The Choice between Arm's-Length and Inside Debt[*]

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Current Version September 2009

JEL Classification: G21, L11, L14, D44

[*]We thank Philip Bond, Shawn Cole, Hans Degryse, Victoria Ivashina, Robert Marquez, Steven Ongena, N. Prabhala, Maria-Fabiana Penas, Raghu Rajan, Phil Strahan, and Greg Udell for stimulating discussions and seminar participants at American University, the ECB, the ISB 2007 Summer Research Conference in Finance, the 2007 European Finance Association Meetings, the Conference "Information in Bank Asset Prices: Theory and Empirics," George Mason, Mannheim, the 3rd New York Fed/NYU Stern Conference on Financial Intermediation, the 2008 American Finance Association Meetings, Wharton, and the 2009 Western Finance Association Meetings for comments. Special thanks are due to an anonymous referee whose comments considerably broadened the scope of the analysis. Jeff Chin provided outstanding research assistance. The views expressed in this research are those of the authors and do not necessarily represent the policies or positions of the Federal Reserve Board, or the Federal Reserve Bank of Chicago.

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Abstract

Using a unique sample of online and in-person loan transactions, we study the consequences of differential information disclosure for arm's-length (online) and inside (in-person) lending resulting from the chosen mode of bank-borrower interaction. We find that soft private information primarily underlies inside lending whereas hard public information drives arm's-length debt. The bank's relative reliance on public or private information in lending decisions then determines trade-offs between the availability and pricing of credit across loan types. Consistent with economic theory, inside debt carries higher interest rates but is more readily available whereas the opposite holds true for arm's-length lending. Firms, however, anticipate the bank's strategic use of inside information in their disclosure decision, lender switching, and default behavior.

1 Introduction

Banks typically offer two very different types of credit to their corporate customers: loans characterized by inside information and arm's-length debt for which banks compete on a much more equal informational footing (see, e.g., Broecker, 1990; Rajan, 1992; Inderst and Müller, 2006; or Hauswald and Marquez, 2006). Although the theoretical implications of competition between differentially informed lenders are well understood much of the empirical work has focused on "relationship" lending, loosely equated with inside debt, in part because data is more readily available (see, e.g., Petersen and Rajan, 1994; Berger and Udell, 1995; or Elsas, 2005). Furthermore, private arm's-length debt with the attributes posited by the theoretical literature is hard to identify in practice. However, recent advances in lending technologies finally make available new data on credit-market transactions that closely fit the theoretical definition of arm's-length debt: online loans. Hence, we propose to fill this gap in the literature by analyzing the comparative determinants of online ("arm's-length") and in-person ("inside") credit transactions.

Using a unique sample of all online and in-person loan requests by small businesses to a large U.S. bank over a 15-month period, we investigate how a firm's decision to disclose inside information as revealed by its choice of a particular application mode shapes the strategic interaction between bank and borrower across debt types. Although lending standards are identical across the two origination modes, loan officers can individually adjust internal credit scores for in-person applications, which therefore contain a soft, subjective component, but not for online requests. Since Arm's-length and inside debt primarily differ in their information content we first orthogonalize each firm's internal score with Experian's Small Business Intelliscore as a measure of publicly available information to obtain a measure of the lender's private information. We then estimate discrete-choice models of the firm's choice of application mode, the bank's and borrower's respective decisions to offer and accept credit, and linear-regression models of the offered loan's all-in cost. Finally, we study the firm's decision to switch lenders and the likelihood of credit delinquency across loan types.

Our results indicate that firms disclose inside information precisely to build lending relationships. At the same time, they anticipate the lender's strategic use of such information and selfselect into debt types accordingly. In particular, the best and worst credit risks pool in the online market. Borrowers of low and intermediate public credit quality with positive estimates of the bank's signal invest in lending relationships by disclosing inside information. In consequence, public and private information play very different roles across debt products. Public information drives online credit decisions and pricing whereas private information disclosed personally by applicants during origination or collected through prior dealings determines inside-debt offers and their terms.

We also find that the differential information content across debt types shapes the predicted trade-off between the availability and pricing of credit for each lending channel (Broecker, 1990; Rajan 1992; and Hauswald and Marquez, 2006). Arm's-length debt is less readily available but carries lower rates because competition among symmetrically informed banks, which rely on public information, not only drive down its price but also restrict access to credit to minimize adverse selection. By contrast, better informed inside lenders strategically use their information advantage so that their borrowers pay higher rates but enjoy easier access to credit. Given that firms disclose confidential information despite the inside bank's rent-seeking behavior, our findings strongly suggest that in-person and returning borrowers also benefit from close ties to their lender through better access to credit or intertemporal insurance effects. At the same time, competition limits the bank's ability to extract rents from inside borrowers who become more likely to switch lenders, the higher are their credit quality and offered rate.

Since online applications do not permit banks to generate much inside knowledge our data provider discounts whatever private information might transpire in arm's-length lending. By contrast, personal interaction not only offers the opportunity to collect confidential information but the length and depth of the relationship are also good indicators of its quality (see, e.g., Agarwal and Hauswald, 2006; or Mian, 2006). The presence of established business ties unsurprisingly enhances the effect of private information on inside lending but has a much smaller and often insignificant effect on online transactions. Taken together, our findings suggest that the ties sought by borrowers and the type of loan which the bank is willing to grant subtly interact to determine both the extent of inside disclosures and the parties' strategic behavior in equilibrium.

Our main contribution consists in showing how the firm's decision to disclose inside information drives exchange in credit markets. We carefully identify, measure, and analyze the resulting differential information content of arm's-length and inside debt on the basis of a large sample of credit transactions in a unified framework. Given the chosen mode of bank-borrower interaction, we find that the extent to which informational considerations shape the choice of debt product critically depends on the bank's ability to solicit, interpret, and use confidential disclosures. An additional contribution lies in establishing that borrowers also learn about their bank's policies. In particular, the latter's strategic use of private intelligence determines the differential response of firms to banks' information-acquisition and lending strategies across debt types. Finally, our results highlight how technological progress such as online banking and credit scoring allows intermediaries to offer competing loan products, thereby helping them to overcome organizational limitations that in the past led to specialization by market segment or bank size (Berger *et al.,* 2005).

To the best of our knowledge, there is no comparative work on the differential effects of private and public information by loan type. Although Petersen and Rajan (1994), Berger and Udell (1995), Degryse and Van Cayseele (2000), Elsas (2005), and Schenone (2007) have analyzed the importance of relationship banking[1] for the collection of inside information they do not consider the respective use of public and private credit-quality signals across lending modes, which is central to our analysis. An exception is Bharath *et al.* (2006) who also find that information asymmetries induce borrowers to self-select into lending relationships but do not consider arm's-length debt. Focusing on the benefits of relationship lending to borrowers Boot and Thakor (2000) argue that the resulting close business ties allow banks to fend off competition from other lenders and transactional debt, which is consistent with our findings.

The paper also contributes to the nascent literature on the effect of the internet on financial intermediation. Wilhelm (1999, 2001), who analyzes the impact of the internet on the structure of banking markets and, especially, relationship banking, argues that technological advances change the collection and use of (private) information through its codification, which is at the heart of our analysis. Anand and Galetovic (2006) offer empirical predictions on the internet's effect on firm-bank relationships in terms of a shift toward non-relationship modes of interaction, which is only partly borne out by our results. Bonaccorsi di Patti *et al.* (2004) investigate demand complementarities between traditional and online provision of banking services and report that e-banking leads to a reduction in per-customer profitability which mirrors our findings on the competitive pricing of transactional debt.

The paper is organized as follows. In the next section, we review the theoretical literature on information disclosure in credit markets and distill pertinent empirical predictions. Section 3

[1] See the excellent surveys by Boot (2000) and Boot and Schmeits (2005).

describes our data and estimation strategy. In Sections 4 and 5, we analyze the firm's choice of a particular application and debt type and the bank's decision to offer credit and at what price. Section 6 investigates the determinants of the borrower's decision to reject the banks' loan offer and seek credit elsewhere as well as credit delinquency across the two lending channels. The last section discusses further implications and concludes. We relegate all tables to the Appendix.

2 Information Disclosure and Lending Modes

The theoretical literature has typically argued that lending relationships offer particular economic benefits to at least one party, if not both, by allowing intermediaries to gain proprietary information (Rajan, 1992 and Petersen and Rajan, 1994), facilitating renegotiation (e.g., Sharpe, 1990) or intertemporal transfers (e.g., Petersen and Rajan, 1995), and permitting borrowers to learn about their bank (Iyer and Puri, 2007). In fact, a lender's ability to gather proprietary information (Bhattacharya and Chiesa, 1995 and Agarwal *et. al.*, 2009) and to informationally capture borrowers have become the defining attributes of relationship debt. By contrast, banks compete on a more equal informational footing for transactional loans, eroding potential rents but at the price of less readily available credit (Broecker, 1990 and Hauswald and Marquez, 2003).

However, this literature views borrowers as curiously passive. Specifically, it abstracts from their ability to actively facilitate the lender's information acquisition through the voluntary disclosure of confidential facts. In addition, banks and borrowers may interact repeatedly which introduces a further strategic element into the clients' actions.[2] Hence, the usual distinction between inside or relationship debt characterized by the lender's private information on the one hand, and transactional or arm's-length lending without an informational advantage on the other hand does not capture the borrower's strategic behavior.[3] In particular, the chosen mode of bank-borrower interaction should affect the loan transactions through the nature of the disclosed information - public vs. private and verifiable ("hard") vs. unverifiable ("soft") - and the lender's ability to benefit from it (Petersen, 2004).

[2] This disconnect stems form the static nature of the underlying models in which arm's-length and inside debt are treated as perfect substitutes from the borrower's perspective.

[3] Relationship and inside debt are often used as synonyms as are transactional and arm's-length lending; however, the various debt types are not really equivalent in a dynamic setting so that we carefully distinguish between the four different loan categories.

