whether a firm receives its first commercial loan in month t using different estimation techniques and different samples. The baseline sample is all firm-month combinations of the six cities of interest that have no history of commercial loans up to month $t-1$. The assignment variable is scaled so that one unit equals a hundred thousand soles (i.e., 0.02 = 2,000 soles). All models use thresholds in soles of month t.The first and second model use distance of total debt in soles in month t to the threshold as the assignment variable. The third model uses distance of total debt in soles in month $t-1$ to the threshold as the assignment variable. All other models calculate distance to the threshold use the firm's loan balance at $t-1$ using the following conversation: USD (US dollar) balance$_{t-1}$ * (new exchange rate in Soles/USD) + Soles balance$_{t-1}$. OLS regressions do not include any control variable.

	Dependent Variable: Transitioned to Commercial Status (1/0)				
Estimation:	RD	OLS			
Focal window:		[-0.02,0.02]	[-0.015,0.015]	[-0.025,0.025]	
	(I.1)	(I.2)	(I.3)	(I.4)	(I.5)
Above threshold	0.125***	0.084***	0.069***	0.087***	0.102***
	(24.90)	(9.51)	(6.74)	(11.09)	(20.01)
Polynomials	No	No	No	No	7
R^2		0.02	0.01	0.01	0.03
Sample size	12M	5553	4177	6861	12M
Number of clusters (firms)					435365

***, **,* significant at the 1%, 5% and 10% level. Standard errors are heteroskedasticity-robust and clustered when indicated.

Table II: Information Shocks and Focal Firm Financing in Local Regression Models

Each entry is from a different model analyzing the impact of above threshold loan amounts on focal firm financing. Observations for each regression are at the firm-month level for all MES firms without COM financing at the moment of measuring them. Debt amounts are in logs of soles. All logs are of one plus the variable of interest. 12-month values include all months between +1 and +12, respectively. The Local Regression models fit non-parametric local linear regressions using the optimal bandwidth of Imbens and Kalyanaraman (2009), calculating the model at different multiples (i.e., 100%, 50%, 200%) of this optimal bandwidth.

	Dependent Variable:	
	Log of new financing	Log of new financing over existing debt
Local Regressions (100%)	0.358***	0.374***
	(3.22)	(3.39)
Local Regressions (50%)	0.328**	0.301*
	(2.07)	(1.92)
Local Regressions (200%)	0.555***	0.579***
	(6.90)	(7.26)

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

Table III: Information Shocks and Institutional Changes among Focal Firms

Each entry is from a different model analyzing the impact of above threshold loan amounts on institutional changes of the focal firm. The dependent variables are binary (1/0) indicators for whether the firm used the financial product of interest for the first time in the 12 months following the information shock. The financial products are cash advances through credit cards and credit card purchases that do not include cash advances. The mean of the dependent variable in the top panel is taken from all 18 million observations in the database. *t*-statistics are shown, based on robust standard errors clustered by district.

	Dependent Variable (1/0):	
	Cash advances through credit cards	Credit card usage not including cash advances
Mean of the DV:	0.021	0.017
Local Regressions (100%)	0.024***	0.022***
	(4.28)	(4.64)
Local Regressions (50%)	0.018**	0.012*
	(2.30)	(1.82)
Local Regressions (200%)	0.033***	0.025***
	(7.78)	(6.81)

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

Standard errors are heteroskedasticity-robust and clustered by district.

Table IV: Descriptive Regressions of COM Status and Local Conditions

In Panel A, observations are at the firm-month level for all MES firms and all commercial firms, excluding pure dollar firms. The first dependent variable is defined as the log of total debt of the firm in month t. The second dependent variable is equal to one when the total debt of the firm is above the MES threshold. The explanatory variable of interest, a dummy for whether the firm has a commercial status, is defined at $t-1$. In Panel B, observations are at the firm-month level for a random sample of 300,000 MES firm-month combinations. The dependent variables are the change in their worst debt classification over the next 12 months and a dummy variable for whether the firm exits the financial system within the next 12 months. For each of these random observations, the same dependent variables are calculated and averaged for all their neighbor firms within 100 meters and used as explanatory variables. Matches are made regardless of whether any of these firms share a bank. The regressions thus explain the conditional correlation of a firm's future performance on its average 100-meter neighbors' performance.

