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MORE DATA, MORE CREDIT? INFORMATION SHARING AND BANK CREDIT TO HOUSEHOLDS

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More Data, More Credit? Information Sharing and Bank Credit to Households

(Több adat, több hitel? Információ-megosztás és lakossági hitelezés)

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Contents

Abstract

We exploit a nation-wide introduction of mandatory disclosure of borrowers' total credit exposures and show that sharing such information increases credit access independent of borrowers' history. Differentiating between borrowers applying to competitor banks and those reapplying to their current banks, as well as between borrowers with and without default history, we find an overall increase in credit access measured by both loan application acceptance and credit amount. While credit access increases, default rates decrease, generating an increase in aggregate welfare. (78 words)

JEL Codes: G21, G28.

Keywords: information sharing, bank lending, household access to credit.

Összefoglaló

A pozitív adóslista kötelező érvényű bevezetésének hatását vizsgálva megállapítottuk, hogy a bankok közötti információ-megosztás javítja a lakosság hozzáférését a hitelekhez; függetlenül attól, hogy a hitelfelvevőknek milyen a hiteltörténete. Becslésünk szerint, melyben a hitelfelvevőket megkülönböztetjük aszerint, hogy a mostani bankjuknál vagy egy új banknál jelentkeznek hitelért, illetve, hogy korábban volt-e már nem-teljesítő hitelük, a hitelhez jutás valószínűsége és a kapott hitel összege egyaránt nő. Azt is találjuk, hogy az információ-megosztás következtében növekvő hitelezés mellett a nem-teljesítések aránya csökken, ami az aggregált jólét növekedését jelzi.

1 Introduction

When making lending decisions, banks need sufficient knowledge about their potential borrowers to identify creditworthy projects. Since the seminar paper by Stiglitz (1981), asymmetric information between banks and individuals applying for loans has been investigated as a key reason generating inefficiencies in the operation of loan markets. Obtaining borrower information is therefore crucial for improving lending decisions. One traditional way through which banks acquire such information is learning about borrower quality over the lending relationship (e.g., (Fischer, 1990); (Sharpe, 1990); (Rajan, 1992); (von Thadden, 2004); (Hauswald, 2006)).[1] Even when borrowers move across banks part of this information – the hard, verifiable data – can be utilized if the bank, where a borrower has outstanding exposure and a history of repayment, can share it with the other bank where the borrower is applying for credit for the first time (or after a long hiatus).

In this paper we study the impact of "positive information sharing" between banks – i.e., banks' disclosing information on borrowers' debt exposure – on bank competition, borrower credit access, and the quality of banks' loan portfolio. The impact of positive information sharing on the credit market is not straightforward *a priori*. On the one hand, such sharing reduces asymmetric information problems thereby reducing the cost of granting a loan. While this *'information effect'* can be present in more general contexts where lenders receive data also from non-lenders (e.g., utility companies, employers), when banks share borrower-level information among themselves, banking competition may intensify, generating an additional, so-called *'competition effect'*. Once competitor banks obtain positive signals about a borrower, increased competition may result in better credit terms by all banks, more borrower poaching, and, consequently, in a loss of established bank relationships. Although the information-based cost reduction is welfare enhancing, more aggressive lending and customer poaching can have negative impact on loan performance and welfare, for a given quality of the borrower population. Hence it is ultimately an empirical question which effect dominates, and the question we set out to answer in this paper.

Combining the nation-wide introduction of positive information sharing with uniquely comprehensive and detailed credit register data, we find that following the introduction of positive information sharing aggregate household credit access increases, while at the same time, the aggregate household default rate decreases. We therefore conclude that the introduction of positive information sharing generates an increase in total welfare.

Indeed, we build our study around the introduction of mandatory positive information sharing (henceforth at times abridged as "the introduction", and in our empirical exercises studied as "the event"), creating, for banks in Hungary, a unique database effectively containing the universe of *all* household credit transactions. Mandatory positive information sharing was introduced in Hungary by the Law CXXII of 2011 and applied to all individual borrowers. According to the Law, lenders, when being approached by a new loan applicant, could inquire about the applicant's outstanding debt exposure at other lending institutions. The Law was implemented in May 2012 by the expansion of an already existing public credit registry that shared only negative data, i.e., data on borrowers' past delinquencies.[2] Thus, the way of implementation allows to examine the impact of positive information sharing on banks' lending to households, by estimating access to credit and allocated amounts for all loan applicants before and after the introduction of the Law.

[1] Reviews of the bank-firm relationship literature can be found in, e.g., Boot (2000), Ongena and Smith (2000), Elyasiani and Goldberg (2004), Degryse, Kim, and Ongena (2009).

[2] The new "Household Registry" was established as part of the existing Hungarian Central Credit Information System (or Központi Hitelinformációs Rendszer, abbreviated as KHR) that shared only negative data. Default information sharing can be mutually beneficial since it can improve lenders' decision vis-à-vis their new borrowers, as well as increase borrower incentives to perform justifying voluntarily information sharing (e.g., Jappelli and Pagano (1993), Padilla and Pagano (1997, 2000), and Bennardo, Pagano, and Piccolo (2015)). Since the 1990ies, credit information sharing institutions around the world have been exchanging information between lenders (Miller (2003)). Their incidence across countries has been associated with more lending to the private sector and fewer defaults (e.g., Jappelli and Pagano (2002), Djankov, McLiesh, and Shleifer (2007), Brown, Jappelli and Pagano (2009)). On the other hand, in Hertzberg, Liberti, and Paravisini (2011), the introduction of of a public "negative" credit register "forces lenders to share negative private assessments about their borrowers, and lenders, while learning nothing new about the firm, reduce credit in anticipation of other lenders' reaction to the negative news about the firm."

In the existing literature there are at least two main challenges with identifying the impact of information sharing. First, information on the affected borrower population is typically available to the researcher only after a registry is introduced. Second, normally all lenders – and their borrowers – are affected by mandatory information sharing making it hard to disentangle the impact of the introduction from potential confounding effects brought by changes in the economic environment (macroeconomic factors for example).

In this paper we can alleviate these concerns by exploiting the fact that at the time of the event, the public credit registry – and thus the database on borrower population – already existed (albeit it contained only shared borrowers' default history). In addition, rich information on potential borrowers' loan applications before and after the event allows us to deploy empirical specifications using fixed effects at the loan applicant level, thereby disentangling credit demand from supply. Furthermore, across borrowers we can distinguish between more intensely treated relationships (those that are revealed to have larger outstanding exposures) from less intensely treated ones (those that are revealed to have smaller exposures).

In our analysis we study the impact of information sharing both on financial inclusion for *new loan applicants*, as well as on the change of credit conditions for *existing borrowers*. For the latter group, we differentiate applicants based on the amount of their outstanding debt exposure. On one hand, banks may be willing to extend credit to loan applicants on whom there is no information available, i.e., loan applicants on whom there is no information available (henceforth, "no-info applicants"), i.e., loan applicants who do not yet have any exposure outstanding recorded in the registry, as well as to borrowers who never defaulted and hence were never revealed in any way by the existing public credit registry (that until then shared only negative data). On the other hand, higher exposure borrowers may represent higher risk, towards whom the bank would rightly want to restrain credit access.

Theoretically, it is not clear in which direction the introduction of positive information sharing would affect loan applications without established credit history. This will depend on the bank's prior about the average risk of such "no-info loan applicants". On the one hand, before the introduction of positive information sharing into the Hungarian credit registry, an applicant, on whom the bank had no prior information, could have been a high-quality applicant, with no record of default and with a previous successful long history of borrowing (that was unobservable for the bank). On the other hand, she could have been a high-risk applicant with no repayment failure history but with an excessively large outstanding debt exposure. After the introduction of positive information sharing, the bank can learn more, for example that the no-info applicant is neither, but a true first-time loan applicant of potentially moderate risk.

While the pre-information sharing risk perception may vary from one bank to another, we find that on average no-info loan applicants benefit from the implementation of the Law: They get their applications accepted by slightly higher probability and obtain higher amounts of credit post information sharing. In particular, our results suggest that no-info loan applicants experience an almost 1 pp increase in the probability of application acceptance and obtain, on average, 8 percent higher amounts after the introduction of positive information sharing.[3] We emphasize that while these numbers represent moderate economic effects, they are conditional to controlling for individual level demand as well as bank level supply factors that do not change over time.

Next, we formulate and test hypotheses regarding loan applicants that hold debt either with the bank where they apply for a new loan or with other banks. In Table 1 we provide a summary of our categorization of applicants into borrower groups with different positive and negative histories (Panel A) as well as the estimated economic effects in our main regressions (Panel B). The bottom part of the table shows that conditional on absence (presence) of default all groups benefit from information sharing, irrespective of whether the signal is absent ("No"), i.e., revealing that an applicant has no other exposure, or present ("Yes"), meaning that the applicant has approved credit elsewhere when applying for a new loan.

[3] Foley, Hurtado, Liberman and Sepulveda (2022) studies the impact of positive information provided to one bank and, contrasting our findings, they find that while for known borrowers' credit terms improve, financial inclusion worsens somewhat for new borrowers compared to prior to the shock.

Our results show that positive information sharing generates a significant increase in lending along *the extensive margin (probability of application acceptance)* for some borrower types. In particular, we find a substantial increase in loan acceptance rates for borrowers with *past negative information,* i.e., borrowers who experienced past defaults.[4] The estimated size of the effect – after controlling for individual level demand as well as bank characteristics – is of 5-11 percentage points in magnitude, depending on whether the applicant has debt exposure at the bank where she is applying (an estimated effect of 10-11 pp) or has debt exposure at a competitor bank (an estimated effect of 5 pp). For borrowers with no past delinquencies, we find a much smaller effect along the extensive margin of lending: The estimated increase in the probability of loan acceptance is only 0.6-1 percentage point conditional on that the borrower is applying to a competitor bank. We find no significant increase in the probability of loan acceptance for applicants with positive exposure reapplying for credit to their incumbent banks.

Our estimated effects are also significant and even larger along the *intensive margin of lending (loan amount)* for both borrower groups: Those with and without a negative credit history. Contrasting the result obtained along the extensive margin, borrowers reapplying for credit to their incumbent bank experience the largest impact. They experience, on average, a 48 percent increase in the allocated amount. Loan applicants with more than one bank relationship obtain, on average, 24 percent higher amounts. Borrowers applying to competitor banks, i.e., to banks where they have no previous debt, experience a smaller but still economically significant effect of a 7 percent average increase in allocated amounts. For borrowers with past default history, we find a somewhat smaller effect along the intensive margin of lending, and we find no effect when borrowers with negative history apply to new banks where they have no past relationship.

In total we estimate that information sharing increases the total amount of bank lending for the average borrower with positive history by about 25 percent,[5] while the subsequent default rates slightly decrease. Confirming that our findings are driven by changes in the supply of bank credit, these results suggest that borrower welfare increases dramatically, leading to an increase in total welfare.

We argue that our estimated impact of information sharing on banks' lending decisions accounts for an *information effect* and a *competition effect.* While the information effect is a direct consequence of banks' acquiring new information on the quality of their loan applicants from competitors, the latter, competition effect results from changes in banks' behaviour due to increased bank market competition. We argue that enhanced competition will improve credit terms for creditworthy applicants following the reduction in adverse selection in the post-information-sharing regime: In response to increased competition, incumbent banks will further adapt their lending. Let us consider, for example, the subsample of individuals applying to a bank where they already have outstanding credit (incumbent bank). Such individuals belong to Group 1 according to the categorization shown in detail in Table 1. For such applicants, through information sharing the incumbent bank learns about the absence of other credit and understands that competitor banks may obtain the same information and may come along with alternative offers. The incumbent bank will thus decide to offer better credit terms to the applicant (by reducing interest rates, for example).