Application type	*De novo*	*Repeat*	**Interaction mode**
Online	HARD-PUBLIC	HARD-PRIVATE	**Arm's length**
In person	PROPRIETARY	SOFT-PRIVATE	**Inside**
Debt type	**Transaction**	**Relationship**	Loan category

Figure 1: Application Mode, Debt Type, and Loan Information

Firms whose representatives apply in person at branch offices and participate in lengthy loan interviews signal their willingness to disclose confidential information and assist in the lenders' effort to gather proprietary intelligence necessary for *inside debt*. By applying online, however, borrowers communicate their reluctance to share such information with the bank, which therefore relies on public information to provide *arm's-length debt*. Firms also choose whether to continue a preexisting *lending relationship*, which permits the bank to use previously gathered soft information, or seek credit for the first time (*transactional loan*). As a result, we would expect lenders to rely primarily on hard public and private information for *de-novo* and returning online applicants, respectively. New in-person requests give rise to proprietary, i.e., a mixture of public and subjective private, intelligence whereas lenders can resort to soft private information for repeat inside applications. Figure 1 summarizes the implications of the application type on bank-borrower interaction, debt type, and information underlying the credit decision.

In-person applications impose costs on firms in terms of not only time and effort but also informational capture (e.g., Rajan, 1992) and spillovers (Bhattarcharya and Chiesa, 1995) from the revelation of privileged information. At the same time, the lender follows up on such intelligence by verifying and interpreting it, which amounts to costly information certification. Hence, one can view the decision to disclose confidential information through in-person applications as the attempt by borrowers to provide a certified signal of creditworthiness in line with Okuno-Fujiwara *et al.* (1990) and Shavell (1994). By contrast, interacting online at arm's-length, which is much less onerous in terms of direct and future indirect costs, corresponds to the voluntary revelation of verifiable information in line with Grossman (1981) and Milgrom (1981).

If confidential information is verifiable by a third party the theory predicts full separation:[4] high-quality borrowers have their disclosures certified by the bank through an inside-lending process whereas low-quality ones opt for arm's-length interaction through online loans, thereby revealing

[4]If the informational costs are sufficiently low the firm reveals all its information in equilibrium which is the "full-disclosure theorem" (see Grossman, 1981; Milgrom, 1981; and Okuno-Fujiwara et al., 1990).

their type. If, however, the relevant information is difficult to verify, e.g., because it is primarily soft, either borrowers attempt to pool by applying online or, in a separating equilibrium, high-quality applicants should withdraw from the market. But this last prediction neglects the bank's ability to generate soft information through inside disclosures and independent verification. Low-quality firms might then apply in person trying to sway the bank in their favor whereas high-quality ones remain in the market but attempt to disguise their creditworthiness by seeking credit online.

The preceding hypotheses rely on a purely static framework, which now views banks as curiously passive. In more realistic settings, repeated interaction affects the parties' informational strategies because firms' disclosure costs fall and lenders build up their soft intelligence over time. Firms estimate not only the cost of confidential disclosures but also what inside information banks might already have when deciding on a particular application process and, in case of an offer, debt type. Given that both online and in-person applicants typically request credit from more than just one lender, including new ones, the simultaneous choice of the parties means that application mode and debt type subtly interact in equilibrium (Figure 1). Once both parties choose, more complex equilibria might result so that empirical evidence can help to identify new avenues for theoretical work on the two-sided matching problem between banks and borrowers.

The advent of online lending without any personal interaction allows us to unambiguously identify arm's-length debt. Similarly, lenders' extensive information acquisition through their branch offices means that in-person applications providing access to confidential facts closely correspond to inside debt. The length and scope of a prior business relationship then reveal whether the parties interact on a transactional or relationship basis. This finer division allows us to differentiate between the business ties that the borrower seeks (arm's length vs. inside) and the type of debt the bank offers (transactional vs. relationship) in equilibrium.

3 Data and Methodology

Our sample consists of all online and in-person applications for new loans to a large U.S. financial institution falling under the purview of small- and medium-sized enterprise (SME) lending in the Basel I Accord (obligation and sales under \$1 million and \$10 million, respectively). During the sample period, the FDIC ranked this lender among the top five deposit-taking institutions. Small-business lending exhibits just the right degree of informational opacity to test theories of information disclosure and production in credit markets. Not only are firms sufficiently opaque for proprietary information to determine lending decisions but also bank competition is intense, several lending channels coexist, and third parties provide credit scores as public measures of credit quality. To the extent that similar informational considerations also affect credit decisions for larger firms, we would expect our results to generalize to the middle-market segment (see Mester *et al.*, 2007).

3.1 Operational Policies

The small-business loans originate both from visits to branch offices and through websites without any personal interaction. If the firm's representative (e.g., owner/manager) personally visits one of the 1,536 branch offices in our sample (out of a total of 1,552)[5] the local loan officer conducts an in-depth interview, transcribes the relevant information into electronic form, and matches it with credit reports for input into the bank's proprietary credit-scoring model.[6] In the process the branch office gathers soft (unverifiable) information, which gives it a considerable amount of autonomy in the assessment, approval, and pricing of loans. In particular, credit decisions ultimately reside with branches because local managers can alter internal credit scores should the client deserve credit in their eyes. These subjective score revisions represent the soft-information component of the bank's internal credit assessment at the center of our analysis. However, branch managers' career prospects and remuneration depend on the overall success of their credit decisions, and local "overrides" are closely monitored by the bank's overall risk management.

To request credit online, the firm submits all the requisite information through a website. A processing center cross-checks the application with credit reports and inputs the relevant data into the lender's scoring algorithm but does not attempt to resolve any informational discrepancies. As a matter of operational policy, there is no personal interaction between the bank and an online applicant so that our lender makes online-credit decision purely based on its internal credit score, which is not subject to any revisions. Similarly, any loan terms, especially interest rates, are solely a function of the firm's credit score, its ability to post collateral, third-party guarantees, etc.

[5]For comparability, the 100 institutions with more than \$10 billion in assets in 2002 operated, on average, 364 branch offices. Their average amount of deposits is about a quarter of our data provider's deposit base.

[6]The whole lending process including the credit decision typically takes four hours to a day from the initial loan interview. In up to 8% of the cases, the branch will invite the applicant back to follow up on open questions, review discrepancies in submitted information with credit reports, discuss the prospects of the firm, etc.

Since the two lending channels effectively compete within the bank neither line of business has an incentive to encourage applicants to simultaneously use the other application mode.

Most monitoring is automated through the daily tracking of current-account movements or balances[7] (whenever available) and prompt debt service. On a monthly basis, the bank collects new credit reports and updates the account's risk profile. Yearly credit reviews and the treatment of overdue loans, however, differentiate ongoing information production across lending channels. On each anniversary of the loan's origination, arm's-length borrowers submit updated financial information online. Inside borrowers have to do so in-person at their branch office, which uses the visit to update its soft information. Similarly, if a payment is between 10 and 20 days late on an inside loan the account officer will personally visit the firm and eventually cut back credit lines.

3.2 Data Description

The sample consists of all applications for new SME loans to our data provider from January 2002 to April 2003 (36,723 observations). We match these records with credit-bureau reports (Experian and Dunn & Bradstreet) on the application date to verify the supplied information and delete applications with missing data (e.g., Experian credit score) or other informational discrepancies such as nonexisting addresses. Since our data provider engaged in several M&A transactions affecting its branch network we omit all re-assigned loan records. Overall, we lose 2,868 credit requests leaving a total of 7,945 online applications and 25,910 in-person ones. Table 1 summarizes our data as a function of the applicant's chosen form of interaction with the bank and reports the P-values of t-tests for the each variable's mean conditional on the lending channel.[8]

To analyze informational effects across lending channels we rely on the bank's own credit assessment summarized by each application's internal credit score. Since our data provider applies a uniform credit-scoring methodology to all loan requests this score is a consistent and meaningful measure of the bank's proprietary information across applicants, branches, and distribution channels. In particular, the algorithm uses a common set of inputs and the same proprietary statistical model. The internal credit score depends neither on the requested loan terms nor the application

[7] Mester *et al.* (2007) find that current-account transactions provide valuable information for loan monitoring in a setting similar to ours.

[8] For confidentiality reasons, the data provider did not allow us to report further descriptive statistics because they could be used to "reverse-engineer" the composition of the loan portfolio.

mode so that it represents the bank's pure credit assessment.[9] Although the lending standards are identical across online and in-branch origination the resulting transactions differ in their information content through the subjective revisions of scores for in-person requests.[10] We use the final scores whose revisions follow bank-wide guidelines and require detailed justification by branches.

Internal scores range from 0 (worst) to 1,850 (best). Their means (medians) are 899 (902) for online applicants and 930 (949) for in-person ones and are significantly different at the 1% level (P-value $< 0.01\%$). To capture public perceptions of credit quality we rely on the firm's Experian Small Business Intelliscores (XSBI). We reverse this widely used score, which measures the likelihood of "serious delinquency" over the next 12 months, and linearly rescale it for comparability with the better known (retail) FICO scores so that the XSBI variable ranges from 300 (worst) to 850 (best). Contrary to the bank score, the average (median) of online applicants' Experian scores is statistically significantly higher: 723 (704) against 716 (705) for in-person applicants (P-value $< 0.01\%$).[11]

Regarding loan terms our data contain the requested amount (means of \$37,333 and \$46,877 for online and in-person applications, respectively), maturity (means of 5.43 and 6.74 years, respectively), existence of collateral (about 42% for online against 55% for in-person applications), and, in case of an offer, annual percentage rate (APR). About 17% (37%) of online (in-person) credit requests were personally guaranteed by guarantors with a monthly income of \$23,745 (\$35,164). 19.6% (28%) of online (in-person) applications are for term loans, the remainder is for credit lines. As a matter of business policy, our bank only offers term loans at fixed rates and credit lines at variable rates so that our Term Loan binary variable also captures the interest-rate type.

To assess the nature of the business relationship, which facilitates the collection of borrower-specific information,[12] we rely on length of the lending relationship (Months-on-Books: 28 and 31 months for online and in-person applications, respectively). Months-on-Books also allows us to define a binary variable Repeat, which takes the value 1 if there exists a prior lending relationship and 0 otherwise (38% for online and 48% for in-person applicants). We also measure the breadth of the business relationship by defining a binary variable Scope in terms of the balance of the firm's

[9]However, the loan terms (amount, maturity, collateral, fixed vs. variable, etc.) affect the pricing decision.

[10]From periodic surveys of its loan officers, the data provider estimates that 20% to 30% of the in-person score ultimately consists of subjective (soft) information.

[11]The U.S. mean (median) for comparable consumer FICO scores is currently 678 (723). See Experian (2000, 2006) for further details on the Small Business Intelliscores and its ability to forecast credit delinquency.