Panel A: COM Status and Debt Amounts

	Dependent Variable:	
	Log of debt amount$_t$ (IV.1)	Above threshold $(1/0)_t$ (IV.2)
COM status$_{t-1}$	0.030***	0.004***
	(4.34)	(15.73)
Debt amount$_{t-1}$ fixed effects	Yes	Yes
Year-month fixed effects	Yes	Yes
R^2	0.80	0.98
Sample size	16M	16M
Number of clusters (districts)	80	80

Panel B: How Important are Local Conditions?

	Dependent Variable:	
	Change in firm classification within 12m (IV.3)	Exit from FS within 12m (IV.4)
DV's average for 100m neighbors	0.028***	0.063***
	(3.99)	(6.43)
District × Year-month fixed effects	Yes	Yes
R^2	0.04	0.04
Sample size	176382	242222
Number of clusters (districts)	79	79

***, **,* significant at the 1%, 5% and 10% level. Standard errors are heteroskedasticity-robust and clustered by district.

Table V: Information Shocks and Neighbor Firms' Financing

Observations are at the focal firm / neighbor firm / bank / month level for all neighbors of all focal firms that are within 100 meters of the focal firm and share a bank with the focal firm. Above threshold is defined for focal firms, as in Table I, and its value is imputed to neighboring firms to explain these neighboring firms' financing in the 12 months following the crossing of the MES threhsold by the focal firm. t-statistics are shown, based on robust standard errors clustered by district.

	Dependent Variable: Log of new financing over existing debt					
Focal window:	$\in$ [-0.02,0.02]		$\in$ [-0.015,0.015]		$\in$ [-0.025,0.025]	
Sample:	Neighbors	Neighbors and Focal	Neighbors	Neighbors and Focal	Neighbors	Neighbors and Focal
	(V.1)	(V.2)	(V.3)	(V.4)	(V.5)	(V.6)
Above threshold	-0.093^{***}	-0.082^{***}	-0.077^{***}	-0.063^{***}	-0.054^{***}	-0.048^{***}
	(-3.79)	(-3.62)	(-4.66)	(-3.57)	(-3.79)	(-3.15)
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Border firms quintile fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
District $\times$ Year-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.07	0.07	0.07	0.07	0.07	0.07
Sample size	269630	278619	205563	212382	332644	339463
Number of clusters (districts)	66	68	65	67	67	68

***, **,* significant at the 1%, 5% and 10% level. Standard errors are heteroskedasticity-robust and clustered by district.

Table VI: Information Shocks, Neighbor Firms' Financing, and Industry Overlap

Observations are at the focal firm / neighbor firm / bank / month level for all neighbors of all focal firms that are within 100 meters of the focal firm and share a bank with the focal firm. Above threshold is defined for focal firms, as in Table I, and its value is imputed to neighboring firms to explain these neighboring firms' financing in the 12 months following the crossing of the MES threshold by the focal firm. t-statistics are shown, based on robust standard errors clustered by district.

	Dependent Variable: Log of new financing over existing debt	
Neighbors' industries:	All industries	Not same as focal firm's
	(VI.1)	(VI.2)
Above threshold	-0.054^{*}	-0.054^{*}
	(-1.70)	(-1.94)
Above threshold $\times$ Same industry as focal firm	-0.157^{***}	
	(-4.39)	
Same industry as focal firm	0.044	
	(0.87)	
Age fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Bank fixed effects	Yes	Yes
Border firms quintile fixed effects	Yes	Yes
District $\times$ Year-month fixed effects	Yes	Yes
R^2	0.07	0.07
Sample size	269630	208827
Number of clusters (districts)	66	66

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

Standard errors are heteroskedasticity-robust and clustered by district.

Table VII: Information Shocks and Neighbor Firms' Substitution of Financing

Observations are at the focal firm / neighbor firm / month level for all neighbors of all focal firms that are within 100 meters of the focal firm and share a bank with the focal firm. New debt from other networks is the new financing in periods through +12 that is not coming from banks of the focal firm at the moment of the threshold measurement; that is, this new financing from other networks can be from existing relationships of the neighbor firms that were not shared with the focal firm, or from non-existing relationships of the neighbor firms at the moment of the threshold measurement. t-statistics are shown, based on robust standard errors clustered by district.