Although intensified competition is likely to result in better credit terms offered by all banks, it is a priori unclear whether a competitor bank will be able to poach a customer. Such ambiguity is mainly due to the incumbent's informational advantage. A bank which already has an established relationship with the loan applicant will command informational advantage, such as non-verifiable and non-shared soft data generated during the life of the already existing credit contract and is likely to eventually win applicants even when the competitor learns information and access to hard data is equalized (Sharpe (1990) and von Thadden (2004)). The bank that is already lending to the current applicant, is likely to improve credit terms based on new data. Such competitive effects may be evidence of potential customer poaching arising due to banks' sharing positive information.

[4] Table 1 provides a summary of our results for loan applicants with positive outstanding debt exposure at the time of submitting the loan application as well as a classification of loan applicants into borrower groups with specific credit histories. We provide a detailed explanation of our classification as well as our main results in subsequent sections.

[5] The increase in aggregate loan portfolio is calculated as a weighted average of the estimated effects along the intensive margin of lending (loan amount), which are 48, 7, and 27 percent for applicants in Group 1, Group 2, and Group 3, respectively. The weights are the proportions of loan applicants in the three borrower type categories, i.e., 25.4, 36 and 38.6 percent, respectively.

The intensity of the above competition effect may depend on the number of competitors that the incumbent faces. Indeed, following reduced information asymmetry, the reduction in the cost of providing credit and hence the increase in credit access will depend on the number of competitor banks in the borrower's area of location. We study the role of competition, and how it interacts with the event, by breaking down our sample based on the level of regional bank competition at the loan applicants' location. We find that when more banks compete based on new information, cost reduction can be significant enough to poach a customer from its bank with an established credit relationship.

Positive information sharing increases competition among banks for precisely those applicants with "good" positive information, i.e., loan applicants with small outstanding exposure or previous success, but can have the opposite effect on the pool of applicants with "bad" positive information, i.e., high outstanding exposure (Karapetyan and Stacescu (2014a), Bennardo, Pagano and Piccolo (2015)), because those with high exposure are on average more likely to default, conditional on income and other observable borrower characteristics.[6] We therefore test and confirm the hypothesis that for loan applicants with a small debt exposure, positive information sharing increases the probability of getting credit and/or the amount received more than for loan applicants with large exposure. In particular, we find that when accounting for the size of borrowers' debt exposure in our estimations, the average borrower in our sample experiences, depending on her banking history, a 12-25 pp increase in the probability of acceptance of a new loan application.[7] For an applicant with exposure equal to 1 million HUF (an amount equivalent to the median exposure in our sample), however, the change in the probability of application acceptance drops to near or below 0 following positive information sharing.

As a final step, we check loan performance across all borrower groups. Theory predicts that when banks share positive information rather than information about historical delinquencies only, they end up reducing default Bennardo, Pagano and Piccolo (2015). Consistent with this prediction, we find that loan performance improves in all borrower populations. The overall decrease in the loan default rate is in the range of 0.8 to 1.85 pp indicating an increase in total welfare post information sharing.[8]

The remainder of the paper is as follows. Section 2 describes the relevant theoretical background and related empirical literature. In Section 3, we introduce our data and in Section 4, we describe our methodology. Section 5 provides a detailed assessment of our results and Section 6 concludes the paper.

[6] Karapetyan and Stacescu (2014a) show the same effect for the case of previous success history instead of high outstanding debt exposure.
[7] See the estimates in column 4, Table 8.
[8] It is possible that borrowers delay reporting insolvency, which could be a reason for the finding. In fact, postponing insolvency could drive the decrease in default rates both before and after the event. We assume that if such phenomena are present, the tendency to postpone reporting the default does not change around the event.

2 Theoretical background and related evidence

Theoretically, information has been identified as an important input for bank profits. Seminal works about the effects of adverse selection in credit markets show that banks will not find it profitable to give their information to competitors, since information on borrowers constitutes a source of informational rent (Sharpe (1990), Rajan (1992), Petersen and Rajan (1995), Dell'Ariccia, Friedman and Marquez (1999), Dell'Ariccia (2001), von Thadden (2004)). Incumbent banks may 'hold-up' their borrowers by charging high interest rates given the uninformed offers by potential new lenders (outside banks), who would treat switching good borrowers as members of an adverse pool. In such settings, credit information sharing will benefit borrowers allowing them to build up reputational capital, reduce information rents captured by lenders, and increase access to credit for creditworthy borrowers (Sharpe (1990), Rajan (1992), Petersen and Rajan (1995), Padilla and Pagano (1997), von Thadden (2004)).

Information sharing, however, may theoretically be beneficial for lenders too, when the basic model set-up is augmented to account for other credit market features. In Japelli and Pagano (1993), information sharing arises endogenously because borrowers migrate to other banks due to exogenous shocks: Losing information to the competitor about the emigrating customer is a negligible price in exchange of receiving valuable information about the arriving immigrants. In Padilla and Pagano (1997), the exchange of information works as a commitment device for the bank not to appropriate the entire surplus from its borrowers, leveling the playing field with other banks and inducing borrowers to exert effort. As a result, private credit bureaus based on voluntary sharing mechanisms may arise.

More recently it has been shown that incentives to share information may depend on the type of information shared – negative (previous default) or positive (success or current credit in good standing) – and their varying impact on competition.[9] In Karapetyan and Stacescu (2014b) information sharing will increase competition – and decrease rents – for borrowers with positive information, but it will decrease competition for defaulting (and thus risky) borrowers, since other banks will then learn about the default. As borrowers with negative history are more likely to stay with their incumbent banks, the banks' incentives to invest in the collection of soft information increase, boosting informational advantage. The opposite happens for borrowers with positive information as they are more likely to switch. As a result, positive information levels the playing field in hard data, and further reduces informational advantage with respect to incumbent's soft data.[10] These together intensify competition between banks.

Therefore, while sharing negative information, data on past default and delinquencies is often linked to bank profits (Japelli and Pagano (1993)), positive information, i.e. data on repayments and outstanding exposure is considered as a major source of the incumbent's informational rents (Padilla and Pagano (1997)), and its sharing may increase competition and generate a loss of customers as has been shown in Foley, Hurtado, Liberman and Sepulveda (2022). Unsurprisingly, across the globe the incidence of positive data sharing has been, until recently, much scarcer (Miller (2003)). Positive information is however no less valuable for borrower welfare: Unlike negative data that penalizes defaulting borrowers, positive information may reward diligent borrowers that pay on time, allowing customers to establish a positive credit history with the entire system.

Banks may not necessarily agree to share especially positive information about their clients, and private solutions for sharing information - credit bureaus - may not emerge for positive data.

[9] The type of information to be shared is a key practical consideration when establishing an information sharing system (Miller (2003))

[10] In Karapetyan and Stacescu (2014a), the acquired soft information is complementary to hard data and acts as a further source of rents by allowing the bank to identify who defaulted or repaid simply due to bad luck versus due to being of bad inherent type.

In line with this intuition, in the past, credit bureaus used to share only negative data, but in recent times, the scope of data sharing has expanded to include positive information as well. Positive information sharing is important from a welfare perspective for at least two reasons. First, sharing only negative information will not reward high-performance borrowers. Second, positive information can help to curb lending to high-risk borrowers with currently large exposure, but not yet in default, and it can help increase access for borrowers with no exposure.

Our study is related to a growing empirical literature studying the impact of information sharing on access to credit. Early work focused on estimating the impact of information sharing in cross-country settings. Japelli and Pagano (2002) offer the first empirical investigation of the existence and impact of credit bureaus in various economies around the world. They find that the presence of private credit bureaus or public credit registries is associated with broader credit markets and lower credit risk. The authors do not find any differential effect between public and private institutions on credit market performance. Instead, they argue that public credit registries are more likely to arise where there is no preexisting private credit bureau and creditor rights are poorly protected, suggesting the two may well be substitutes. Similar empirical results are obtained in Djankov et al. (2007), who use macro level data from 129 countries and find that credit rises after improvements in information sharing. Love and Mylenko (2005) and Brown, Jappelli and Pagano (2009) also find that introducing information sharing increases access to credit.

With the advent of micro-level datasets, more recent research has analyzed transaction level information, yet mostly focusing on default information. Doblas-Madrid and Minetti (2013) use contract-level evidence from the United States to find that the entry of lenders into the credit bureau reduces the incidence of contract delinquencies and reduces the size of contracts but increases the use of guarantees, a result in line with the theory Karapetyan and Stacescu (2014a).

Beck, Behr, de Freitas Oliveira (2023) exploit a change in reporting threshold in the Brazilian credit registry and find that risky firms experienced increased borrowing (mostly due to formation of new bank-firm relationships) while safer firms benefited from lower interest rates (mostly due to incumbent lenders driving the interest rate reduction). In contrast, we focus on the role of positive information and total indebtedness and show how effects may differ across borrowers with varying ex-ante indebtedness, and across heterogeneous local banking competition levels. Grajzl and Laptieva (2016) use bank-level information for a subsample of Ukrainian banks to study the impact of information sharing on credit volume for private and public registers and find no effect of the latter. Instead, we use individual level information for the entire Hungarian household credit market, which allows us to better identify and differentiate effects across borrowers with various banking relationships.

Closer to our work, two papers evaluate the impact of positive information disclosure, albeit from the perspective of one lender only. De Haas, Millone and Bos (2021) study the impact of introducing a credit registry sharing both negative and positive information, on one microfinance lender's credit decisions and find that the lender starts to put more weight on the shared hard data following the regime change, leading to smaller and higher quality loans. Foley, Hurtado, Liberman and Sepulveda (2022) study the competitive effects between differentially informed lenders (banks and non-banks) for the same borrower using registry data from Chile. Exploiting an experiment where a non-bank lender's exclusive positive data becomes available to a competitor bank, they show that as a result of information sharing, safe borrowers receive offers with higher limits from the competitor and that such competing offers are further matched by the incumbent. They also show that new borrowers may be less likely to receive credit.

In contrast, we examine the whole economy, which is important not only from the aggregate quantitative perspective, but also qualitatively, since information sharing can have contrasting impacts for various groups of borrowers depending on their ex-ante pool of risky and creditworthy applicants. We are able to analyze the entire population which consists of borrowers with small and large exposures, borrowers with and without past default history. Furthermore, we improve identification by using loan application and approval information and our data allows us to account for individual level loan demand characteristics by employing individual fixed effects. Finally, our implications concern the impact of sharing only positive, rather than negative information or both.

Finally, our research is connected to the growing body of literature on open banking, which explores the sharing of financial data. Both open banking and credit registers involve sharing financial information, but with some distinctions. Open banking primarily focuses on real-time customer banking and transaction data shared with authorized third-party providers, while credit registers collect and maintain credit-related data (Babina, Buchak and Gornall (2023); Nam (2023)). However, the common objective is to promote competition and increase access to credit by facilitating the availability of relevant financial information. Our findings demonstrate that even sharing a single aspect of borrower information, such as total debt exposure, can have a positive impact on competition and encourage broader participation in the credit market for the entire population.[11]

[11] Both open banking and credit registers require customer consent for the sharing of their financial data. In open banking, customers must explicitly grant permission for third-party providers to access their banking information. Similarly, credit registers obtain consent from individuals or entities before collecting and sharing their credit data.

3 Data

The Household Registry of the Hungarian Central Credit Information System (KHR) contains information on all loans extended to individuals by all credit institutions in Hungary. As such this credit register contains detailed information on mortgage-backed housing loans, mortgage-backed consumption loans, non-collateralized consumption loans, personal loans, current account credit lines, car leasing and other car purchase loans, credit card contracts, and other loan contracts. Credit institutions in Hungary include commercial banks, branch offices of foreign banks, saving cooperatives, credit unions, specialized credit institutions, financial enterprises, and other financial companies. The major players in the consumer loan market are the 8 biggest commercial banks (sometimes through their subsidiaries), together with two other commercial banks and two large non-bank lenders with reasonable market share in consumer lending. We use data from these twelve financial intermediaries in our analysis which cover almost 90 percent of the credit market in Hungary during our sample period.[12]

The Household Registry of KHR was populated with positive information in April 2012, meaning that data on all loans outstanding at or originated after that month are available to us. In addition to loan originations, we observe the information queries by banks to the KHR when receiving loan applications. The data on queries stretches back prior to the introduction of positive information sharing (since a registry of borrowers in default already existed) and includes queries for rejected loan applications.