[12]James (1987), Lummer and McConnell (1989), and Elsas (2005) present evidence suggesting that banks gain access to private information over the course of the lending relationship.

current account (at least \$5,000) together with the purchase of at least one other (non-credit) banking product (Scope: about 12.90% of online against 26.44% of in-person applications).

We capture the ease and cost of personally transacting with the bank in terms of time and effort by the driving distance in miles between each firm and its branch office (set to 0 for online ones) and the distance to the closest full-service branch of a competitor.[13] To control for the availability of public information and firm-specific attributes, we rely on the months a particular applicant has been in business (64 vs. 103 months for online and in-person applications, respectively), the firm's monthly net income (\$64,734 vs. \$101,109 for online and in-person applications, respectively), and 38 industry dummy variables based on the applicants' two-digit SIC codes (see Table 1). Similarly, we use state and quarterly dummy variables to account for regional and business-cycle effects. To control for the competitiveness of local credit markets, we rely on the number of bank branches and active lenders in a firm's zip code from the FDIC's Summary of Deposits data base by year. Since banks and their customers might choose to locate in certain areas based on local economic conditions, we include the Case-Shiller Home Price Index (see Case and Shiller, 1987, 1989) matched by application zip code and month.

3.3 Methodology

Our estimation strategy simply retraces the steps of the loan-origination process starting with logistic models of the firm's application mode and the bank's credit decision by lending channel. For loan offers we next specify a linear model of the quoted all-in cost (APR) once again taking into account the debt type. Successful loan applicants then accept or decline loan offers, which allows us to explore the differential information effects on bank competition across lending modes as revealed by an applicant's decision to switch lenders. Lastly, we study loan performance by estimating the likelihood of borrower delinquency by lending channel to assess the incidence of information disclosure on the quality of the bank's credit decision.

For every decision in the lending process, we specify logistic discrete-choice models with separate equations for each application type so that we can compare informational effects across different forms of debt and directly test empirical predictions in a unified econometric framework. Defining

[13] See Degryse and Ongena (2005) on the importance of transportation costs in credit markets.

binary variables 1_{APP} for $APP = repeat, online$ we can report results by application type as

$$E\left[\hat{Y}_i \left| \mathbf{x}_i \right.\right] = \Lambda\left(\mathbf{x}_i'\hat{\boldsymbol{\beta}} + 1_{APP} \cdot \mathbf{x}_i'\hat{\boldsymbol{\gamma}}\right) = \begin{cases} \Lambda\left(\mathbf{x}_i'\left(\hat{\boldsymbol{\beta}} + \hat{\boldsymbol{\gamma}}\right)\right) & \text{for } 1_{APP} = 1 \\ \Lambda\left(\mathbf{x}_i'\hat{\boldsymbol{\beta}}\right) & \text{for } 1_{APP} = 0 \end{cases} \quad (1)$$

and similarly for the linear-regression model of the offered loan's all-in cost (APR) r_i.

We focus on the following key variables: each firm's Experian Small Business Intelliscore ($XSBI$) as a measure of publicly available information, its internal credit score as a measure of the lender's proprietary information, the Scope and Months-on-Book variables measuring the depth of the lending relationship, and a measure of soft private information. To extract this purely private component of credit screens we orthogonalize the internal and Experian scores because the former relies on a mix of public and private intelligence as inputs into the proprietary scoring model. Specifically, we estimate the bank's private credit assessment as the residual $\hat{u}_i$ of the regression

$$\ln\left(1 + IntScore_i\right) = \beta_0 + \beta_1 \cdot \ln\left(1 + XSBI_i\right) + 1_{online}\left[\gamma_0 + \gamma_1 \cdot \ln\left(1 + XSBI_i\right)\right] + u_i \quad (2)$$

which we label the Private-Information Residual (PIR). The R^2 of the above regression is 0.70 and the XSBI coefficients are both positive and statistically significant at 1%.[14]

Given its construction, the online PIR captures hard private intelligence only to the degree that it exists through repeat business, verification of self-reported information with credit reports, and the lender's proprietary scoring methodology. In addition to such hard private information, the in-person PIR also comprises a soft subjective component such as personal impressions of borrower quality which branches incorporate into the internal score through the interview, follow-up, and revision process. Since we compare the PIR across equations in the same specification the online transactions become the *de facto* benchmark that we use to measure the additional and, hence, soft information content of in-person credit applications.

To control for systematic effects in self-selection and approval practices across branches and lending channels, we estimate all our specifications including the internal-score orthogonalization with branch fixed effects and rely on clustered standard errors that are adjusted for heteroskedas-

[14] For confidentiality reasons we cannot report any results for the orthogonalization. The log-linear specification best agrees with the nonlinear nature of Experian's Small Business Intelliscore.

ticity across bank branches and autocorrelation within offices including the online-loan processing center. The estimation of all discrete-choice models proceeds by full-information maximum likelihood and we report their pseudo R^2, which is simply McFadden's likelihood ratio index. Since several of the variables fit better in logarithms than levels we use the former whenever appropriate. In the interest of readability, we suppress all control variables in the tabulation of our results.

Since firms choose lenders that, in turn, make credit decisions the match and resulting loan terms are to some extent endogenous as pointed out by, e.g., Berger *et al.* (2005), who address such problems through instrumental variables. This issue is less of a concern in our case because we analyze all credit applications and offers rather than booked loans so that potential borrowers have not yet chosen whether or not to accept the bank's terms. By including the 1,335 ultimately declined offers, whose omission might give rise to the joint endogeneity of borrower, bank, and loan attributes, we avoid potential simultaneity biases through sample selection. Furthermore, we control for the applicant's choice of bank by including the distance to the branch and nearest full-service competitor as measures of transaction costs.

4 Borrower Disclosure and Inside Information

Specification 1 in Panel A Table 2 reveals that the absence of a prior lending relationship is by far the most important determinant of the firm's decision to select arm's-length debt and not to reveal inside information. Repeat ("relationship") borrowers are almost 22% less likely to apply online than *de-novo* ("transactional") customers. This result is consistent with the notion that firms apply for inside credit precisely to establish long-term lending relationships and are therefore willing to disclose confidential information. The negative marginal effects of the relationship's scope and length, which are only statistically significant in the repeat equation, lend further credence to this interpretation. At the same time, both applicant groups are less likely to opt for arm's-length debt, the higher their public credit score is, but the effect is significantly more pronounced for relationship borrowers (log-likelihood ratio test's $\chi^2 = 3.08$ with a P-value of 0.02%).

Before requesting credit, firms presumably attempt to gauge the likely outcome by assessing banks' operational policies (e.g., Iyer and Puri, 2007). Prior dealings (past origination interview, purchase of other products) might also reveal bank-internal information, especially to returning borrowers. To capture this facet of bank-borrower interaction, we construct a proxy for the firm's estimate of the lender's private information, which we label the Private-Information Estimate (PIE). We predict the firm's internal score in a linear model similar to Equation (2) on the basis of its owner's personal credit score (Experian's National Risk Model), which lenders sometimes use as a substitute (for new firms) for and complement (for established firms) to business scores. The PIE, which measures the estimated divergence between a firm's proprietary and public credit score, is simply the difference between its predicted internal and Experian (XSBI) scores. We see that the results are very similar when we replace the XSBI with the PIE (Specification 2, Panel A).

Since the theoretical literature argues that a firm's own perception of its credit quality should determine its decision to disclose information we would expect applicants to self-select into arm's-length and inside debt on the basis of their public credit quality and Private-Information Estimate. To test this hypothesis, we split the XSBI into terciles, which roughly correspond to lenders' initial sorting of credit requests into accept-review-decline categories, and interact the corresponding binary variables with the PIE (Specification 1, Panel B, Table 2).[15] High-quality firms are now more likely to apply online, especially the higher their estimate of the lender's private opinion is. Good credit risks, who know that they are likely to get a loan offer, apply online to avoid the higher cost of inside debt in terms of time and disclosure requirements. Although the effect appears to be more pronounced for first-time than for repeat customers it is only marginally significantly different across equations (log-likelihood ratio test's $\chi^2 = 1.09$, P-value of 10.28%).

By contrast, firms with observably low credit quality have to assess the value of providing inside information in terms of a loan offer against the cost of doing so. Although they are overall more likely to apply online (Panel A) Specification 1 in Panel B shows that low-quality applicants with a high estimate of the lender's private credit signal are more likely to apply in person. Branch visits allow them to explain problems or economic prospects and to trade inside disclosures for access to credit. Firms with a low public score and Private-Information Estimate might as well save themselves the cost of visiting a branch and disclosing information. Consistent with our initial hypothesis, they attempt to pool with high-quality borrowers in the online market. Once again, the effect is more pronounced for repeat customers (log-likelihood ratio test's $\chi^2 = 2.19$, P-value

[15]To properly assess the interaction terms' sign, marginal effect, and statistical significance in nonlinear specifications such as ours, we follow Ai and Norton (2003).

of 3.26%), if only because of the signalling value of prior loan offers.

Borrowers of middling credit quality face an interesting quandary. Since banks almost automatically review initial credit decisions for such applicants they have the most to gain from confidential disclosures, which might tip the balance in their favor. Consistent with this conjecture, we see that repeat customers in this category are more likely to seek inside credit, especially the ones who think that the bank has a favorable impression of them, i.e., high PIE (log-likelihood ratio test's $\chi^2 = 4.28$, P-value $< 0.01\%$). By contrast, first-time applicants of intermediate credit-quality apparently discount the benefits of disclosing confidential information so that they are indifferent between arm's-length and inside debt (statistically insignificant PIE$\cdot 1_{XSBI-Medium}$). When we reestimate Specification 1 in Panel B for the *de-novo* and repeat subsamples separately as a robustness check we see that the results are virtually unchanged (Specifications 2 and 3).

Firms know that longstanding business ties facilitate the access to credit precisely because loan officers tend to have a better picture of their prospects. In line with our hypotheses, borrowers of low and intermediate credit quality invest in lending relationships through confidential disclosures, hoping for preferential treatment by their bank. High-quality firms with generally easier access to credit and those with the lowest public and private credit-quality signals, which have nothing to lose, pool in the online market. Contrary to the simple predictions of static disclosure models, this finding suggests that borrowers bring about a semi-separating equilibrium, in which their estimates of the lender's private information is the crucial determinant of debt choice, through their decision to provide inside information.