	Dependent Variable:		
	Log of new financing from other networks within 12m	Log of new financing from other networks within 12m deflated by log of debt	Number of new banking relationships within 12m
	(VII.1)	(VII.2)	(VII.3)
Above threshold	-0.132^{***}	-0.117^{**}	-0.002
	(-6.62)	(-2.19)	(-1.48)
Age fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Border firms quintile fixed effects	Yes	Yes	Yes
District × Year-month fixed effects	Yes	Yes	Yes
R^2	0.06	0.06	0.06
Sample size	269630	269630	269630
Number of clusters (districts)	66	66	66

***, **,* significant at the 1%, 5% and 10% level. Standard errors are heteroskedasticity-robust and clustered by district.

Table VIII: Exit and Subsequent Performance among Neighbor Firms

Observations are at the neighbor firm-month level in all models except in the third, which uses information at the bank-shock-month level. The first model uses as a dependent variable the difference in loan classification of the worst-classified loan of a neighbor firm between months $t+36$ and t across all banking relationships; the loan classification scheme goes from 0 (normal) to 4 (loss). The second model uses the difference in loan classification of the worst-classified loan of a neighbor firm with the same bank shared with the focal firm. The third model uses a binary (1/0) dependent variable capturing exit from the financial system by month $t+36$, where exit from the financial system is defined as the absence of any banking relation for neighbor firms.

	Dependent Variable:		
	Change in firm classification within 36m (VIII.1)	Change in loan classification within 36m (VIII.2)	Exit FS within 36m (VIII.3)
Above threshold	-0.021^{**}	-0.013^{***}	0.009^{***}
	(-2.49)	(-2.89)	(3.09)
Age fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Bank fixed effects	No	Yes	No
Border firms quintile fixed effects	Yes	Yes	Yes
District × Year-month fixed effects	Yes	Yes	Yes
R^2	0.03	0.04	0.04
Sample size	54503	31667	92963
Number of clusters (districts)	55	53	56

***, **,* significant at the 1%, 5% and 10% level. Standard errors are heteroskedasticity-robust and clustered by district.

Figure 1: Density of Exchange-rate adjusted Distance to Threshold

This figure shows McCrary tests in the vicinity of the discontinuity point.

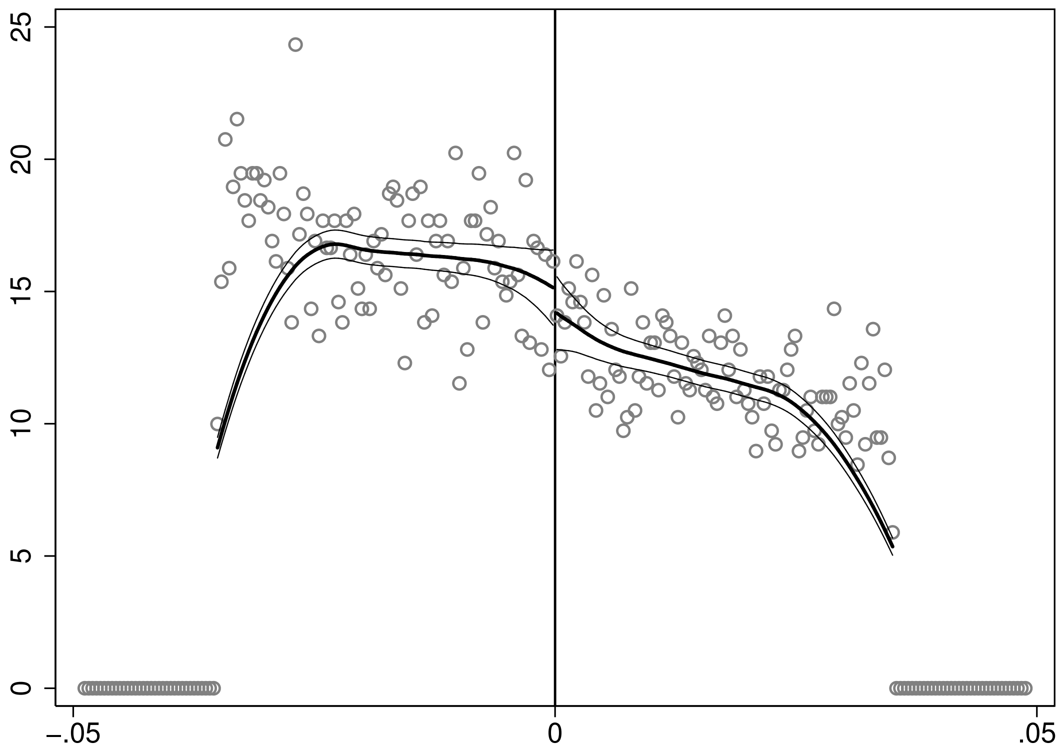

Figure 2: Exchange-rate adjusted Distance to Threshold and Observable Characteristics