For each query, we know the date of the query, the identity of the bank where the individual applies and an identifier of the applicant. We match this information with the cross section of loans outstanding on or originated after April 2012. A query is matched to a loan if the bank that made the query originated a loan to the applicant within 90 days after the query. This gives us a dataset of loan applications including information on approval as well as the characteristics of loans and borrowers for accepted applications. For each accepted application, we observe the time of loan origination, loan amount, time to maturity, age, and area of location, whether the loan defaults in the coming 6 years, as well as the history of the borrower's past delinquencies.[13] In addition to information gathered from the credit registry, for a subsample of the borrowers in our sample we obtain monthly income from pension registry data.

We restrict our sample to loan applications made to and actual loans originated by the twelve lenders mentioned above. Bank-level heterogeneity in loan exposure may affect our coefficients when estimating the impact of information sharing on banks' lending decisions. Small size commercial banks and saving cooperatives with small total exposures may experience a different impact of information disclosure than commercial banks with large credit exposures. In our empirical estimations we use a sample of the largest banks that are likely to be homogenous in their exposures.

We consider loan applications in the period between February and October 2012. Our sample includes applications made within a period of three months before and six months after the introduction of the credit registry in May 2012.[14] We choose May as the event date because that was the first full month when banks could query the positive information in

[12] The number of loans offered by the 12 banks in our sample is 563,926 during the sample period, February-October 2012. The total number of loans offered by the banks in Hungary (as registered by the Hungarian Credit Registry) is 635,396.

[13] This combined dataset, however, has some limitations. For *rejected applications*, we do not observe the type of the loan or the loan amount that the applicant intended to borrow. Even for the *accepted applications*, we do not know if the originated amount was the full amount the borrower wanted to borrow. But then it needs to be noted that very few single-bank loan-granted datasets such as the one used in Brown, Kirschenmann and Ongena (2014) or survey data, e.g., the National Survey of Small Business Finance studied by Berger and Udell (1995) or Cole (1998), contain information on requested amounts. Some credit registers record whether banks accessed credit record of a non-current client as implying that a loan application took place but no information on the requested loan amount is available (Jimenez, Ongena, Peydro and Saurina (2012)). For *rejected applications*, we also have no way of knowing if multiple queries refer to the same loan application, as it would be the case if a bank queried a debtor and the co-signer. And for existing loan contracts, we do know the identity of every debtor and co-signer named in the contract.

[14] Employing similar but symmetric windows leaves estimates mostly unaffected.

the credit registry. Our choice of a relatively short (i.e., three month) pre-event period is done with the purpose to avoid possible sample selection biases.[15]

Between November 2011 and January 2012 borrowers with foreign currency denominated mortgages had the opportunity to repay these loans at below market exchange rates. Many borrowers used this opportunity to take on local currency loans and repay their foreign currency mortgages, resulting in a frenzy of lending activity in this period. Given the special nature of this event we want to exclude this period from our estimation sample.

A more technical reason for shortening the pre-event sample period is that we only have information on loans that were outstanding in April 2012. With a long pre-event period we would risk biasing downwards our estimate of loan acceptance probabilities in the pre-event period for the simple reason that loans to borrowers who have repaid prior to April 2012 would not be observed in our data and applications corresponding to such loans would be erroneously classified as rejected.[16]

Tables 2 and 3 provide descriptive statistics on the characteristics of individuals applying for loans as well as the loans granted in our sample. In our sample period, February-October 2012, 1,136,520 individuals' credit history was queried by the twelve largest lenders in Hungary. 289,374 (over 20 percent) of these were queried more than once for a loan during our sample period. The total number of queries thus considered in our sample is 1,581,480. Interestingly, statistics in the first two lines of the table show how the information sharing regime improved access to credit: From before to after the event, the unconditional rate of loan acceptance increased by 8 pp, from about 31.4 percent to nearly 39.6 percent. At the same time, the average loan size decreased by about 10 percent, from 431,817 to 387,621 Hungarian forint (HUF).[17]

Some loan applicants had neither negative nor positive credit record prior to the application according to the Hungarian credit registry; we will refer to them as *"No-info loan applicants".*[18] In our sample, 40 percent of the queries, that is 632,796 queries in total, are submitted for such individuals. Given the special status of these applicants, relative to those with earlier credit records at any bank in our sample, we run separate regressions (on a simplified empirical model) to examine our hypotheses. Furthermore, the total number of loan applications by borrowers with existing credit history is 948,684 in the sample. We split the group of borrowers with existing credit history into three subsamples, based on the information that the prospective lender (where the application is made) might know about the borrower.

"Loan applicants with exposure at the bank" are applicants who have outstanding debt exclusively with the bank where the loan application is made. Even in this case, the expanded registry reveals new information to the bank: The certainty that the applicant has no debt to other institutions.

"Loan applicants with exposure at other banks" are loan applicants with outstanding debt from creditors other than the bank where the application is made. Information about these loans would not have been available to potential creditors before the introduction of the registry. In fact, such loan applicants appeared to be identical to no-info loan applicants before the introduction of the law.

Finally, "*Loan applicants with exposure at the bank and other banks"* are applicants with outstanding debt from the bank where the application is made as well as from other banks. Before the introduction of the registry, these loan applicants were indistinguishable, from the banks' point of view, from applicants we categorized as *"Loan applicants with exposure at the bank"*.[19]

[15] All loan contract samples face potential borrower discouragement and loan application approval biases (e.g., Cole (1988), Brown, Kirschenmann and Ongena (2014)). Employing similar but symmetric windows leaves our estimates mostly unaffected.

[16] Having a very short event window is also not feasible because we control for demand effects by running fixed-effect regressions. This requires a long enough sample period so that we can observe multiple applications by the same individual and thereby ensure that the fixed-effect terms do not soak up all the variation in our outcome variables.

[17] The table also shows that the decrease is mainly driven by the increase in the number of "no-info" borrowers, who get typically smaller loan amounts.

[18] This definition can include those borrowers who have taken loans that had been fully repaid preceding the introduction of the credit registry in May 2012, but records of those transactions do not appear in our dataset. These borrowers should rather be understood as borrowers without any information (either past negative or current positive).

[19] Appendix Table A.1 tabulates the definitions of these four groups, and also of the later introduced key variables.

The new information allows potential lenders to know loan applicants' total indebtedness, including exposures with other banks. The three subgroups vary in the number of loan applications submitted (applications numbers range from 239,000 to 389,000) during the sample period, implying that we have sufficient observations in each subgroup to measure the impact of information sharing by estimating separate coefficients for the three subgroups in our regressions.[20]

For no-info loan applicants, acceptance probability is noticeably low in the entire sample, i.e., 28 percent, while for applicants with exposure at the bank where the application is made, i.e., the incumbent bank, it is above 40 percent. However, as expected, this probability increases, for no-info loan applicants, dramatically from 24.7 percent before the event to 31.9 percent after information sharing, as banks learn which applications carry no outstanding debt. We interpret this increase in the likelihood of acceptance as the outcome of banks' unfavorable prior about the average borrower's outstanding debt compared to the real scenario.

Table 2 shows that the number of applications submitted by borrowers to banks where they have outstanding exposure decreases to some extent: as can be seen from column 3, in the 6-month post-event period this number is about 116,712 down from its value of 121,871 in the 3-month pre-event period. This decrease is in line with the idea that the other banks, where borrowers have no credit history, learn positive information about the borrowers and attempt to poach them by offering better terms of credit with the aim to become their new lenders (Karapetyan and Stacescu (2014b)). Indeed, the number of applications grows considerably for the latter two groups, from approximately 178,000 to 210,000, and 141,000 to 179,000, respectively, consistent with stronger competition.

The application pool that remains with the given bank is expectedly of higher quality, as any bank is likely to hold-up its best borrowers by reacting with more competitive offers to any poaching attempt by other banks. This possibility is corroborated in the stark increase in acceptance rate in the group of "Loan applicants with exposure at the bank", from 36 to 47 percent.[21]

Furthermore, the descriptive statistics indicate that poaching by new banks after information sharing is moderate: On average, loan applicants with exposure at other banks have a 35.5 percent probability of having their applications accepted. At the same time, this number is 33.7 percent in the pre-event period, increasing to 37.3 percent following information sharing. This is also in line with existing work on bank competition in an adverse selection setting, in which some good borrowers may decide to switch to new banks.[22]

The average loan amount in the subsample of accepted applications is approximately 406,000 HUF (equivalent to 1,370 EUR using the 2012 end-of-the-year exchange rate), exhibiting a 10 percent decrease in the post-event period. The decrease happens for each of the four subgroups of loan applications, but it is most pronounced for the applications submitted by no-info loan applicants. Yet this is not surprising, since the acceptance rate is much higher and borrowers without a historical exposure are likely to start with smaller loans.[23]

[20] Due to the high number of defaults on foreign currency loans subsequent to the financial crisis, a large-scale debt restructuring program was initiated by the Hungarian government in November 2011. The program entitled all households to repay mortgage debt denominated in foreign currency at a fixed exchange rate, approximately 25 percent below the market rate. As the gains from such a repayment opportunity were high, a massive share of housing loans was repaid in December 2011 and January 2012. In fact, many households applied for credit denominated in Hungarian forint in order to repay the foreign currency mortgage debt. Therefore, by including months preceding February 2012 in our sample, we would include applications whose only purpose was to alter the currency denomination of previously initiated foreign currency debt. In addition, including those months would imply that we omit actual (foreign currency) loans that were repaid without new (forint) loan initiations.

[21] Numbers in lines 8 and 12 in Table 1 indicate that for Applicants with exposure at the bank where they apply, the pre-event period acceptance rate equals (43,443/121,871) = 35.64 percent, while the post-event acceptance rate equals (54,469/116,712 = 46.66 percent).

[22] In the simultaneous-move game in Rajan (1992) and von Thadden (2004), and follow-up extension of information sharing in Karapetyan and Stacescu (2014b), switching and credit granting by new banks can occur for borrowers with good standing. For empirical evidence see Ioannidou and Ongena (2010), Barone, Felici and Pagnini (2011), Stein (2015), and Bonfim, Nogueira and Ongena (2021). Switching of good borrowers does not take place in Sharpe (1990), where banks move sequentially.

[23] Consistent with this explanation, note that repeat borrowers in fact receive loans that are on average 10 percent larger after the introduction of information sharing.

4 Methodology and hypotheses

To understand how sharing positive information affects households' credit access, we run two sets of *first difference* regressions on two independent variables. First, we investigate how the *probability of a loan application being accepted* changes around the time of the introduction of the law. Second, we examine, for accepted applications, how the introduction of the law changes the *amount of credit* banks originate.

Sharing information on outstanding loan amounts helps banks to assess the overall indebtedness of individuals applying for a loan. The introduction of the registry thus allows a bank to justify whether new loan applicants have outstanding credit from other institutions.[24] The impact of gaining access to such positive information on a bank's lending decision will depend on the extent to which the information is new to the bank. In this respect, as we detail in Section 3, we categorize loan applicants based on individual credit history into four separate groups: (i) *No-info loan applicants*; (ii) loan applicants with outstanding debt from the bank where the application is made, *Loan applicants with exposure at the bank*; (iii) loan applicants with outstanding debt from other banks, *Loan applicants with exposure at other banks*; and (iv) loan applicants with outstanding debt from the bank where the application is made as well as from other banks, i.e., *Loan applicants with exposure at the bank and other banks*.