5 Credit Decision by Lending Channel

To see how the firms' disclosure decision affects the differential information content of arm's-length and inside debt, we next analyze the availability and pricing of credit by application mode. Table 1 shows that rejection rates are much higher for online applications (about 61% as compared to 49% for in-person requests) but that online credit spreads are on average much lower for arm's-length than for inside loans (279 and 453 basis points, respectively). Credit appears to be much less readily available online but, when it is, loan rates are much more favorable.

5.1 Credit Availability

Access to credit crucially depends on a firm's willingness to disclose inside information. Both specifications in Panel A of Table 3 reveal that applying online lowers the probability of a loan offer by up to 10% controlling for borrower quality. Lenders know that they compete on a much more level informational playing field in the online market, if not at an outright disadvantage should the firm also be seeking inside credit elsewhere. To avoid potential adverse-selection problems they have to be much more circumspect in their arm's-length lending and refrain from offering credit more often, thereby lowering the probability of an online loan offer (see, e.g., Broecker, 1990 and von Thadden, 2004). Having obtained a prior loan ($1_{repeat} = 1$) surprisingly does not help because it lowers the likelihood of a online loan offer by a further 10%. By contrast, the existence of an inside lending relationship ($1_{repeat} = 1$) is statistically insignificant in the in-person equation.

Specification 1 in Panel A shows that the likelihood of obtaining credit online increases in both the public and proprietary credit-quality signal (XSBI and Internal Score, respectively) but the latter's effect is very small. In the in-person equation, the Experian score (XBSI) is not statistically significant. Instead, positive proprietary credit assessments containing a mixture of soft private and hard public information primarily decide the access to inside credit. This finding suggests that not only the origin of the bank's information - public or confidential sources - but also how it processes and interprets its intelligence matters for inside lending. It may also explain why prior borrowing disproportionately hurts online applicants. Private information garnered from a lending relationship affects inside credit decisions through its soft component. Given that no credible disclosure mechanism exists online, any private information from a prior loan might be more likely than not negative, which would increase rejection probabilities and be consistent with our previous finding that the worst credit risks attempt to pool with the best ones in this market.

To carefully distinguish private from public information, we next replace the Internal Score with its Private-Information Residual and add relationship-PIR interaction terms to the model (Specification 2, Panel A, Table 3). In line with our informational hypotheses (Figure 1), public information drives arm's-length credit decisions because the marginal effect of the private signal (PIR) is negligible (19 times smaller than that of a positive public credit signal). Similarly, private information is the overriding factor in the decision to offer inside credit because the public signal

(XSBI) is again statistically insignificant in the in-person equation. Comparing the relative impact of private information on credit availability across application modes we see that the marginal effect of a positive private credit assessment (PIR) is 15 times greater for inside (in-person) than for arm's-length (online) debt (log-likelihood ratio test's $\chi^2 = 8.99$, P-value $< 0.01\%$). We take this finding as further evidence for the value of information disclosure to both the bank and the borrower.

Banks specifically gather more soft information for borrowers that through their chosen mode of interaction facilitate its collection, certify its credibility, and signal their willingness to disclose confidential facts. The differential impact of the length and scope of the banking relationship across application types confirms this interpretation. Scope and Months-on-Books are statistically insignificant in the decision to offer arm's-length credit but highly significant both in statistical and marginal terms for inside-loan offers. Taken together these effects suggest that a prior lending relationship enhances the likelihood of obtaining inside credit precisely because the disclosure of confidential information is costly and, therefore, credible for in-person applicants, who assist the lender in its collection and interpretation. By contrast, prior interaction is harmful to online borrowers because there is no opportunity for them to credibly disclose privileged intelligence nor for the bank to revise their internal scores in light of such information.

In Panel B of Table 3, we study disclosure effects in credit decisions for two subsamples, which are polar opposites in terms of (inside) information. For first-time online applicants, the bank has to rely on public and self-reported data (Specifications 1 and 3). By contrast, returning in-person borrowers not only facilitate the production of inside information through confidential disclosures but the repeated interaction also makes more private intelligence available over time (Specifications 2 and 4). The results are virtually identical to the full-sample ones in Panel A, which confirms our interpretation of the different informational effects associated with each lending channel.

5.2 Loan Pricing

To investigate the pricing implications of information disclosure, we next estimate linear models of the loan's offered all-in cost (APR). We control for the interest-rate environment with the maturity-matched (interpolated) U.S. Treasury Yield on the loan date and the difference between the 5-year and 3-months US Treasury yield (Term Spread: yield-curve shape). Since loan-rate offers are contingent on the prior credit approval we estimate the specifications with the Heckman correction for sample-selection bias as a precaution. We take the inverse Mills ratio (Lambda) from the preceding discrete-choice model for the bank's credit decision, which is identified by its nonlinear functional form and the omission of the control variables for the interest-rate environment.

Table 4 shows that arm's-length offers are up to 116 basis points (bps) less expensive than inside ones. Similarly, returning borrowers pay a further 64 bps less online but only about 44 bps in person. The credit signals have the same relative importance across lending modes as in the prior credit decision. An increase in the Experian score (XSBI) greatly reduces online loan rates whereas bank perceptions of higher credit quality (Internal Score) lead to a much more modest reduction (Specification 1). The exact opposite is true for inside loans whose quoted price is much more affected by the Internal Score than the XSBI one. Since the Experian score is highly nonlinear in implied credit quality these effects are even more pronounced.

Replacing the bank's credit score with the Private-Information Residual (Specification 2, Table 4), it is statistically insignificant in the online equation but retains its high significance for in-person requests. Private information is presumably of poorer quality online, with the possible exception of returning borrowers, so that our bank disregards it in the pricing of arm's-length debt. The relationship variables Repeat, Scope, and Months-on-Books (statistically) significantly reduce the offered APR for both in-person and online requests. Given the low online switching costs (see also Schenone, 2007), prior business ties might matter less for informational considerations, which the bank addresses through the decision to grant credit, than to retain a customer of proven profitability. In fact, the relationship-PIR interaction terms increase the private-information effect on the pricing of inside loans but are statistically insignificant in the online equation.

Similarly, firm profitability (Net Income) only matters for the pricing of inside debt because financial data are self-reported in online-loan applications and, therefore, susceptible to manipulation. By contrast, loan officers can easily verify such information during the branch visit by in-person applicants (from, e.g., tax filings) and, hence, place more trust in financial statements. The results highlight how the firm's willingness to disclose information subtly interacts with the bank's ability to verify and process it. For arm's-length debt, repeated interaction becomes a substitute for confidential disclosures whereas it acts as a complement in inside lending. Specifications 3 and 4 confirm this interpretation by replicating the analysis for applications with the least soft private information (first-time online) and the most (repeat inside). A comparison of the constants shows that the impact of soft information becomes even more pronounced in this case.

The ability to post collateral or to personally guarantee a loan reduces loan rates by up to 239 and 70 basis points, respectively, depending on the lending channel. This finding contrasts with previous work such as Berger and Udell (1995) and Carey, Post, and Sharpe (1998) who report that collateral is associated with higher spreads. However, their results are probably due to the fact that collateral acts as a proxy for nonmeasured risk characteristics. Our finding that, once we explicitly control for borrower risk through the inclusion of various credit-quality measures (XSBI, internal score, PIR), collateral and guarantees reduce loan rates, and, given our specification, credit spreads bears out this conjecture (see also Inderst and Müller, 2006). In fact, Booth and Booth (2006) also find that, controlling for the interdependence between the decision to pledge collateral and borrowing costs, secured loans typically carry lower spreads.

5.3 The Role of Information Disclosure

Our findings suggest that, consistent with our informational hypotheses (see Figure 1), the nature, quality, and hence use of proprietary intelligence radically differs across lending modes. The limited access to inside information in online lending forces banks to discount any private intelligence and instead to rely on public credit-quality signals. Banks compete on a much more equal informational footing, which borrowers recognize and incorporate into their choice of loan product. By contrast, banks heavily rely on private information gathered through confidential disclosures in inside-credit decisions. Although lenders can use their informational advantage to soften competition through the threat of adverse selection and to extract rents (see, e.g., Hauswald and Marquez, 2006) information disclosure also facilitates inside borrowers' access to credit.

The results also provide very strong empirical evidence for the predicted trade-off between the availability and pricing of credit across lending modes. Firms engage in costly information disclosure only when the benefits in terms of access to credit outweigh the inconvenience of transacting in person and the higher all-in cost controlling for credit quality. As a result, both the best and worst credit risks pool online so that more competitive arm's-length debt combines lower interest rates with a lower probability of an offer. Firms of intermediate credit quality or those with positive estimates of the bank's opinion apply in person to build lending relationships and provide information, which might tip the credit decision in their favor. Although the disclosure of confidential facts facilitates the access to credit it also allows the bank to act strategically as reflected in the higher price of inside debt, controlling for the firm's credit quality. Borrowers essentially trade inside information, which is costly through rent extraction, for more readily available credit.

Our results also shed light on the evolving role of soft information in credit markets. Berger *et al.* (2005) report evidence that small banks rely more on soft information in lending decisions relative to large ones. To the extent that online transactions represent the hard-information benchmark in our two-equation framework, the differential effects of the Private-Information Residual capture the additional soft component of inside information, especially for the two polar informational subsamples. Hence, our findings suggest that technological progress in the form of credit scoring and online lending allows large banks to enter informationally opaque markets while serving the arm's-length segment, too. Combined with soft-information collection through branch offices, they might even hold a competitive advantage in inside debt for small firms due to their larger scale. Given the observed self-selection into arm's-length and inside debt through the application process, our results suggest that bank consolidation and scale might actually benefit small business lending.

6 Lending Competition and Credit Delinquency

In this section we study the decision to decline a loan offer in favor of a competing one and the differential loan performance across origination mode.

6.1 Switching Lenders

By comparing credit offers to actually booked loans and to competing offers inferred from credit-bureau information, we identify 1,335 applicants that decline the bank's terms and seek credit from a competitor.[16] When the degree of information asymmetry varies by borrower, credit transactions become more contested as the informational advantage of the inside lender falls. Since the threat of adverse selection decreases less informed competitors can bid more aggressively by offering credit more often and at lower rates (see, e.g., Hauswald and Marquez, 2006). Hence, the less private information a bank has, the more frequently firms should switch lenders as borne out by Table

[16]This decision is very different from borrower's choice of single vs. multiple banking relationships; see Detragiache *et al.* (2000) and Farinha and Santos (2002).