Each scattered dot represents a bin of the distance to debt threshold variable. The dashed lines represent 95% confidence intervals of 7th-degree polynomial fits of the dependent variable of interest on the exchange rate-adjusted distance to debt threshold values. All dependent variables are for month t. Age in the financial system is for the firm-year observation and is expressed in years. Number of banking relationships is a stock of the count of relationships for the firm in month t. Firm classification is defined as the worst-classified loan of a firm in month t; the loan classification scheme goes from 0 (normal) to 4 (loss). Troubled debt is the amount in soles of troubled loans defined as refinanced, restructured, past due, or in judicial process, divided by total debt. The estimated differences for each of these variables when compared below and above the threshold with a Chi-squared test have a p-value of 0.46, 0.70, 0.50, and 0.38, respectively.

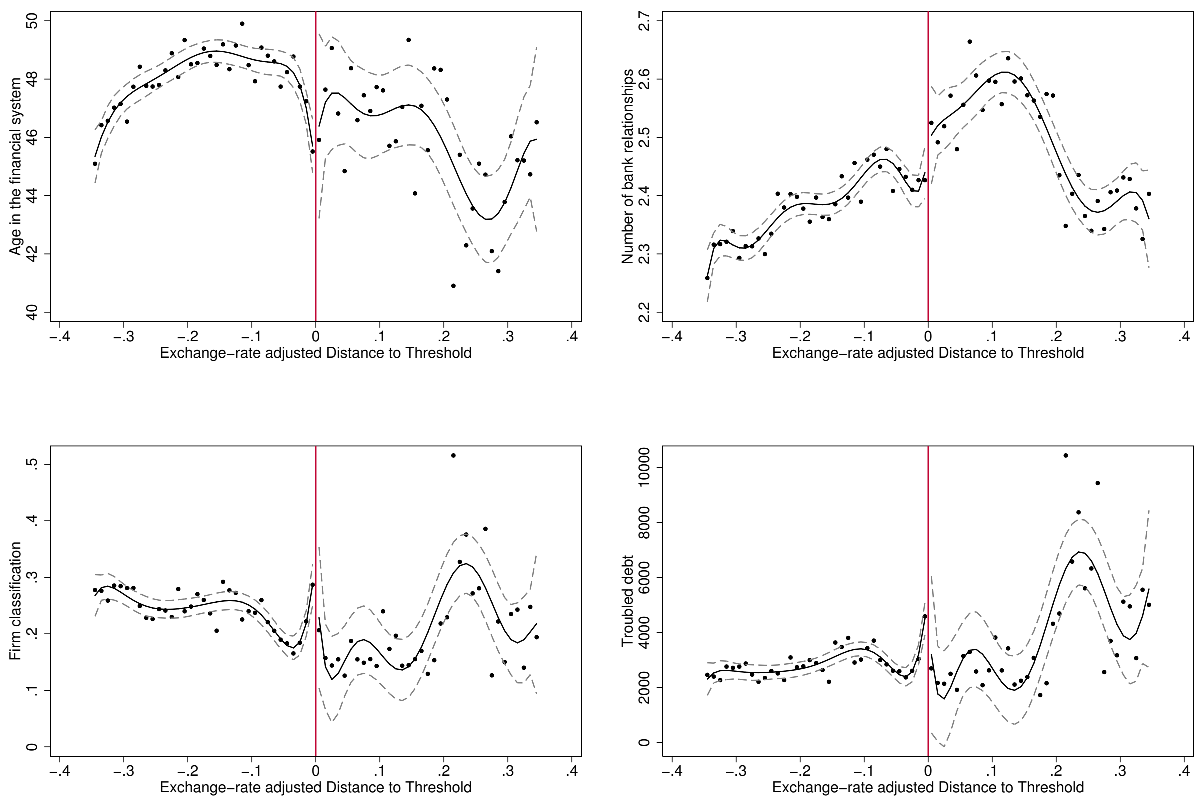

Figure 3: Exchange-rate adjusted Distance to Threshold and Probability of Receiving a Commercial Loan

Each scattered dot represents a bin of the distance to debt threshold variable. The dashed lines represent 95% confidence intervals of 7th-degree polynomial fits of whether the firm received a commercial loan on the exchange-rate adjusted distance to debt threshold values. The estimated difference for this variable when compared below and above the threshold with a Chi-squared test has a p-value of 0.00.