For *No-info loan applicants*, with no history of accepted applications, we estimate the following empirical model for the probability of acceptance as dependent variable:

$$Acceptance_{it} = \alpha_i + \beta_b + \gamma \times Post_t + \delta \times Log(Income)_{it} + \theta + \varepsilon_{it} \quad (1)$$

where $Acceptance_{it}$ is a binary variable taking the value of 1 if the loan application made by applicant *i* in month *t* is accepted and 0 if it is not; $Post_t$ is a binary variable taking the value of 1 in the period subsequent to the introduction of the registry in May 2012 and 0 in the period before; $Log(Income)_{it}$ is the (log of) the individual's monthly income; α_i is an individual fixed effect, β_b is a bank fixed effect, and θ is a constant. The coefficient of interest is γ that shows the increase in the probability of acceptance from the pre- to the post-event period for the group of applicants with no credit history prior to the submission of the loan application. Individual fixed effects capture all observable and unobservable time-invariant heterogeneity across individuals, while bank fixed effects capture all observable and unobservable time-invariant heterogeneity across banks. ε_{it} is the error term which captures unobserved heterogeneity which is assumed to be independently and identically distributed across applicants and over time. We test the following hypothesis.

Hypothesis 1a. *After positive information sharing, no-info loan applicants are more likely to get their loan applications accepted.*

Underlying the hypothesis is the premise that banks possess a certain prior about the average applicant's outstanding credit before information sharing. Upon sharing, as banks learn that the applicant has in fact zero outstanding credit, a positive reaction is likely to follow.

We then move to investigate whether borrowers are affected along the intensive margin. We test the following hypothesis about the impact of positive information on the amount of lending. Similar to hypothesis 1a, we expect a positive effect for no-info loan applicants.

[24] Even if self-reporting may have helped banks to assess the overall indebtedness of a loan applicant before the introduction of positive information sharing, in principle, banks had no information on applicants' total debt exposures.

Hypothesis 1b. *After positive information sharing, no-info loan-applicants will receive a larger amount of credit.*

To do so, we re-estimate equation (1), for the subsample of accepted applications, using the logarithm of loan amount as dependent variable. Besides individual fixed effects, we include in the regressions loan-type fixed effects to account for potential differences in average amounts borrowed across loan-types.

For the group of applicants with existing credit outstanding at the time of the application, we estimate a more complex specification that comprehensively accounts for the extent of information asymmetry between the bank and the loan applicant concerning the applicant's credit history:

$$\begin{aligned}
&Acceptance_{it} = \gamma_0 \times Post_t \times Loan\ applicant\ with\ exposure\ at\ the\ bank_{it} \\
&+\gamma_1 \times Loan\ applicant\ with\ exposure\ at\ other\ banks_{it} \\
&+\gamma_2 \times Loan\ applicant\ with\ exposure\ at\ other\ banks_{it} \times Post_t \\
&+\gamma_3 \times Loan\ applicant\ with\ exposure\ at\ the\ bank\ and\ other\ banks_{it} \\
&+\gamma_4 \times Loan\ applicant\ with\ exposure\ at\ the\ bank\ and\ other\ banks_{it} \times Post_t + \delta \times X_{it} \\
&\qquad\qquad + \alpha_i + \beta_b + \theta + \varepsilon_{it}
\end{aligned} \tag{2}$$

where the variables $Acceptance_{it}$, $Post_t$, as well as the parameters α_i, β_b, θ, and ε_{it} are defined as for equation (1). X_{it} is a vector of control variables including the (log of) the individual's monthly income, the (log of) the individual's total outstanding debt, and two dummy variables indicating if the applicant had a negative credit history.

The first dummy "*Bad credit history with the bank*" equals to one if the individual had earlier default with the bank where she is applying at time t and equals zero otherwise. The second dummy *"Bad credit history with other banks"* is equal to one if the individual had earlier default, recorded in the credit registry, with another bank in a five-year period preceding the time of the application and equals zero otherwise. The binary variables *Loan applicant with exposure at the bank*, *Loan applicant with exposure at other banks* and *Loan applicant with exposure at the bank and other banks* indicate the type of applicant based on the classification of the applicant's credit history with the bank where the application is made, as defined above.

The key coefficients of interest in specification (2) are γ_0, γ_2 and γ_4. We expect that upon release of new information, the information gap between the bank where the applicant has no outstanding credit and where she does have a positive debt exposure is reduced, leveling the playing field, and, potentially, facilitating competition and switching (positive γ_2). At the same time, acceptance rate at banks where applicants have a positive history may go up, as the incumbent retains the best borrowers from its own pile, rendering γ_0 positive, consistent with theories of von Thadden (2004), Rajan (1992) and Karapetyan and Stacescu (2014a,b). If the applicant is also a current customer at another bank, competition may intensify even more, conditional on given history of performance.

By estimating a coefficient on the *Post* variable for each of the three subgroup of loan applicants, our first difference estimations account for borrower specific credit history with the bank where the loan application is being made. Moreover, our empirical setup ensures that new information on applicant's indebtedness can play a different role in the three groups depending on the relative importance of other, i.e. negative, information. To make the structure of our analysis and the presentation of results clearer, we compartmentalize the role of credit history and present the impact of the event for the various subsamples of loan applications (i.e., Groups 1, 2, and 3) in the summary table, Table 1, Panel A and Panel B. Group 1 includes applicants with exposure only with the incumbent bank, while Group 1 "No default" indicates its subpopulation of borrowers with no negative history. Group 2 consists of loan applicants with exposure at other (competitor) banks, while Group 3 contains applicants with exposure at both the incumbent and competitor banks. In Panel A of the table, we demonstrate how the event changes the "No" data environment with respect to positive information from other banks into a "Yes" data environment for applicants in Groups 2 and 3 while reveals "No" new information (outstanding credit) for applicants in Group 1.

Banks, when making lending decisions, act as rational agents. Their prior concerning the applicant's level of indebtedness should reflect the average level of indebtedness of the borrower population. Information sharing then affects the lending decision via revealing the actual level of the borrower's indebtedness thereby reducing the lender's information asymmetry vis-á-vis the borrower. Excluding other factors, in theory, the impact of information sharing on borrowers with high versus low outstanding debt exposures would work in opposite directions relative to the bank's average prior. Information sharing, however, affects incumbent banks via a second channel – a "competitive effect". As competitor banks also learn information about the loan applicant, their behavior may further alter the incumbent's lending decision. More intensified competition will therefore imply more lending for creditworthy borrowers. As a result, in what follows, we assume that all 3 borrower groups weakly benefit when banks learn positive information about their loan applicants.

Hypothesis 2a. *Following positive information sharing, loan applicants with positive outstanding exposures are more likely to receive credit, conditional on a given history.*

Subsequently, we estimate Model (3), for the subsample of accepted loan applications, on our second dependent variable, the amount of credit granted to the loan applicant. In addition to individual fixed effects, we include loan-type fixed effects in the specification:

$$\begin{aligned}
&Log(Loan\ Amount)_{ijt} \\
&\qquad = \alpha_i + \beta_b + \mu_j + \theta + \gamma_0 \times Post_t \times Loan\ applicant\ with\ exposure\ at\ bank_{it} \\
&+\gamma_1 \times Loan\ applicant\ with\ exposure\ at\ other\ banks_{it} \\
&+\gamma_2 \times Loan\ applicant\ with\ exposure\ at\ other\ banks_{it} \times Post_t \\
&+\gamma_3 \times Loan\ applicant\ with\ exposure\ at\ the\ bank\ and\ other\ banks_{it} \\
&+\gamma_4 \times Loan\ applicant\ with\ exposure\ at\ the\ bank\ and\ other\ banks_{it} \times Post_t + \delta \times X_{it} + \varepsilon_{ijt}
\end{aligned} \tag{3}$$

Log(Loan Amount)$_{ijt}$ is the natural logarithm of the amount given to applicant *i* for a loan of type *j* in month *t*; the parameters α_i, β_b, θ, and ε_{it} are defined as for equation (1), μ_j represents loan-type fixed effects. All other variables are defined as earlier. The key coefficients of interest are the same as in specification (2).

Hypothesis 2b. *After positive information sharing, loan applicants with outstanding debt will receive larger amount of credit, conditional on a given history.*

To remove very small and very large loan amounts granted from the sample, we winsorize the loan amount variable at the 1st and 99th percentiles.

5 Results

5.1 MAIN FINDINGS

We present our results for the two main subsamples of loan applicants separately. We first discuss estimations based on the sample of *No-info loan applicants* who had no credit history at the time of submitting the loan application. Then, we present the results for the subsample of loan applicants that had debt outstanding at the time of the application: *Loan applicants with exposure at the bank*, *Loan applicants with exposure at other banks* and *Loan applicants with exposure at the bank and other banks*.

Results in Table 4 assess the impact of information sharing on the extensive and intensive margins of lending for the group of applicants categorized as No-info loan applicants. The coefficient in column 2 indicates that the introduction of positive information sharing increases the probability of application acceptance by 0.8 pp.[25] The result assumes that we control for the applicants' income in the regression. This marginal increase in the effect along the extensive margin of lending is consistent with a moderate but significant increase in access to finance for borrowers without credit history following information sharing. More importantly, columns 4 to 6 show that the introduction of the law significantly increases the amounts lent and the estimated effect is economically significant independent of whether we control for the applicant's income: No-info loan applications obtain, on average, about 8 percent higher amounts after the introduction of positive information sharing suggesting that information sharing brings about a significant improvement in access to finance for applicants with no past credit records.

Applicants with Credit History: Probability of Loan Acceptance

Next, in Tables 5 and 6, we turn to our results for applicants with existing credit history at the time of the loan application and present specification (2) for all qualifying applicants: *"Loan applicants with exposure at the bank"* (Group 1), "*Loan applicants with exposure at other banks"* (Group 2) and "*Loan applicants with exposure at the bank and other banks"* (Group 3). We first discuss in detail the empirical results of the extensive margin in Table 5. We then turn to the discussion of our findings along the intensive margin of lending in Table 6.

A concise summary of our main findings in Tables 5 and 6, also describing the size of the estimated effects, can be seen in Panel A and B, in Table 1. As a way of preview, our main finding is that credit access increases for all three groups along the intensive margin of lending implying that borrowers receive significantly larger amounts post information sharing. Along the extensive margin, economically significant effects are estimated in all three groups for the subsample of applicants with past delinquencies suggesting that an important benefit of information sharing is that it clears loan applicants with tainted credit histories.

In models 1 and 2 of Table 5, we present regressions estimated on the full population of the three groups of applicants. Regression 2 extends the specification of Regression 1 by adding the borrower's monthly income as well as the two negative credit history dummies as control variables. Since income is available only for a small subset of the applications, the sample is substantially reduced in specification 2. In Models 3-6, we refine the sample and estimate our regressions on subsamples of applicants with a similar default history. Models 3 and 4 are run on the sub-sample of individuals with no delinquent loans during the 5 years preceding the loan application, while models 5 and 6 are estimated on the sub-sample of individuals with previous bad credit history, at any financial institution.

The estimated coefficients on the interaction terms with the Post variable in models 5 and 6 indicate that along the extensive margin of lending the obvious beneficiaries of positive information sharing are borrowers with past negative

[25] We include, in our tables, regressions with and without income as a control variable, because income data is observed only for a subset of the borrower population.

history. Acceptance probabilities from pre- to post information sharing increase by 9-11 pp for applicants applying to their incumbent banks (applicants in Groups 1 and 3) and by about 5 pp for applicants applying to a competitor bank (applicants in Group 2). Upon release of new information, the informational advantage between the competitor bank and the incumbent is reduced facilitating competition and switching. In particular, the estimated coefficients on the interaction terms "*Post x Loan applicants with exposure at other banks"* show that this difference decreases by about 5 pp in the post-May 2012 period, confirming that information asymmetries between banks and loan applicants without credit history at the bank where they apply decrease.[26]

We find substantially smaller effects along the extensive margin in the subsample of loan applications by borrowers with no past delinquencies. Based on estimates shown in columns 3 and 4, we conclude that *Applicants with exposure at other banks* (Group 2) experience, when applying for a new loan*,* a roughly 1 pp increase in the probability of acceptance and the result survives when we control for the borrower's income. Furthermore, *"Loan applicants with exposure at the bank and other banks"* (in Group 3) experience a marginal increase in the probability of acceptance but the coefficient becomes insignificant in the subsample of borrowers with information on income.