1. Arm's-length borrowers, whose low transaction costs typically entail many online requests, are almost twice as likely as inside ones, who incur higher application and information costs, to decline a loan offer and seek credit elsewhere (13.39% against 6.98%).

To investigate differences in competitiveness across debt type, we estimate logistic models of the successful loan applicant's decision to switch banks. Specification 1 in Panel A of Table 5 shows that online borrowers are 3% more likely to decline loan offers and seek credit elsewhere. Although repeat borrowers are less likely to change lenders, by far the most important factor in a firm's decision to switch lenders is its estimate of the bank's private information (PIE). However, the marginal effect is almost twice as large for inside borrowers who are more likely to suffer rent extraction through the acquisition of soft private information. Repeating the analysis for our *de-novo* online and repeat in-person subsamples confirms these findings (Specification 2, Panel A).

Since firms are aware of their credit quality we next include their Experian score (Panel B, Table 5). To the extent that banks communicate with customers, if only through loan offers, the latter might also learn about the former's private information so that we add the PIR to both specifications. We see that the public credit-quality signal (XSBI) is by far the most important factor in inducing applicants to decline loan offers. The higher a firm's public score, the easier it becomes to switch lenders, explaining the variable's high marginal effect even for inside borrowers, whose decisions otherwise are more strongly correlated with the PIR. Firms gauge their likely success in obtaining credit from other sources in terms of their publicly observable credit quality. By contrast, private credit-quality signals (PIR) or their estimates (PIE) have a relatively smaller marginal effect. High-quality firms anticipate that banks might attempt to informationally capture inside borrowers and act accordingly. Hence, private information, whose amount and quality is higher for in-person applicants through inside disclosures, also predicts switching behavior.

Unsurprisingly, the higher the quoted loan rate, the more likely firms are to decline the offer and seek credit elsewhere irrespective of the interaction mode. Not only is it easier for better credit risks to obtain competing loan offers, they are also the primary targets for rent extraction through loan pricing and therefore have a larger incentive to switch lenders. Consistent with theoretical predictions, the effect is more pronounced for inside borrowers. Curiously, the relationship variables (Scope, Months-on-Books) reduce the likelihood of declining a loan offer for both online and inside borrowers. The large marginal effects and high statistical significance of the relationship-PIR interaction terms in the in–person equation suggest that informational effects are at work. The bank's desire to retain prior customers might explain a similar effect for transactional borrowers.

Our results are broadly consistent with strategic lending by inside banks.[17] The better the bank's information, i.e., the higher the quality of its credit screen due to the disclosure of inside information or repeated interaction, the easier it becomes to extract rents because the lender has a larger informational advantage over its competitors. Such attempts, however, fail in the arm's-length market where similarly informed competitors can compete more aggressively for online borrowers, who then switch lenders more readily.

6.2 Information Production and Credit Delinquency

Our credit-bureau data also allow us to trace type I (denying a loan to a good credit risk) and type II (offering a loan to a bad credit risk) errors in credit decisions. Regarding the former, 69% of unsuccessful online applicants obtained credit from another source around their request's rejection. By contrast, less than half in-person applicants were able to do so. Although online borrowers have a lower *ex ante* probability of obtaining credit (see Table 1) their application cost is lower, too so that they typically file more loan requests and, therefore, have a higher success probability *ex post*.

In terms of type II errors the incidence of credit delinquency, i.e., loans at least 60 days past-due, is significantly higher for online (3.5%) than inside (2.7%) borrowers within 18 months of origination.[18] To put these rates into perspective, 4.5% of successful arm's-length and 5.8% of inside applicants that switched lenders became delinquent, which is much worse than our bank's own loan performance. Delinquency rates for unsuccessful applicants that obtained a loan elsewhere are very high but do not vary much by lending channel: 24.79% and 24.63% for online and in-person (denied) applications, respectively. Our data provider clearly minimizes type II error in credit decisions by trying to avoid lending to bad credit risks. In doing so, the bank is more successful for inside loans than arm's-length ones, which shows again how the acquisition of inside information through disclosure and lending relationships helps to mitigate adverse-selection problems.

[17] See also Sharpe (1990), Rajan (1992), and von Thadden (2004) on this point. For evidence on the resulting winner's curse in banking see Shaffer (1998).

[18] We choose this window so that the likelihood of a loan becoming overdue is still related to the initial credit assessment and not to subsequent economic events beyond the bank's control. Although the technical definition of default is 180 days past-due lenders typically take action after at most 60 days past-due either writing off the loan, selling it off, or assigning it for collection. As a result, we do not know which of the delinquent loans ultimately experience default although over 90% of loans that are 60 days overdue eventually do according to our data provider.

Table 6, which tabulates the results from estimating a logistic model of credit delinquency, shows that online borrowers are up to 2.9% more likely to default than inside ones. The results also exhibit the usual pattern in information effects across equations (Panel A). Public information (XSBI score) has by far the largest impact on the likelihood of default for both loan types. Positive private information (internal score, PIR) only affects the performance of inside loans in an economically significant manner. Again, proprietary intelligence is primarily useful for mitigating credit risk in inside lending but adds less to the bank's ability to predict the performance of arm's-length loans. The marginal effects of the relationship variables, which are much larger for in-person than online loans, and, especially, the PIR-relationship interaction terms confirm this effect. Confidential disclosures improve inside information, which allows lenders to decrease their borrower-specific credit exposure. Similarly, firm age (Months in Business) significantly decreases the risk of delinquency across both lending modes presumably because more private or public information is available.

In Panel B of Table 6, we study the borrowers' nonpayment decision by replacing our informational variables with their Private-Information Estimate. We see that the better the estimated private credit assessment the less likely borrowers are to fall behind their debt service (Specification 1). Not only is it easier for good credit risks to service their debt but they also have more to lose in terms of the bank's good will. However, the effect is almost three times as large for inside borrowers who increase the amount and quality of the lender's private information through their disclosures. In Specification 2 we confirm the informational effect for our usual two polar subsamples.

7 Conclusion

The advent of online lending and banks' distinct operational practices across distribution channels offer the opportunity to unambiguously identify borrowers who reveal inside information through personal contacts and those who do not and prefer arm's-length debt. Using an exhaustive sample of online and in-person loan requests by small firms, we study the consequences of such disclosures and the respective roles of private and public information in arm's-length and inside debt transactions. We find that borrowers trade inside information, which allows the lender to engage in strategic loan pricing, for easier access to credit. As a result, banks rely on different information for each debt type. Public information primarily drives credit availability and pricing in arm's-length lending whereas soft private information determines inside credit transactions. Since banks have less opportunity to generate borrower-specific information online they compete on a more symmetrically informed basis, which drives down both the price and availability of arm's-length debt.

However, the benefits of inside debt must ultimately outweigh its higher cost. Our results are consistent with the notion that firms selfselect into disclosing inside information when it is in their interest to build lending relationships. At the same time, they recognize the strategic value of such disclosures for banks in their decision to decline loan offers and seek credit elsewhere. Hence the interplay of a firm's decision to disclose inside information or to renew a lending relationship with the bank's strategic use of proprietary intelligence leads to equilibria which are more complex than the typical characterization in terms of transactional vs. relationship or arm's-length vs. inside debt prevalent in the literature. In consequence, our findings point to new avenues for theoretical inquiries into borrowers' and banks' informational strategies arising from confidential disclosures.

Our results also provide support for the contention that inside borrowers profit from the closer ties with their banks. The fact that inside borrowers seek much longer and deeper relationships with their bank than online applicants lends additional credence to this interpretation. Such benefits typically revolve around intertemporal transfers between the parties, i.e., the notion that banks are more willing to finance borrowers that would otherwise not be able to find funding if they can recover the initial costs through future rent extraction or better loan performance. To directly investigate the existence of such benefits, however, one would need panel data on bank-borrower interaction over a longer time period. We leave this question for future research.

Table 1: **Descriptive Statistics**

Lending Channel	**Online Application**			**In-Person Application**			**t-Test**
Variable	Mean	Median	Std Dev	Mean	Median	Std Dev	P-val
Loan Offer (3,135 online, 13,102 in person)	39.46%			50.57%			N/A
Offered annual percentage rate (APR)	6.91%	6.86%	1.93%	8.46%	8.13%	2.72%	< 0.001
Spread over maturity-matched UST (bps)	279	232	191	453	418	278	< 0.001
Decline Offer (420 online, 915 in person)	13.39%			6.98%			N/A
Loan Amount	\$37,333	\$34,320	\$124,921	\$46,877	\$39,749	\$42,693	< 0.001
Maturity (years)	5.43	5.18	2.05	6.74	6.20	5.34	< 0.001
Term Loan (vs. Credit-Line)	19.57%		38.01%	28.06%		46.86%	< 0.001
Collateral	41.54%		41.75%	54.91%		48.64%	< 0.001
Primary Guarantor	17.09%		39.83%	36.59%		47.59%	< 0.001
Primary Guarantor's Monthly Salary	\$23,745	\$20,821	\$107,148	\$35,164	\$32,012	\$88,582	< 0.001
SBA Guarantee	3.74%		14.59%	6.41%		15.90%	< 0.001
Internal Credit Score	899.22	902.05	73.40	930.51	949.38	133.29	< 0.001
Public (XSBI) Credit Score	723.57	704.67	55.87	716.74	703.78	57.55	< 0.001
Private-Information Residual (PIR)	0.0059	0.0003	0.4975	0.0003	0.0005	0.6316	0.468
Private-Information Estimate (PIE)	0.049	0.040	0.287	-0.038	-0.011	0.290	< 0.001
Lending Relationship (prior loan: Repeat)	37.92%			47.72%			N/A
Loan Offer given prior loan ($1_{repeat} = 1$)	17.72%		23.87%	37.06%		24.73%	< 0.001
Months-on-Books	27.68	23.32	48.52	30.79	22.65	43.20	< 0.001
Scope of Banking Relationship	12.90%		17.03%	26.44%		20.66%	< 0.001
Monthly Deposit Account Balance	\$12,649	\$10,835	\$16,040	\$14,363	\$11,014	\$41,669	0.0003
Months in Business	63.88	54.30	41.62	103.56	89.24	103.08	< 0.001
Firm's Monthly Net Income	\$64,734	\$58,521	\$77,808	\$101,109	\$90,108	\$315,463	< 0.001
Case-Shiller House Price Index	168.53	152.10	36.08	166.40	154.79	31.14	< 0.001
Firm-Bank Distance (miles by car)				10.29	2.82	25.12	N/A
Firm-Comp Distance (miles by car)	0.89	0.54	1.16	1.02	0.52	1.53	< 0.001
Number of Branches	4.51	2.77	4.53	4.78	3.00	5.36	< 0.001
Number of Institutions	3.58	2.57	4.15	3.55	2.99	3.38	0.463
Number of Observations		7,945			25,910		33,855

This table presents summary statistics for the variables described in Section 3 for our full sample of 33,855 data points in function of the firm's choice of lending channel. The last column indicates the P-values of a two-sided t-test for the equality of the variables' mean conditional on the application type (wherever appropriate).

Table 2: **Information Disclosure and Loan Type**

Panel A: Application Type and Lending Channel

Specification	**1**						**2**					
Application Type	*De Novo*			Repeat			*De Novo*			Repeat		
Variable	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg
Constant	-2.030	0.001					-2.033	0.001				
Repeat ($1_{repeat} = 1$)				-1.620	0.001	-21.73%				-1.627	0.001	-21.82%
ln(1+XSBI)	-0.711	0.001	-4.51%	-0.913	0.001	-7.86%						
Private-Info. Est.							-0.712	0.001	-4.53%	-0.920	0.001	-7.93%
Scope	-0.330	0.441	-0.06%	-0.376	0.001	-1.73%	-0.332	0.445	-0.06%	-0.376	0.001	-1.75%
ln(1+M. on Books)				-0.778	0.000	-0.83%				-0.781	0.001	-0.85%
Scope·ln(1+XSBI)	-0.280	0.839	-0.07%	-0.128	0.348	-0.03%						
ln(1+MOB)·ln(1+XSBI)				-0.311	0.785	-0.10%						
Scope·PIE							-0.285	0.846	-0.07%	-0.130	0.349	-0.03%
ln(1+MOB)·PIE										-0.317	0.790	-0.10%
ln(1+M. in Business)	0.216	0.962	0.18%	0.226	0.845	0.00%	0.220	0.972	0.18%	0.229	0.852	0.00%
ln(1+Net Income)	-0.019	0.154	-0.48%	-0.025	0.068	-1.49%	-0.019	0.156	-0.48%	-0.025	0.068	-1.51%
Collateral	-0.403	0.597	-0.32%	-0.015	0.234	-0.33%	-0.408	0.609	-0.32%	-0.015	0.237	-0.33%
Primary Guarantor	-0.004	0.272	0.00%	-0.026	0.628	0.00%	-0.004	0.273	0.00%	-0.026	0.632	0.00%
SBA Guarantee	-0.331	0.301	-0.51%	-0.004	0.002	-0.58%	-0.332	0.302	-0.51%	-0.004	0.003	-0.59%
Term Loan	-0.126	0.421	-0.11%	-0.236	0.542	-0.03%	-0.126	0.423	-0.11%	-0.240	0.549	-0.03%
Number of Obs	33,855						33,855					
Pseudo R^2	6.73%						6.75%					

Panel B: Credit Quality and Information Disclosure

Specification	**1**						**2**			**3**		
Application Type	*De Novo*			Repeat			*De Novo*			Repeat		
Variable	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg
Constant	-2.036	0.001					-2.091	0.001		-1.658	0.001	
Repeat ($1_{repeat} = 1$)				-1.608	0.001	-19.99%						
PIE·$1_{XSBI-Low}$	-0.739	0.001	-7.53%	-1.767	0.001	-9.04%	-0.756	0.001	-7.70%	-1.820	0.001	-9.20%
PIE·$1_{XSBI-Medium}$	-0.302	0.279	-0.11%	-1.047	0.001	-5.56%	-0.313	0.282	-0.11%	-1.075	0.001	-5.74%
PIE·$1_{XSBI-High}$	0.100	0.001	2.29%	0.348	0.057	1.70%	0.104	0.001	2.35%	0.358	0.059	1.76%
Scope	-0.311	0.385	-0.05%	-0.375	0.001	-1.66%	-0.317	0.396	-0.05%	-0.377	0.001	-1.67%
ln(1+M. on Books)				0.975	0.001	-0.78%				0.989	0.000	-0.78%
ln(1+M. in Business)	0.213	0.931	0.16%	0.232	0.795	0.00%	0.219	0.961	0.17%	0.239	0.809	0.00%
ln(1+Net Income)	-0.018	0.144	-0.45%	-0.026	0.064	-1.39%	-0.018	0.149	-0.45%	-0.027	0.064	-1.40%
Collateral	-0.377	0.534	-0.29%	-0.015	0.217	-0.30%	-0.388	0.549	-0.29%	-0.015	0.221	-0.31%
Primary Guarantor	-0.004	0.257	0.00%	-0.026	0.581	0.00%	-0.004	0.258	0.00%	-0.026	0.582	0.00%
SBA Guarantee	-0.336	0.268	-0.49%	-0.004	0.002	-0.54%	-0.344	0.277	-0.49%	-0.004	0.002	-0.55%
Term Loan	-0.125	0.390	-0.10%	-0.248	0.507	-0.03%	-0.128	0.397	-0.10%	-0.255	0.512	-0.03%
Number of Obs	33,855						18,479			15,376		
Pseudo R^2	6.81%						5.71%			7.47%		

The table reports the coefficients ("Coeff"), their P-values ("P-val"), and marginal effects ("Marg") for the firm's decision to apply online ($Y = 1$: 7,945 observations) or in-person ($Y = 0$: 25,910 observations). We estimate logistic specifications $\Pr\{Y_i = 1 \,|\mathbf{x}_i\} = \Lambda\left(\mathbf{x}_i'\boldsymbol{\beta} + 1_{repeat} \cdot \mathbf{x}_i'\boldsymbol{\gamma}\right)$, where $1_{repeat} = 1$ for repeat borrowers and 0 otherwise, with branch fixed effects and compute clustered standard errors that are adjusted for heteroskedasticity across and correlation within branch offices. The explanatory variables are proxies for public (XSBI) and private (Private-Information Estimate abbreviated "PIE") information, bank-borrower relationship characteristics (Scope, Months-on-Books abbreviated "MOB"), and firm attributes. We suppress the results for all control variables, i.e., the number of competing lenders and branches, firm-bank and firm-competitor distances, the Case-Shiller house-price index, and business cycle, state, and industry dummies (see Section 3 for details). In panel B, we split the XSBI score by terciles which we interact with the PIE.

We construct the firm's estimate of the bank's private information PIE by regressing the internal score on the owner's personal NRM score, i.e., $IntScore_i = \beta_0 + \beta_1 \cdot \ln(1 + NRM_i) + 1_{online}\left[\gamma_0 + \gamma_1 \cdot \ln(1 + NRM_i)\right] + \varepsilon_i$, and taking the difference between the predicted internal and Experian scores $PIE_i = \widehat{IntScore}_i - XSBI_i$. We obtain the marginal effects by simply evaluating $\frac{\partial \Pr}{\partial x_j} = \Lambda'\left(\mathbf{x}_i'\boldsymbol{\beta}\right)\beta_j$ at the regressors' sample means and coefficient estimates $\hat{\boldsymbol{\beta}}$. The pseudo-R^2 is McFadden's likelihood ratio index $1 - \frac{\log L}{\log L_0}$.

Table 3: **The Credit Decision by Application Type**

Panel A: Full-Sample Results

Specification	**1**						**2**					
Application Type	Online			In-Person			Online			In-Person		
Variable	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg
Constant				-1.5656	0.001					-1.5174	0.001	
eLoan ($1_{online} = 1$)	-1.948	0.001	-8.76%				-2.019	0.001	-10.54%			
Repeat ($1_{repeat} = 1$)	-0.797	0.001	-10.23%	-0.094	0.270	-0.63%	-0.898	0.001	-9.31%	-0.069	0.370	-0.46%
ln(1+XSBI)	0.417	0.001	18.82%	0.238	0.139	0.25%	0.405	0.001	19.07%	0.253	0.142	0.24%
ln(1+Internal Score)	0.186	0.041	0.99%	0.617	0.001	15.02%						
Private-Info. Res.							0.190	0.041	0.99%	0.604	0.001	14.89%
Scope	0.261	0.214	0.25%	0.868	0.001	2.50%	0.246	0.291	0.32%	0.849	0.001	2.22%
ln(1+M. on Books)	0.342	0.764	0.12%	0.921	0.001	1.60%	0.345	0.787	0.12%	0.808	0.001	1.69%
Scope·PIR	0.061	0.418	0.41%	0.148	0.064	1.66%	0.061	0.430	0.41%	0.142	0.062	1.66%
ln(1+MOB)·PIR	0.301	0.395	0.24%	0.040	0.001	1.60%	0.301	0.393	0.24%	0.040	0.001	1.56%
ln(1+M. in Business)	0.864	0.001	0.66%	0.361	0.001	2.64%	0.843	0.001	0.63%	0.345	0.001	2.59%
ln(1+Net Income)	0.669	0.001	1.36%	0.853	0.001	1.12%	0.637	0.001	1.63%	0.829	0.001	0.99%
Collateral	0.521	0.001	2.29%	0.578	0.001	1.94%	0.525	0.001	2.66%	0.561	0.001	1.77%
Primary Guarantor	0.049	0.013	0.18%	0.606	0.001	4.06%	0.049	0.013	0.24%	0.536	0.001	3.88%
SBA Guarantee	-0.355	0.896	-0.33%	-0.122	0.420	-0.39%	-0.336	0.891	-0.34%	-0.117	0.509	-0.30%
Term Loan	-0.026	0.069	-0.07%	-0.482	0.001	-0.64%	-0.025	0.080	-0.06%	-0.446	0.001	-0.62%
Number of Obs	33,855						33,855					
Pseudo R^2	12.40%						12.35%					