Most coefficients estimated for other explanatory variables turn out to have the expected signs. Higher amount of *Total debt* decreases acceptance probabilities. A 1 percent increase in the total outstanding debt amount decreases the probability of loan acceptance by 4 pp and the variable is significant at 1 percent level. Higher level of income also increases the probability of loan acceptance, and the estimated coefficient is significant at conventional levels.

When estimating the regression on the full sample of loan applicants with positive debt exposure (model 2), we include the two dummy variables indicating: *"Bad credit history with the bank"* and *"Bad credit history with other banks"*. The coefficient estimates on the dummy variables *"Bad credit history with the bank"* and *"Bad credit history with other banks"* indicates that lenders in general tend to avoid applicants with bad credit history. The probability of accepting loan applications from borrowers that have defaulted at the bank where they are applying is approximately 3.5 pp lower than the acceptance probability for borrowers with no negative history. *"Bad credit history with other banks"* seems to have a significantly larger effect: Applicants with a negative history with other banks experience an almost 6 pp lower acceptance probability compared to applicants with no bad credit records.

Applicants with Credit History: Loan Amount

Regressions in Table 6 focus on the intensive margin of lending, with loan amount as dependent variable as in equation (3), using the sample of accepted loan applications.[27] The structure of Table 6 is equivalent to that of Table 5: Columns 1 and 2 are run on the full sample of applications submitted by borrowers with positive debt exposure, columns 3 and 4 are based on the subgroup of borrowers with no previous delinquency, while columns 5 and 6 focus on applications submitted by individuals with bad credit records.

Our findings in Table 6 indicate that each of the three borrower categories receive higher amounts in the post event period. The relevant effects for Groups 1 and 3 are shown in column 4 by the coefficient estimates of the interaction terms *"Post X Loan applicant with exposure at the bank"* and *"Post X Loan applicant with exposure at the bank and other banks"*, respectively. We find that relative to the pre-event period, the log of the amounts granted to the two groups increases by 39 and 22 percent, a change equivalent to a 48 and 24 percent raise in Forint amounts (exp(0.39)=1.48 and exp(0.22)=1.24) for the average applicant in the two groups, respectively. The estimated numbers are somewhat lower, 22 and 24 percent (equivalent to 25 and 27 percent increase in Forint amounts), respectively, for Group 1 and Group 3 borrowers reapplying for loans with negative past credit history.

[26] Note that this increase in the probability of acceptance does not bring potential new lenders to a perfect competition setting with the incumbent bank, suggesting that applicants with no outstanding credit history may still be "disadvantaged" in the allocation of credit, even after the introduction of the law, due to other, soft information that incumbent banks possess.

[27] Our data is limited to originated amounts, and we do not see the amount a borrower requests in the loan application. Since our purpose is to estimate loan supply effects, requested amounts are less interesting from our perspective than the actual amounts allocated.

For applicants applying to competitor banks (Group 2), the change relative to the pre-event period is substantially smaller but still economically significant. Borrowers with no negative credit history experience on average a 7 percent increase in the average Hungarian Forint amount lent by competitor banks in the sample. Borrowers applying to competitors with negative credit history represent the only group in our sample that does not experience a significant increase in credit access along the intensive margin.

We summarize the above detailed results estimated on the three subsample groups in Table 1. Comparing borrowers with default history to those without, (i.e., comparing, in Panel B, the bottom row "Yes" on default to the row above "No" on default), we confirm that the effect of information sharing is positive and significant along both margins of lending and that its magnitude depends on the borrower's credit history vis-à-vis positive (total debt exposure) as well as negative (past default) information. Along the extensive margin, the impact turns out to be strongest for borrowers with past negative information as indicated by the economic effects shown in the bottom row of Table 1 ("Yes" on default). In addition, conditional on absence of past negative information ("No" on default), applicants applying to competitor banks, i.e., applicants in Group 2, also experience a smaller but still positive effect on the likelihood of application acceptance. At the same time, in absence of negative information, applicants in Group1 applying to their incumbent banks, seem not to benefit from information sharing along the extensive margin.

Our results along the intensive margin of lending are less dependent on borrowers' past repayment histories. Applicants turning to their incumbent banks, i.e., applicants in Group 1 and 3, experience a substantial raise in allocated amounts independent of whether they experienced delinquencies in the past. Applicants applying to competitor banks also receive higher amounts post information sharing but only conditional of absence of past defaults. Applicants applying to competitors with past delinquencies are, however, unaffected by positive information sharing along the intensive margin of lending. This may seem surprising from the perspective of a rational bank: A rational bank knows before the event that information sharing will reveal a good ("no outside credit") or a bad signal ("positive debt exposure"). Hence, its lending policy before the event should be based on information that aggregates a population of unrealized signals regarding an applicant's outstanding debt exposure at the time of submitting the loan application. Following information sharing, access to lending would move in opposite directions relative to the average prior for applicants with high versus low debt exposures. This is the information effect.

Yet, information sharing also means new data received by the competitor bank, and the latter can improve credit terms for creditworthy applicants following the reduction in adverse selection. In response to this the incumbent may further adapt its lending. We call this the *competition effect*. In Table 1, focusing on defaulting borrowers first, in Group 1 the incumbent learns about the absence of other credit, but it also knows that a potential competitor may learn the same information and may try to poach the customer; it responds by potentially reducing interest rates and increasing acceptance rate (by 10 pp in our sample). The increase in acceptance also happens for the other signal of positive credit: For applicants in Group 3, acceptance rate increases by 11 pp when the bank learns about positive exposure with another bank.

Although intensified competition means more accessible credit terms offered by all banks, as long as the incumbent has some informational advantage it is not clear that the competitor will be able to increase its lending. This is because the bank who already has an established relationship will command informational advantage, such as non-verifiable and non-shared soft data generated during the life of the already existing credit and is eventually likely to win the applicants even when the competitor learns more information and access to hard data is equalized (Sharpe (1990), von Thadden (2004)). This is confirmed for Group 2, where the roles of the incumbent bank and the competitor are reversed. The incumbent bank that is lending to the current applicant is likely to improve credit terms based on new data to attract creditworthy borrowers. However, we find a near zero effect: While both banks now have the same hard information, the incumbent is likely to win with informational advantage coming from the already established relationship. Theoretically, however, it is possible that some borrowers still contract the competitor bank with less information, as shown by von Thadden (2004). In the next section, we break down our analysis further to study the potential presence of such borrowers depending on market conditions.

5.2 HETEROGENEITY: BANK COMPETITION

The intensity of the competition effect is likely to depend on the number of competitors that the incumbent faces. In the extreme, envisage a situation in which the bank learns useful information about a borrower who has just migrated to a new location from a distant bank with whom the new bank would not compete. In this case while new information will increase credit access via reducing information asymmetry and costs of granting credit for the monopolist, there will be no competitive response in the market. On the other hand, the presence of one or several competitors in the same market, will trigger competitive action as described above, with an intensity depending on the number of competing banks in the market. Indeed, following information sharing, the reduction in the cost of providing credit and hence the increase in credit access will depend on the number of competitors. To investigate this, we consider the bank's competitive situation in the region where the loan applicant is located.

For actual loans, our database includes information on the region of the loan applicant's location. We complete this information, from Central Bank Statistics, by the total number of bank branches in the region of the applicant's location and re-estimate our main regressions for subsamples of loan applications submitted to banks in regions with different branch densities. We use the simplest measure of bank competition: The number of bank branches in the region where the applicant is applying for a loan.

Since location information is available for applicants that obtain the loan, we are able to re-estimate our regressions for the intensive margin of lending, i.e., the logarithm of loan amount as dependent variable.[28] Technically, we rerun specification 4 in Table 6 on subsamples based on the total number of bank branches in the region of the applicant's location for the subsample of applicants without negative credit history. Table 7 shows our results.

The estimates for subsamples of borrowers in above median, below median, and below 25th percentile population branch density are shown in columns 1, 2 and 3, respectively. In column 4 we exclude loan applications to branches located in the capital city, Budapest, and present our results for the subsample of borrowers in the remaining 19 other regions. Budapest accounts for one fifth of Hungary's population thus representing a cluster with the highest population density and, correspondingly, bank branch density, implying that from the perspective of bank competition, the region may be an outlier compared to other regions in the country. We therefore check whether our results hold for regions outside of the capital city. Columns 5 and 6 further divide the sample into applications from above and below median branch density counties focusing only on the 19 counties, excluding loan applications to branches located in Budapest.

Looking at Table 7, we do not observe much difference relative to our earlier findings in the two borrower groups reapplying for credit to banks where they already have outstanding exposures (Group 1 and 3). The primary difference relative to our earlier results arises for the group of applicants applying for credit to competitor banks (Group 2). Our main results so far, for the subsample of such loan applicants reflect a rather small average effect along both the extensive and intensive margins. In contrast, in Table 7 a significant and sizeable coefficient on the interaction term "*Post x Applicant has exposure at other banks"* indicates the positive impact of information sharing for applicants applying for loans to competing banks. The estimates are significant only in the subsamples of applications made to banks in high branch density regions, i.e., in columns 1 and 5 of the table, indicating that borrowers are likely to obtain higher loan amounts only when the level of bank competition in the region where they apply for the loan is high. At the same time, loan applicants applying to competitor banks and living in below median branch density regions seem to experience no significant increase in the amounts obtained. This finding suggests that when more banks are competing based on new information, the cost reduction in lending generated by information sharing can be significant enough to poach a customer from its bank with an established credit relationship.

Calculating the economic significance of our result based on the estimate in model (1) Table 7, we find that in a region with above median number of bank branches, loan applicants applying to banks where they have no debt exposure obtain 14 percent higher amount (exp(0.13)=1.14) after positive information sharing. This is an economically significant number given the average loan amount in our sample is 406,224 HUF. The estimated coefficient on the interaction term

[28] Since our aim is to understand the impact of information sharing on poaching, depending on the banks' competitive situation, we consider applications by individuals with positive debt exposure. No-info loan applicants play no role in this part of the analysis.

"*Post x Applicant has exposure at other banks"* in column (5) shows that the estimate is robust to the exclusion of loan applications to banks located in Budapest, the highest branch density region. These results indicate that in line with the theory (e.g., Karapetyan and Stacescu (2014b)), positive information sharing induces poaching and bank competition.