Panel B: De Novo Online vs. Repeat In-Person Applications

Specification	**1**			**2**			**3**			**4**		
Application Type	*De Novo* Online			Repeat In-Person			*De Novo* Online			Repeat In-Person		
Variable	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg
Constant	-1.517	0.001		-1.996	0.001		-1.311	0.001		-2.065	0.001	
ln(1+XSBI)	0.378	0.001	17.53%	0.250	0.120	0.22%	0.338	0.001	18.39%	0.236	0.137	0.24%
ln(1+Internal Score)	0.158	0.034	0.91%	0.631	0.001	14.91%						
Private-Info. Res.							0.222	0.040	0.94%	0.748	0.001	13.62%
Scope	0.311	0.184	0.24%	1.070	0.001	2.14%	0.277	0.246	0.28%	0.880	0.001	2.08%
ln(1+M. on Books)				0.852	0.001	1.33%				0.693	0.001	1.76%
Scope·PIR	0.050	0.444	0.38%	0.142	0.059	1.63%	0.058	0.392	0.39%	0.124	0.058	1.54%
ln(1+MOB)·PIR				0.039	0.001	1.34%				0.035	0.001	1.36%
ln(1+M. in Business)	0.826	0.001	0.56%	0.357	0.001	2.31%	0.810	0.001	0.62%	0.291	0.001	2.20%
ln(1+Net Income)	0.796	0.001	1.19%	1.051	0.001	1.14%	0.709	0.001	1.42%	0.979	0.001	0.87%
Collateral	0.523	0.001	2.11%	0.476	0.001	1.90%	0.515	0.001	2.47%	0.576	0.001	1.70%
Primary Guarantor	0.045	0.013	0.17%	0.615	0.001	3.77%	0.050	0.011	0.22%	0.559	0.001	3.61%
SBA Guarantee	-0.407	0.868	-0.32%	-0.135	0.353	-0.32%	-0.405	0.801	-0.31%	-0.139	0.526	-0.31%
Term Loan	-0.026	0.060	-0.07%	-0.427	0.001	-0.65%	-0.022	0.069	-0.06%	-0.454	0.001	-0.55%
Number of Obs	4,932			12,363			4,932			12,363		
Pseudo R^2	13.31%			10.20%			13.28%			10.71%		

This table reports the results from estimating logistic discrete-choice models of the bank's credit decision by loan type for our full sample (Panel A) and the first-time online vs. repeat in-person applications (Panel B) using maximum likelihood with branch fixed effects and clustered standard errors that are adjusted for heteroskedasticity across and correlation within branch offices. The dependent variable is the bank's decision to offer credit ($Y = 1$: 3,135 and 13,102 observations for online and in-person loans, respectively) in the specification $\Pr\{Y_i = 1\,|\mathbf{x}_i\} = \Lambda\left(\mathbf{x}_i'\boldsymbol{\beta}+1_{online}\cdot\mathbf{x}_i'\boldsymbol{\gamma}\right)$, where $1_{online} = 1$ for online applications and 0 otherwise and Λ is the logistic distribution function (see Table 2 for further methodological details).

The explanatory variables are our proxies for public (Experian's XSBI), proprietary (Internal Score) and private (Private-Information Residual) information, bank-borrower relationship characteristics, firm attributes, and various (nonreported) control variables (see Section 3 for a description of the variables). The Private-Information Residual (abbreviated "PIR") measures the bank's private credit assessment that we obtain from orthogonalizing the internal and Experian scores. Specifically, the PIR for each observation is the residual $\hat{u}_i$ of the branch fixed-effects regression $\ln(1 + IntScore_i) = \beta_0 + \beta_1 \cdot \ln(1 + XSBI_i) + 1_{online}\left[\gamma_0 + \gamma_1 \cdot \ln(1 + XSBI_i)\right] + u_i$.

Table 4: **Determinants of the Offered Loan Rate**

Specification	**1**				**2**				**3**		**4**	
Loan Type	Online		In-Person		Online		In-Person		*De Novo* Online		In-Person Repeat	
Variable	Coeff	P-val	Coeff	P-val	Coeff	P-val	Coeff	P-val	Coeff	P-val	Coeff	P-val
Constant			7.382	0.001			6.843	0.001	7.845	0.001	6.138	0.001
eLoan ($1_{online} = 1$)	-1.164	0.001			-0.954	0.001						
Repeat ($1_{repeat} = 1$)	-0.642	0.021	-0.440	0.019	-0.642	0.012	-0.388	0.036				
ln(1+XSBI)	-1.048	0.001	-0.543	0.001	-0.924	0.001	-0.475	0.001	-0.588	0.001	-0.326	0.001
ln(1+Internal Score)	-0.293	0.001	-1.313	0.001								
Private-Info. Res.					-0.100	0.377	-0.460	0.001	-0.055	0.257	-0.370	0.001
Scope	-0.424	0.001	-0.274	0.001	-0.390	0.001	-0.291	0.001	-0.298	0.001	-0.192	0.001
ln(1+M. on Books)	-0.711	0.045	-0.322	0.001	-0.604	0.030	-0.341	0.001			-0.249	0.001
Scope·PIR					-0.026	0.687	-0.163	0.001	-0.024	0.565	-0.181	0.001
ln(1+MOB)·PIR					-0.009	0.928	-0.121	0.018			-0.088	0.018
ln(1+M. in Business)	-0.791	0.180	-0.130	0.354	-0.737	0.054	-0.126	0.350	-0.545	0.036	-0.132	0.292
ln(1+Net Income)	-0.279	0.310	-0.702	0.001	-0.267	0.350	-0.630	0.001	-0.231	0.314	-0.693	0.001
Collateral	-2.169	0.001	-2.179	0.001	-2.390	0.001	-1.959	0.001	-1.764	0.001	-2.091	0.001
Primary Guarantor	-0.699	0.043	-0.274	0.001	-0.689	0.023	-0.243	0.001	-0.393	0.012	-0.191	0.001
SBA Guarantee	0.409	0.381	0.300	0.025	0.380	0.328	0.296	0.026	0.259	0.203	0.314	0.031
Term Loan	1.242	0.037	0.350	0.001	1.060	0.043	0.268	0.001	0.959	0.027	0.192	0.001
ln(1+Maturity)	-0.339	0.001	-0.675	0.001	-0.266	0.001	-0.494	0.001	-0.233	0.001	-0.391	0.001
UST Yield	0.241	0.001	0.254	0.001	0.254	0.001	0.271	0.001	0.206	0.001	0.263	0.001
Term Spread	0.266	0.001	0.384	0.007	0.266	0.001	0.382	0.000	0.204	0.001	0.334	0.000
Lambda	0.540	0.236	-0.283	0.464	0.506	0.218	-0.251	0.411	0.513	0.181	-0.190	0.303
Number of Obs	16,237				16,237				1,902		6,608	
Adjusted R^2	17.25%				17.20%				7.90%		6.39%	

This table reports the results from estimating linear models of the offered loan rate (APR: all-in cost of the loan) of the form $r_i = \mathbf{x}_i'\boldsymbol{\beta}+1_{online} \cdot \mathbf{x}_i'\boldsymbol{\gamma} + \varepsilon_i$, where $1_{online} = 1$ for online applications and 0 otherwise (Specifications 1 and 2), by OLS with branch fixed effects and clustered standard errors that are adjusted for heteroskedasticity across and correlation within branch offices. The explanatory variables are our proxies for public, proprietary, and private information, bank-borrower relationship characteristics, firm attributes, and various control variables whose estimates we do not report in the interest of readability. To control for the interest-rate and yield-curve environment we include the maturity-matched US Treasury yield (UST Yield) and the spread between five-year and three-month US Treasury yields (Term Spread) on the offer date. Lambda is the inverse Mills ratio (hazard rate) for the logistic distribution required by the Heckman procedure for sample-selection bias. Specifications 3 and 4 report the results for the first-time online and returning in-person applicants, respectively. See Section 3 for a description of the variables.

Table 5: **The Decision to Decline a Loan Offer**

Panel A: Borrower's Private-Information Estimate and Subsample Results

Specification	**1**						**2**			**3**		
Loan Type	Online			In-Person			*De Novo* Online			Repeat In-Person		
Variable	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg
Constant				-3.1000	0.001		-1.845	0.001		-1.533	0.001	
eLoan ($1_{online} = 1$)	0.947	0.001	3.17%									
Repeat ($1_{repeat} = 1$)	-0.213	0.012	-1.17%	-0.345	0.001	-2.51%						
Private-Info. Est.	0.840	0.016	7.52%	0.968	0.001	13.83%	0.584	0.012	4.47%	0.661	0.001	10.35%
Scope	-1.435	0.001	-4.02%	-0.925	0.033	-2.96%	-1.207	0.001	-2.05%	-0.793	0.024	-2.31%
ln(1+M. on Books)	-1.365	0.001	-3.07%	-1.303	0.001	-2.58%				-0.910	0.001	-1.68%
Scope·PIE	0.095	0.596	0.42%	0.469	0.001	2.79%	0.059	0.414	0.31%	0.316	0.001	2.09%
ln(1+MOB)·PIE	0.037	0.750	0.19%	0.499	0.001	2.93%				0.289	0.001	1.85%
ln(1+M. in Business)	-0.194	0.262	-0.25%	-0.222	0.026	-0.14%	-0.110	0.231	-0.17%	-0.168	0.023	-0.13%
ln(1+Net Income)	1.518	0.001	2.32%	1.459	0.001	1.93%	1.098	0.001	1.88%	1.317	0.001	1.00%
Collateral	0.029	0.767	0.14%	0.113	0.596	0.18%	0.021	0.627	0.09%	0.064	0.405	0.15%
Primary Guarantor	1.705	0.001	2.72%	1.542	0.001	3.02%	1.247	0.001	1.47%	1.070	0.001	2.22%
SBA Guarantee	0.880	0.001	0.06%	0.187	0.023	0.09%	0.580	0.001	0.05%	0.122	0.012	0.06%
Term Loan	-0.481	0.001	-0.28%	-0.010	0.596	-0.06%	-0.333	0.001	-0.16%	-0.007	0.382	-0.03%
APR	0.222	0.001	7.69%	0.272	0.001	7.52%	0.113	0.001	5.69%	0.179	0.001	4.19%
ln(1+Loan Amount)	-1.568	0.001	2.80%	-1.731	0.001	-1.83%	-1.036	0.001	2.53%	-1.344	0.001	-1.46%
ln(1+Maturity)	-0.153	0.001	-0.84%	-0.218	0.001	-1.14%	-0.105	0.001	-0.58%	-0.186	0.001	-0.84%
Number of Obs	16,237						1,902			6,608		
Pseudo R^2	6.44%						5.04%			5.87%		

Panel B: Lender's Private Information

Specification	**1**						**2**					
Loan Type	Online			In-Person			Online			In-Person		
Variable	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg
Constant				-3.817	0.001					-4.280	0.001	
eLoan ($1_{online} = 1$)	0.900	0.001	4.19%				1.006	0.001	3.71%			
Repeat ($1_{repeat} = 1$)	-0.276	0.015	-1.69%	-0.325	0.001	-2.61%	-0.283	0.019	-1.83%	-0.397	0.001	-2.97%
ln(1+XSBI)	1.593	0.001	22.27%	0.638	0.001	25.09%	1.401	0.001	21.75%	0.723	0.001	27.69%
ln(1+Internal Score)	0.238	0.001	2.71%	0.478	0.001	7.86%						
Private-Info. Res.							0.301	0.018	3.49%	0.445	0.001	9.26%
Scope	-1.865	0.001	-4.47%	-0.972	0.020	-3.91%	-1.767	0.001	-4.16%	-1.022	0.043	-3.16%
ln(1+M. on Books)	-1.387	0.001	-2.91%	-1.491	0.001	-3.62%	-1.460	0.001	-3.64%	-1.465	0.001	-3.39%
Scope·PIR							0.128	0.660	0.42%	0.508	0.001	3.32%
ln(1+MOB)·PIR							0.051	0.875	0.20%	0.683	0.001	3.11%
ln(1+M. in Business)	-0.250	0.315	-0.25%	-0.260	0.018	-0.19%	-0.269	0.275	-0.29%	-0.294	0.028	-0.20%
ln(1+Net Income)	2.299	0.001	1.41%	1.730	0.001	2.22%	1.945	0.001	2.36%	1.955	0.001	2.37%
Collateral	0.039	0.797	0.13%	0.163	0.527	0.16%	0.037	0.838	0.15%	0.157	0.764	0.24%
Primary Guarantor	1.798	0.001	3.37%	1.806	0.001	4.55%	1.748	0.001	3.37%	1.818	0.001	4.11%
SBA Guarantee	1.198	0.001	0.03%	0.235	0.023	0.10%	1.033	0.001	0.08%	0.238	0.025	0.11%
Term Loan	-0.626	0.001	-0.37%	-0.012	0.897	-0.03%	-0.560	0.001	-0.30%	-0.010	0.852	-0.06%
APR	0.265	0.001	9.44%	0.358	0.001	12.18%	0.233	0.001	8.67%	0.329	0.001	10.61%
ln(1+Loan Amount)	-1.883	0.001	3.96%	-1.891	0.001	-2.04%	-1.966	0.001	3.71%	-1.896	0.001	-2.17%
ln(1+Maturity)	-0.162	0.001	-0.87%	-0.257	0.001	-1.36%	-0.162	0.001	-0.87%	-0.230	0.001	-1.45%
Number of Obs	16,237						16,237					
Pseudo R^2	6.47%						6.72%					

We estimate logistic models of the borrower's decision to decline ($Y = 1$: 420 online and 915 in-person observations) a loan offer by full-information maximum likelihood for successful applicants with branch fixed effects and clustered standard errors that are adjusted for heteroskedasticity across and correlation within branch offices. In addition to our usual control variables we include the maturity-matched US Treasury yield and the spread between five-year and three-month US Treasury yields on the offer date but do not report the results. In Panel A we replace the usual informational variables (Panel B) with the firm's estimate of the lender's private information (PIE) and split the sample. See Section 3 for a description of the variables and the notes to Tables 2 and 3 for further details.

Table 6: **The Likelihood of Credit Delinquency**

Panel A: Lender's Private Information

Specification	**1**						**2**					
Loan Type	Online			In-Person			Online			In-Person		
Variable	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg
Constant				-1.035	0.001					-1.051	0.001	
eLoan ($1_{online} = 1$)	1.072	0.001	2.69%				0.968	0.001	2.92%			
Repeat ($1_{repeat} = 1$)	-0.260	0.001	1.10%	-0.440	0.001	1.94%	-0.298	0.001	1.27%	-0.489	0.001	2.03%
ln(1+XSBI)	-1.697	0.001	-19.37%	-0.773	0.001	-19.47%	-1.538	0.001	-20.25%	-0.785	0.001	-19.35%
ln(1+Internal Score)	-0.218	0.001	-4.41%	-0.387	0.001	-8.19%						
Private-Info. Res.							-0.233	0.001	-3.79%	-0.087	0.001	-10.39%
Scope	-0.410	0.001	-1.04%	-0.663	0.001	-2.52%	-0.510	0.001	-1.05%	-0.614	0.001	-2.44%
ln(1+M. on Books)	-0.950	0.024	-0.78%	-0.290	0.001	-3.39%	-0.861	0.001	-0.87%	-0.276	0.001	-2.61%
Scope·PIR							-0.557	0.001	-1.67%	-0.317	0.001	-3.25%
ln(1+MOB)·PIR							-0.454	0.338	-0.30%	-0.168	0.012	-1.54%
ln(1+M. in Business)	-0.776	0.048	-2.75%	-0.015	0.730	-2.94%	-0.760	0.076	-3.43%	-0.017	0.814	-3.12%
ln(1+Net Income)	-0.492	0.001	-2.00%	-0.080	0.001	-1.63%	-0.480	0.001	-2.36%	-0.090	0.001	-1.65%
Collateral	-0.460	0.001	-1.37%	-0.175	0.001	-1.79%	-0.534	0.001	-1.52%	-0.188	0.001	-2.01%
Primary Guarantor	-0.345	0.001	-2.53%	-0.491	0.001	-1.21%	-0.384	0.001	-2.28%	-0.431	0.001	-1.52%
SBA Guarantee	2.809	0.001	0.28%	0.479	0.001	2.55%	3.015	0.001	0.22%	0.454	0.001	3.03%
Term Loan	0.235	0.001	0.41%	0.629	0.001	0.21%	0.251	0.001	0.49%	0.654	0.001	0.27%
APR	2.036	0.001	4.83%	0.914	0.018	6.65%	1.737	0.001	4.75%	0.955	0.010	6.41%
ln(1+Loan Amount)	-0.895	0.001	-8.56%	-1.339	0.001	-9.17%	-0.989	0.001	-10.84%	-1.369	0.001	-8.35%
ln(1+Maturity)	-0.421	0.001	-0.91%	-0.694	0.001	1.28%	-0.412	0.001	-1.08%	-0.687	0.001	-1.49%
Number of Obs	14,902						14,902					
Pseudo R^2	12.19%						12.09%					

Panel B: Borrower's Private-Information Estimate and Subsample Results

Specification	**1**						**2**			**3**		
Loan Type	Online			In-Person			*De Novo* Online			Repeat In-Person		
Variable	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg	Coeff	P-val	Marg
Constant				-1.083	0.001		-0.992	0.001		-0.909	0.001	
eLoan ($1_{online} = 1$)	1.080	0.001	2.55%									
Repeat ($1_{repeat} = 1$)	-0.231	0.001	1.18%	-0.463	0.001	1.60%						
Private-Info. Est.	-0.264	0.001	-3.16%	-0.099	0.001	-8.80%	-0.220	0.001	-2.08%	-0.073	0.001	-7.32%
Scope	-0.585	0.001	-0.86%	-0.658	0.001	-2.01%	-0.516	0.001	-0.60%	-0.487	0.001	-1.62%
ln(1+M. on Books)	-0.862	0.001	-0.78%	-0.309	0.001	-2.50%	-0.771	0.001	-0.56%	-0.219	0.001	-2.48%
Scope·PIE	-0.562	0.001	-1.34%	-0.343	0.001	-2.76%	-0.492	0.001	-1.19%	-0.254	0.001	-2.79%
ln(1+MOB)·PIE	-0.455	0.305	-0.29%	-0.189	0.011	-1.36%	-0.421	0.082	-0.26%	-0.149	0.009	-1.27%
ln(1+M. in Business)	-0.411	0.001	-1.98%	-0.491	0.001	-1.38%	-0.768	0.047	-2.41%	-0.011	0.969	-2.62%
ln(1+Net Income)	-0.837	0.064	-2.77%	-0.018	0.671	-2.79%	-0.440	0.001	-1.76%	-0.082	0.001	-1.34%
Collateral	-0.542	0.001	-2.20%	-0.103	0.001	-1.33%	-0.569	0.001	-1.00%	-0.189	0.001	-1.61%
Primary Guarantor	-0.544	0.001	-1.42%	-0.199	0.001	-1.62%	-0.458	0.001	-1.37%	-0.357	0.001	-1.44%
SBA Guarantee	3.037	0.001	0.20%	0.488	0.001	2.87%	3.125	0.001	0.14%	0.324	0.001	2.51%
Term Loan	0.286	0.001	0.42%	0.681	0.001	0.24%	0.287	0.001	0.29%	0.676	0.001	0.21%
APR	2.059	0.001	4.59%	0.991	0.009	5.84%	1.587	0.001	4.15%	0.849	0.005	4.58%
ln(1+Loan Amount)	-0.996	0.001	-9.69%	-1.582	0.001	-7.27%	-0.979	0.001	-7.77%	-1.206	0.001	-7.67%
ln(1+Maturity)	-0.413	0.001	-0.98%	-0.770	0.001	-1.31%	-0.376	0.001	-0.71%	-0.590	0.001	-1.24%
Number of Obs	14,902						1,792			6,093		
Pseudo R^2	12.26%						6.94%			8.02%		

We estimate logistic models of the likelihood of credit delinquency (60 days overdue; $Y = 1$: 91 and 319 online and in-person observations, respectively) within 18 months of origination for the actual loans booked by the bank (14,902 observations) with branch fixed effects and clustered standard errors that are adjusted for heteroskedasticity across and correlation within branch offices. In Panel B we replace the informational variables with the applicant's estimate of the lender's private information (PIE) and separately estimate the model for the de-novo online and repeat in-person subsamples. See Section 3 for a description of the variables and the notes to Table 5 for further details.

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