5.3 HETEROGENEITY: SIZE OF DEBT EXPOSURE

In this section, we refine our empirical specification to assess how the actual size of an applicant's debt exposure, i.e., total indebtedness, affects the impact of the law on banks' lending policies. The bank's prior about a borrower's outstanding debt amount is likely affect the way the introduction of the law impacts bank's behavior. When following information sharing, a borrower turns out, ceteris paribus, to have lower exposure than the bank's prior (i.e., 'good' positive information), the borrower is expected to be treated better by the post-information sharing regime. Learning about small (high) debt exposure will thus increase (decrease) the probability of receiving credit and the size of the loan due to the increased (reduced) competition. The hypotheses we test, are:

Hypothesis 3a. *Positive information sharing will increase the probability of getting credit more for borrowers with smaller debt exposure.*

Hypothesis 3b. *Positive information sharing will increase the amount of credit received more for borrowers with smaller debt exposure.*

We thus refine our empirical model by allowing for the effect of information-sharing to depend on the actual size of the applicant's debt exposure. Such a specification may capture more precisely the value of additional information available for lenders in the expanded credit registry from May 2012 onwards. We modify equation (2), by expanding it further with triple interaction terms of the post-event dummy, applicant type, and the size of the applicant's debt exposure. We estimate the following equation:

$$
\begin{aligned}
&Acceptance_{it} = \alpha_i + \beta_b + \gamma_0 \times Post_t \\
&+\gamma_1 \times Loan\ applicant\ with\ exposure\ at\ other\ banks_{it} \\
&+\gamma_2 \times Loan\ applicant\ with\ exposure\ at\ other\ banks_{it} \times Post_t \\
&+\gamma_3 \times Loan\ applicant\ with\ exposure\ at\ other\ banks_{it} \times Post_t \times Size\ of\ debt\ exposure_{it} \\
&+\gamma_4 \times Loan\ applicant\ with\ exposure\ at\ the\ bank\ and\ other\ banks_{it} \\
&+\gamma_5 \times Loan\ applicant\ with\ exposure\ at\ the\ bank\ and\ other\ banks_{it} \times Post_t \\
&+\gamma_6 \times Loan\ applicant\ with\ exposure\ at\ the\ bank\ and\ other\ banks_{it} \times Post_t \\
&\qquad\qquad \times Size\ of\ debt\ exposure_{it} \\
&+ \delta \times X_{it} + \theta + \varepsilon_{it}
\end{aligned}
\tag{4}
$$

We also estimate equation (4) with the logarithm of loan amount as dependent variable, using the subsample of accepted applications and extending the specification with loan-type fixed effects similar to the more concise specification of equation (3).

To increase the precision of our estimates, we winsorize the debt exposure size variable at the 1 and 99 percentiles.

Our results on size exposure heterogeneity are shown in Table 8 for the extensive and Table 9 for the intensive margin. The results confirm that, on average, after the introduction of positive information borrowers are better treated both along the intensive and extensive margins of lending.

The results in Table 8 are largely in line with our earlier findings for borrowers with no negative history applying for a loan to a bank where they already have exposure (Group 1 and Group 2 applicants). The statistically significant coefficients in columns 3 and 4 on the interaction variables (*Post x Group*) indicate that the probability of application acceptance increases in the post-event period. The estimated standard errors for the average applicants are smaller indicating that accounting for the size of debt exposure makes our estimations more accurate.

The negative and significant estimates on the triple interaction variables (*Post x Group x Size of exposure*) confirm Hypothesis 3a that borrowers with smaller outstanding debt exposure are more likely to have their loan applications accepted.

As shown in Column 2, a Group 1 borrower applying for a loan with a bank where she already has exposure will experience on average an increase of 25 pp in the probability of application acceptance, Group 2 – an increase of 22 pp, Group 3 – an increase of 12 pp. However, for an exposure equal to the 1 million HUF (about the median exposure reported in Table 2), these changes drop to near or below 0.

Next, in Table 9, we estimate our results on the effect of the size of debt exposure for the intensive margin of lending, using the logarithm of loan amount as dependent variable. The results are significant for each of the three types of applicants (with no past delinquencies) categorized earlier in our sample: applicants of the incumbent bank (Group 1), applicants of a competitor bank (Group 2), as well as applicants that are customers of the incumbent bank and another bank (Group 3). The effect is similar for the three groups: Borrowers with lower outstanding debt exposures benefit more from positive information. Large exposure applicants will experience a decrease in access to credit – this is consistent with the findings of Bos, De Haas and Millone (2015) who find that lending standards tighten after positive info sharing.

Finally, in Table 10 we reestimate our triple interaction regressions for subsamples of loan applicants residing in above and below median branch density regions. The table follows the structure of Table 7 and shows estimations for the above median, below median, and below 25th percentile branch density counties in columns 1, 2, and 3 respectively. In column 4 we exclude loan applications to branches located in the capital city, Budapest, and present our results for the subsample of borrowers in the remaining 19 other regions. Columns 5 and 6 further divide the sample into applications from above and below median branch density counties focusing only on the 19 counties, excluding loan applications to branches located in Budapest. Estimates on the interaction with exposures confirm earlier findings: Borrowers with lower outstanding debt exposures benefit more from positive information especially in areas with a high bank branch density.

5.4 LOAN PERFORMANCE

In light of our previous results, we conclude that credit allocation improved for the average loan applicant. In addition, we find that heterogeneity in applicants' debt exposure has an impact both along the extensive and intensive margins, implying a change in the quality of the borrower pool post information sharing. Indeed, as both incumbent and competitor banks turn out to be more likely to reject high exposure applicants (or give them less credit), we may expect loan default rates to reduce, when credit approved following positive information sharing. Such effects may indicate that positive information sharing raises aggregate borrower welfare.

To assess the impact of positive information sharing on borrowers' default we run, in Table 11, a specification similar to regression (3) using a dummy variable that takes the value of 1 if the borrower defaults on the loan within a six-year period following loan granting as dependent variable. As default may occur only for applicants with actual loans, the regressions are run for the subsample of accepted loan applications. Since default at the individual borrower level is a less frequent experience than obtaining a loan, in our analysis of borrower default we are unable to use borrower fixed effects. We include, instead, bank fixed effects in addition to loan type fixed effects.

Table 11 confirms our hypothesis that positive information sharing decreases the probability of default for borrowers receiving credit post information sharing. Coefficient estimates of the interaction terms with the Post variable in columns 3 and 4 suggest that for borrowers with no negative history the probability of default decreases by 0.4 to 1.85 pp. We confirm, in Appendix table A.2, that this result is not driven by heterogenous effects in our sample: The likelihood of default decreases for all loan applicants with no past default history, even for applicants that are financially vulnerable ex-ante when applying for a loan. We estimate the impact of information sharing on default rates in the subsample of applicants with above median debt-to-income ratios. Our findings suggest that, depending on the applicant's banking history, information sharing has either no impact or a significant negative impact on the likelihood of future delinquency in the subsample of high debt-to-income ratio loan applicants.

In contrast to our results for applicants with no past delinquencies, estimates in columns 5 and 6 suggest that borrowers applying for credit with negative history to their incumbent banks (applicants in Group 1 and 3) experience higher default rates post information sharing: For such borrowers applying to their incumbent banks, the probability of default relative to the pre-event period increases by 3.6 to 5.1 pp.

The positive estimate for the subsample of negative history loan applicants may, however, be a consequence of our choice of sample construction: Since we control for negative credit history in our regressions, borrowers experiencing a default event, should not be included in the sample when applying for loan the second time. The first default event includes information for the next application by the borrower (the control variable "Bad credit history with the bank" switches from zero to one for this applicant) implying that the observations are not necessarily independent.

We therefore rerun our estimations of default as dependent variable on the subsample on non-repeat borrowers and present our findings in Table 12. For loan applicants with no past delinquency, our findings are similar to what is indicated by Table 11. In contrast, for the group of borrowers with negative credit history, we now find a negative impact of information sharing on the probability of default. The estimates in columns 5 and 6 indicate that even for such loan applicants, default rates decline significantly confirming our hypothesis that information sharing affects the quality of the borrower population, thereby generating welfare effects.

6 Robustness test

As a robustness test, we choose to conduct a placebo exercise with some adjustments to the specificities of our data. In fact, shifting the date of the event back in time for a placebo is unfortunately not possible in our data for two reasons. First, in the months immediately preceding our pre-event period, foreign exchange loans could be repaid on favorable terms, creating a potential cofounder. Second, since the credit registry was first populated with positive data only starting in April 2012, we do not know the loans that existed before that time (we have data only on the loans that were still outstanding in April 2012). Our investigation uses a short pre-period exactly for the reason to accommodate for this problem (as it is highly unlikely that a loan which was, for example, originated in February 2012 was repaid before April 2012). However, the more we go back in time to set up the placebo, the more this data censoring becomes an issue. Therefore, for an appropriate placebo period (i.e., before November 2011), we face a potential survivorship bias: The further we go back in time the less likely we will find a loan origination that matches a loan application. This, unfortunately, means that in a placebo test we are essentially guaranteed to find a positive Post coefficient, but that is likely just an artefact of our data.

To remedy the situation, we predict the acceptance probabilities of the applications in the placebo period based on a probit regression run on our data from the original pre-period (February to April 2012) and run the placebo test on these predicted probabilities. In the first stage, we merge employment and income data of all loan applicants (i.e., birth year, gender, county of residence, income, recent income history, type of occupation, hours worked per week) along with bank identity, and use this information to predict loan acceptance. We find that this prediction model modulates survivorship bias in the data. In the second stage, we conduct the placebo test based on loan acceptances imputed from the earlier period. In the resulting placebo test we get a significant negative estimated coefficient for the Post variable possibly suggesting that the introduction of positive information-sharing turned a negative pre-trend into a positive impact. The estimates of both stages are shown in Appendix Tables A.2 and A.3.

7 Conclusion

We study the impact of positive information sharing on borrowers' credit access both along the intensive and extensive margins. Exploiting a nation-wide introduction of a mandatory sharing regime, we are able to analyze loan applicants with various credit histories: Applicants applying to banks where they already have an established relationship, applicants applying to competitor banks, as well as applicants with and without past negative credit histories. We find an overall increase in credit access across both the extensive and intensive margins of lending and in (almost) all borrower groups. We also find that default rates decrease post information sharing consistent with an aggregate increase in welfare.

When studying the interaction between regional bank competition and the event of information sharing, we find that when more banks compete based on new information, reduction in the cost of lending will be sufficient to poach a customer from the bank where she has an established credit relationship. Such competitive effects generating aggressive bank behaviour will not, however, decrease loan performance. We thus conclude that information sharing has an overall positive effect on the operation of credit markets and welfare in society.

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Table 1.
Classification of applicants in the sample and summary of results by applicant subsamples

Panel A. Banks' information on loan applicants before information sharing

	Group 1		**Group 2**		**Group 3**	
	Applicants who have exposure only at the incumbent bank		Applicants who have exposures only at other banks		Applicants who have exposures at both the incumbent and other banks	
Default? Negative history w/ any bank?	Credit from incumbent?	Data from other banks?	Credit from incumbent?	Data from other banks?	Credit from incumbent?	Data from other banks?
No	Yes	No	No	No	Yes	No
Yes	Yes	No	No	No	Yes	No

Panel B. Banks information on loan applicants after information sharing and size of estimated effects

	Group 1		**Group 2**		**Group 3**	
	Applicants who have exposure only at the incumbent bank		Applicants who have exposures only at other banks		Applicants who have exposures at both the incumbent and other banks	
Default? Negative history w/ any bank?	Credit from incumbent?	Data from other banks?	Credit from incumbent?	Data from other banks?	Credit from incumbent?	Data from other banks?
No	Yes	No	No	**Yes**	Yes	**Yes**
Yes	Yes	No	No	**Yes**	Yes	**Yes**
	Change in probability of loan acceptance and change in loan amount post information sharing					
Default? Negative history w/ any bank?	*Loan acceptance*	*Loan amount*	*Loan acceptance*	*Loan amount*	*Loan acceptance*	*Loan amount*
No	*0 pp*	*48%*	*1 pp*	***7%***	*0.6 pp*	***24%***
Yes	*10 pp*	*25%*	*5 pp*	***0%***	*11 pp*	***27%***

Notes: The Table shows categorization of loan applicants with positive history in our sample into three distinct borrower groups based on their past bank relationships (Panel A) and the size of our estimated effects along the extensive and intensive margins for the three groups, separating applications by applicants with and without negative credit history (Panel B) at the time of submitting the loan application. The values are calculated based on estimates from the relevant most saturated specifications (i.e., column 4) in Table 4 (for the extensive margin) and Table 5 (for the intensive margin). "Credit from incumbent" refers to outstanding credit from the bank where the loan application is being submitted. "Data from other banks" refers to new information about the applicant's outstanding debt brought about by information sharing.

Table 2
Summary statistics for the Number of applications, the Number of accepted applications, and the Mean loan ammount if application is accepted during the pre-event and post-event period

			Full Sample	Pre-event Period	Post-event Period
1	Number of applications in sample		1 581 480	755 697	825 783
2	Number of of applications accepted		564 705	237 697	327 008
3	Number of of applications by applicants with pre & post applications		407 434	199 237	208 197
4	Number of of applications accepted, by applicants with pre & post applications		153 701	73 824	79 877
5	Mean loan amount if accepted (HUF), full sample		406 224	431 817	387 621
6	Mean loan amount if accepted (HUF) by loan applicants with pre & post applications		346 454	349 803	343 358
7	**Number of of applications by**	No-info loan applicants	632 796	313 753	319 043
8		Loan applicants with exposure at the bank	238 583	121 871	116 712
9		Loan applicants with exposure at other banks	389 460	178 672	210 788
10		Loan applicants with exposure at the bank & other banks	320 641	141 401	179 240
11	**Number of accepted applications**	No-info loan applicants	179 261	77 553	101 708
12		Loan applicants with exposure at the bank	97 912	43 443	54 469
13		Loan applicants with exposure at other banks	138 893	60 216	78 677
14		Loan applicants with exposure at the bank & other banks	148 639	56 485	92 154
15	**Mean loan amount if application is accepted**	No-info loan applicants	434 796	490 726	392 148
16		Loan applicants with exposure at the bank	405 998	401 195	409 828
17		Loan applicants with exposure at other banks	438 543	447 330	431 818
18		Loan applicants with exposure at the bank & other banks	341 715	357 947	331 766

Notes: The table shows descriptive statistics based on our loan-application level dataset, for two dependent variables, the loan acceptance dummy variable and the loan amount. The full sample period is from February 2012 to October 2012. The pre-event period is from February to April 2012, the post-event period is from May to October 2012. A "No-info applicant" has no outstanding debt exposure or previous credit history at any bank. A "Loan applicant with exposure at the bank" is a loan applicant with outstanding debt exclusively with the bank where the loan application is made, a "Loan applicant with exposure at other banks" is a loan applicant with outstanding debt from creditors other than the bank where the application is made, and a "Loan applicant with exposure at the bank and other banks", is a loan applicant who has outstanding debt at the bank where the application is made and at least one other bank. Statistics for the group of loan applicants with both pre- and post-event applications are presented to indicate the number of obervations used for identification in subsequent regression tables using applicant-level fixed effects.

Table 3
Descriptive statistics for % of Applications accepted, Log(Loan amount) if application accepted, and Total debt exposure

		Mean	Std. Dev.	Min.	Median	Max.
% of Applications accepted		0.3571	0.4791	0	0	1
	No-info loan applicants	0.2833	0.4506	0	0	1
	Loan applicants with exposure at the bank	0.4104	0.4919	0	0	1
	Loan applicants with exposure at other banks	0.3566	0.4790	0	0	1
	Loan applicants with exposure at the bank & other banks	0.4636	0.4987	0	0	1
Log(Loan amount) if application accepted		12.1076	1.1996	0	12.0137	18.7922
	No-info loan applicants	12.0321	1.3625	0	12.1007	18.0486
	Loan applicants with exposure at the bank	12.2263	1.1999	0	12.1007	18.0485
	Loan applicants with exposure at other banks	12.2128	1.0413	0	12.1548	18.133
	Loan applicants with exposure at the bank & other banks	12.0203	1.1176	0	11.8494	17.7275
Total debt exposure (Hungarian Forint)		4 544 452	20 500 000	1	1 052 905	2 380 000 000
	Loan applicants with exposure at the bank	1 578 807	4 925 168	1	220 845	320 000 000
	Loan applicants with exposure at other banks	4 886 282	22 500 000	1	1 166 180	1 790 000 000
	Loan applicants with exposure at the bank & other banks	6 336 204	24 600 000	42	2 303 531	2 380 000 000
Log(Income)		10.1843	4.5209	0	11.9612	16.4026
Applicant with earlier delinquency at the bank		0.0049	0.0695	0	0	1
Applicant with earlier delinquency with another bank		0.0703	0.2557	0	0	1

Notes: The table shows descriptive statistics based on our loan-application level dataset, for the . A "No-info applicant" has no outstanding debt exposure or previous credit history at any bank. A "Loan applicant with exposure at the bank" is a loan applicant with outstanding debt exclusively with the bank where the loan application is made, a "Loan applicant with exposure at other banks" is a loan applicant with outstanding debt from creditors other than the bank where the application is made, and a "Loan applicant with exposure at the bank and other banks", is a loan applicant who has outstanding debt at the bank where the application is made and at least one other bank.

Table 4
The extensive and intensive margins of lending, Loan applicants with neither positive nor negative credit history

	Acceptance probability All applications			Log(loan amount) Accepted applications		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.0016	0.0082*	0.0082*	0.0795***	0.0762**	0.0772**
	(0.86)	(1.71)	(1.71)	(3.16)	(2.10)	(2.13)
Log(Income)		0.0002			-0.0054	
		(0.25)			(-0.93)	
Constant	0.0986***	0.3029***	0.3049***	13.6241***	13.5458***	13.4755***
	(9.28)	(12.99)	(13.87)	(28.86)	(23.51)	(23.59)
Loan Applicant Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	No	No	No	Yes	Yes	Yes
N	627 916	155 539	155 539	166 418	70 768	70 768
R^2	0.9478	0.9136	0.9136	0.9918	0.9907	0.9907
Descriptive Statistics on Dependent Variable in the Subsample:						
Mean	0.3524	0.4208	0.4208	12.1207	12.3195	12.3195
Standard deviation	0.4777	0.4937	0.4937	1.1651	1.1794	1.1794

*Notes: The table shows difference-in-difference regressions of the probability of acceptance and the logarithm of loan amount for accepted applications by loan applicants with no past negative history and no outstanding debt exposure at the time of the loan application (no-info loan applicants). Total number of loan applications by no-info applicants in the sample is 632,796. 627,916 applications are made by individuals with no past delinquency. In this group of loan applications, income data is available for a subset of 155,539 applications. "Post" is a dummy variable taking the value of 1 if the loan application is made in or subsequent to May 2012. Log(Income) is the logarithm of the borrower's monthly income. Regressions (1)-(3) include individual fixed effects, regressions (4)-(6) include individual and loan type fixed effects. The dependent variable in regressions (4)-(6), Log(loan amount) is winsorized at the 1st and 99th percentiles. The sample period is from February 2012 to October 2012. Only applicants with no past delinquency, that is loan applicants with no delinquent loan during the 5 years prior to the date of the loan application are in the sample. * p<0.1, ** p<0.05, *** p<0.01.*

Table 5.
The extensive margin of lending, Loan applicants with positive history

Acceptance Probability	All Applications		Applicants with No Past Delinquency		Applicants with Past Delinquency	
	(1)	(2)	(3)	(4)	(5)	(6)
Post X Loan applicant with exposure at the bank	-0.0013	-0.0043	-0.0033	-0.0063	0.0946***	0.0942***
	(-0.48)	(-0.98)	(-1.15)	(-1.39)	(6.97)	(4.03)
Loan applicant with exposure at other banks	0.0015	-0.0061	0.0130***	0.0036	-0.0613***	-0.0516**
	(0.37)	(-1.01)	(3.06)	(0.56)	(-3.91)	(-1.99)
Post X Loan applicant with exposure at other banks	0.0224***	0.0161***	0.0185***	0.0105***	0.0505***	0.0535***
	(10.06)	(4.81)	(7.58)	(2.89)	(10.66)	(7.16)
Loan applicant with exposure at the bank and other banks	-0.0277***	-0.0364***	-0.0295***	-0.0392***	-0.0228	-0.0142
	(-6.62)	(-5.69)	(-6.64)	(-5.84)	(-1.44)	(-0.54)
Post X Loan applicant with exposure at the bank and other banks	0.0204***	0.0136***	0.0059***	-0.0019	0.0998***	0.1121***
	(10.01)	(4.38)	(2.60)	(-0.55)	(25.88)	(17.70)
Log(Total debt exposure)	-0.0379***	-0.0400***	-0.0393***	-0.0405***	-0.0053*	-0.0133***
	(-31.09)	(-22.12)	(-29.65)	(-20.85)	(-1.78)	(-2.88)
Log(Income)		0.0019**		0.0020**		0.0004
		(2.51)		(2.44)		(0.17)
Bad credit history with the bank		-0.0343*				0.0230
		(-1.83)				(1.62)
Bad credit history with other banks		-0.0584***				
		(-5.88)				
Constant	0.6587***	0.7321***	0.6895***	0.7509***	0.0477	0.1495**
	(37.19)	(26.20)	(35.73)	(24.99)	(1.12)	(2.11)
Loan Applicant Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	907 562	403 100	799 914	357 471	107 648	45 629
R^2	0.8568	0.8509	0.8492	0.8429	0.9444	0.9461
Descriptive Statistics on Dependent Variable in the Subsample:						
Mean	0.4083	0.3968	0.4057	0.3946	0.4277	0.4140
Standard deviation	0.4915	0.4892	0.4910	0.4888	0.4947	0.4925

*Notes: The table shows difference-in-differences regressions of the probability of acceptance as dependent variable. Only applicants with positive debt exposure at the time of submitting the application are included in the sample. The total number of loan applications by applicants with positive outstanding debt exposure in the sample is 907,652 and income data is available for a subset of 403,100 applications. "Post" is a dummy variable taking the value of 1 if the loan application is made in the month of or subsequent to May 2012. "Log(Total debt exposure)" is the value of the applicant's total debt exposure taking into account all banks where the applicant has outstanding credit. "Log(Income)" is the logarithm of the borrower's monthly income. "Bad credit history with the bank" is a dummy variable taking the value of 1 if the applicant has past delinquency with the bank where the application is submitted. "Bad credit history with other banks" is a dummy variable taking the value of 1 if the applicant has past delinquency with another bank. Regressions (1) and (2) are based on the full sample, regressions (3)-(4) are based on a subsample of loan applications by applicants with no past delinquency, that is loan applicants with no delinquent loan during the 5 years prior to the date of the loan application, and regressions (5)-(6) are based on a subsample of loan applicants with past delinquency. All regressions include loan applicant fixed effects. The sample period is from February 2012 to October 2012. * p<0.1, ** p<0.05, *** p<0.01.*

Table 6
The intensive margin of lending, Loan applicants with positive history

Log(Loan Amount)	All Applications		Applicants with No Past Delinquency		Applicants with Past Delinquency	
	(1)	(2)	(3)	(4)	(5)	(6)
Post X Loan applicant with exposure at the bank	0.3244***	0.3777***	0.3504***	$\boxed{0.3945^{***}}$	0.1677***	$\boxed{0.2209^{***}}$
	(15.75)	(9.57)	(15.33)	$\boxed{(9.02)}$	(3.39)	$\boxed{(2.60)}$
Loan applicant with exposure at other banks	-0.0310	-0.1437**	-0.0660*	-0.1789***	0.3688***	0.4518***
	(-1.01)	(-2.57)	(-1.94)	(-2.88)	(4.92)	(3.47)
Post X Loan applicant with exposure at other banks	-0.0063	0.0584*	0.0101	$\boxed{0.0695^{*}}$	-0.0059	0.0395
	(-0.34)	(1.81)	(0.49)	$\boxed{(1.90)}$	(-0.17)	(0.72)
Loan applicant with exposure at the bank and other banks	-0.1199***	-0.1200**	-0.0891***	-0.0748	-0.0174	0.0785
	(-3.91)	(-2.12)	(-2.59)	(-1.18)	(-0.24)	(0.61)
Post X Loan applicant with exposure at the bank and other banks	0.2474***	0.2474***	0.2392***	$\boxed{0.2167^{***}}$	0.2015***	$\boxed{0.2362^{***}}$
	(18.80)	(10.02)	(14.74)	$\boxed{(7.11)}$	(12.90)	$\boxed{(9.15)}$
Log(Total debt exposure)	-0.0536***	-0.0671***	-0.0684***	-0.0759***	-0.0010	-0.0268
	(-7.03)	(-4.94)	(-7.63)	(-4.78)	(-0.08)	(-1.43)
Log(Income)		0.0015		-0.0029		0.0165*
		(0.19)		(-0.30)		(1.85)
Bad credit history with the bank		-0.0777				-0.0122
		(-0.49)				(-0.13)
Bad credit history with other banks		0.0213				
		(0.30)				
Constant	1.6276***	2.0080***	1.8416***	2.3461***	-0.7920	-4.1680***
	(8.53)	(6.35)	(8.61)	(6.56)	(-1.60)	(-4.29)
Loan Applicant Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	370 592	159 958	324 551	141 065	46 041	18 893
R^2	0.9418	0.9464	0.9415	0.9456	0.9567	0.9686
Descriptive Statistics on Dependent Variable in the Subsample:						
Mean	11.8309	11.8952	11.8900	11.9649	11.4140	11.3743
Standard deviation	2.0595	2.3080	2.1249	2.3772	1.4534	1.6117

*Notes: The table shows difference-in-differences regressions of the logarithm of loan amount as dependent variable. Only accepted loan applications (i.e., actual loans) by applicants with positive debt exposure at the time of submitting the application are included in the sample. The total number of loans given to applicants with positive outstanding debt exposure in the sample is 370,592, income data is available for a subset of 159,958 applicants. "Post" is a dummy variable taking the value of 1 if the loan application is made in the month of or subsequent to May 2012. "Log(Income)" is the logarithm of the borrower's monthly income. "Bad credit history with the bank" is a dummy variable taking the value of 1 if the applicant has past delinquency with the bank where the application is submitted. "Bad credit history with other banks" is a dummy variable taking the value of 1 if the applicant has past delinquency with another bank. Regressions (1) and (2) are based on the full sample, regressions (3)-(4) are based on a subsample of loans given to applicants with no past delinquency, that is applicants with no delinquent loan during the past 5 years prior to the loan application, and regressions (5)-(6) are based on a subsample of loans given to applicants with past delinquency. The dependent variable Log(loan amount) is winsorized at 1st and 99th percentiles. All regressions include loan applicant and loan type fixed effects. The sample period is from February 2012 to October 2012. * p<0.1, ** p<0.05, *** p<0.01.*

Table 7.
Impact of bank competition on poaching, the intensive margin of lending, loan applicants with positive history

Loan Amount	**Loan applicants living in** *By branch density*	**19 Regions + Budapest** *Above median*	*Below median*	*Below 25th Pctile*	**19 Regions**	**19 Regions** *Above median*	*Below median*
		(1)	(2)	(3)	(4)	(5)	(6)
Post X Applicant with exposure at the bank		0.3751***	0.4106***	0.3141***	0.3993***	0.3755***	0.4106***
		(6.44)	(6.15)	(3.24)	(8.67)	(5.91)	(6.15)
Applicant with exposure at other banks		-0.1880**	-0.1490	-0.1648	-0.1614**	-0.1677*	-0.1490
		(-2.26)	(-1.57)	(-1.15)	(-2.46)	(-1.83)	(-1.57)
Post X Applicant with exposure at other banks		0.1275***	-0.0116	-0.1024	0.0652*	0.1369**	-0.0116
		(2.60)	(-0.21)	(-1.23)	(1.67)	(2.49)	(-0.21)
Applicant with exposure at the bank and other banks		-0.0412	-0.0909	-0.1728	-0.0679	-0.0408	-0.0909
		(-0.48)	(-0.94)	(-1.19)	(-1.02)	(-0.44)	(-0.94)
Post X Applicant with exposure at the bank and other banks		0.1792***	0.2557***	0.2334***	0.2205***	0.1883***	0.2557***
		(4.39)	(5.50)	(3.38)	(6.89)	(4.28)	(5.50)
Log(Total debt exposure)		-0.0722***	-0.0700***	-0.0282	-0.0668***	-0.0661***	-0.0700***
		(-3.47)	(-2.89)	(-0.77)	(-4.01)	(-2.89)	(-2.89)
Log(Income)		0.0066	-0.0136	-0.0315	-0.0053	0.0039	-0.0136
		(0.52)	(-0.95)	(-1.54)	(-0.54)	(0.28)	(-0.95)
Constant		1.7609***	3.1632***	1.8578*	2.4309***	1.8209***	3.1632***
		(3.83)	(5.34)	(1.69)	(6.22)	(3.44)	(5.34)
Loan Applicant Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
N		78 265	62 830	28 707	122 783	59 953	62 830
R^2		0.9489	0.9403	0.9405	0.9432	0.9472	0.9403
Descriptive Statistics on Dependent Variable in the Subsample:							
Mean		12.0258	11.9072	11.8710	11.9359	11.9659	11.9072
Standard deviation		2.3657	2.3672	2.3900	2.3634	2.3592	2.3672

*Notes: The table shows subsample estimations of difference-in-differences regressions of the logarithm of loan amount as dependent variable. Accepted loan applications by applicants with positive debt exposure are included in the sample (no negative history applicants). Subsamples are based on the total number of bank branches in the loan applicant's region. Applications by applicants with past delinquencies are not included in the sample. "Post" is a dummy variable taking the value of 1 if the loan application is made in the month of or subsequent to May 2012. "Log(Total debt exposure)" is the value of the applicant's total debt exposure taking into account all banks where the applicant has outstanding credit. "Log(Income)" is the logarithm of the borrower's monthly income. "Bad credit history with the bank" is a dummy variable taking the value of 1 if the applicant has past delinquency with the bank where the application is submitted. "Bad credit history with other banks" is a dummy variable taking the value of 1 if the applicant has past delinquency with another bank. All regressions include loan applicant and loan type fixed effects. The sample period is from February 2012 to October 2012. The total number of bank branches in Budapest is 369, while the average number of bank branches in the 19 other counties is 96 (with minimum of 52 and maximum of 189). * p<0.1, ** p<0.05, *** p<0.01.*

Table 8.
Exposure heterogeneity, the extensive margin of lending, loan applicants with positive history

Acceptance Probability	All Applications		Loan Applicants with No Past Delinquency		Loan Applicants with Past Delinquency	
	(1)	(2)	(3)	(4)	(5)	(6)
Post X Applicant with exposure at the bank	0.2871***	0.2536***	0.2857***	0.2563***	0.2012*	-0.0342
	(13.09)	(7.28)	(12.57)	(7.14)	(1.74)	(-0.17)
Post X Applicant with exposure at bank X Size of exposure at the bank	-0.0238***	-0.0211***	-0.0238***	-0.0214***	-0.0092	0.0109
	(-13.24)	(-7.43)	(-12.78)	(-7.33)	(-0.95)	(0.67)
Applicant with exposure at other banks	0.0942***	0.0198	0.0635**	-0.0053	0.1213	-0.1653
	(3.37)	(0.47)	(2.16)	(-0.12)	(1.08)	(-0.93)
Post X Applicant with exposure at other banks	0.2092***	0.2166***	0.2245***	0.2242***	0.0629	0.1740***
	(11.70)	(8.05)	(11.57)	(7.74)	(1.56)	(2.79)
Post X Applicant with exposure at other banks X Size of exposure at other banks	-0.0134***	-0.0143***	-0.0149***	-0.0153***	-0.0008	-0.0084*
	(-10.51)	(-7.51)	(-10.71)	(-7.45)	(-0.28)	(-1.93)
Applicant with exposure at the bank and other banks	0.0199	0.0394	0.0269	0.0303	-0.0031	-0.1206
	(0.60)	(0.78)	(0.76)	(0.56)	(-0.03)	(-0.65)
Post X Applicant with exposure at the bank and other banks	0.1832***	0.0910***	0.2150***	0.1208***	0.1291***	0.0130
	(8.71)	(2.84)	(9.19)	(3.45)	(3.20)	(0.20)
Post X Applicant with exposure at the bank and other banks X Size of total exposure	-0.0113***	-0.0053**	-0.0145***	-0.0084***	-0.0021	0.0067
	(-7.78)	(-2.43)	(-8.97)	(-3.51)	(-0.75)	(1.49)
Applicant with exposure at other banks X Size of exposure at other banks	-0.0231***	-0.0284***	-0.0252***	-0.0297***	0.0044	-0.0211
	(-11.17)	(-8.97)	(-11.64)	(-9.00)	(0.49)	(-1.48)
Applicant with exposure at the bank and other banks X Size of total exposure	-0.0089***	-0.0036	-0.0057**	-0.0010	-0.0148	0.0092
	(-4.04)	(-1.08)	(-2.44)	(-0.27)	(-1.58)	(0.63)
Applicant with exposure at the bank X Size of exposure at the bank	-0.0061**	-0.0074*	-0.0065**	-0.0068*	-0.0036	0.0087
	(-2.42)	(-1.94)	(-2.41)	(-1.68)	(-0.37)	(0.58)
Log(Income)		0.0018**		0.0019**		0.0003
		(2.38)		(2.30)		(0.17)
Bad credit history with the bank		-0.0313*				0.0195
		(-1.67)				(1.37)
Bad credit history with other banks		-0.0553***				
		(-5.56)				
Constant	0.4826***	0.5950***	0.5225***	0.6235***	-0.0677	0.2405
	(18.07)	(14.23)	(18.54)	(14.23)	(-0.62)	(1.38)
Loan Applicant Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	907 562	403 100	799 914	357 471	107 648	45 629
R^2	0.8570	0.8511	0.8494	0.8431	0.9444	0.9462

*Notes: The table shows difference-in-differences regressions of the probability of acceptance as dependent variable. Only applicants with positive debt exposure at the time of submitting the application are included in the sample. The total number of loan applications by applicants with positive outstanding debt exposure in the sample is 911,212 and income data is available for a subset of 470,233 applications. "Post" is a dummy variable taking the value of 1 if the loan application is made in the month of or subsequent to May 2012. The "Size of exposure at the bank, of exposure at other banks, or of total exposure" is the logarithm of the value of the applicant's debt exposure to the bank, other banks, or all banks where the applicant has outstanding credit. "Log(Income)" is the logarithm of the borrower's monthly income. "Bad credit history with the bank" is a dummy variable taking the value of 1 if the applicant has past delinquency with the bank where the application is submitted. "Bad credit history with other banks" is a dummy variable taking the value of 1 if the applicant has past delinquency with another bank. Regressions (1) and (2) are based on the full sample, regressions (3)-(4) are based on a subsample of loan applications by applicants with no past delinquency, that is loan applicants with no delinquent loan during the 5 years prior to the date of the loan application, and regressions (5)-(6) are based on a subsample of loan applicants with past delinquency. All regressions include loan applicant fixed effects. The sample period is from February 2012 to October 2012. * p<0.1, ** p<0.05, *** p<0.01.*

Table 9.
Exposure heterogeneity, the intensive margin of lending, loan applicants with positive history

Log(Loan Amount)	All accepted applications		Loan Applicants with No Past Delinquency		Loan Applicants with Past Delinquency	
	(1)	(2)	(3)	(4)	(5)	(6)
Post X Applicant with exposure at the bank	1.4220*** (7.95)	1.8059*** (5.63)	1.6128*** (8.27)	2.0308*** (5.79)	-0.4678 (-0.58)	-1.8250 (-1.37)
Post X Applicant with exposure at bank X Size of exposure at the bank	-0.0897*** (-6.07)	-0.1126*** (-4.35)	-0.1032*** (-6.43)	-0.1290*** (-4.57)	0.0667 (0.94)	0.1895 (1.63)
Applicant with exposure at other banks	0.0801 (0.40)	-0.4522 (-1.26)	0.2365 (1.05)	-0.3484 (-0.87)	-2.2790*** (-3.32)	-2.7489*** (-2.59)
Post X Applicant with exposure at other banks	0.1870 (1.27)	0.4744* (1.82)	0.2269 (1.37)	0.5287* (1.79)	0.0138 (0.05)	0.1631 (0.36)
Post X Applicant with exposure at other banks X Size of exposure at other banks	-0.0140 (-1.31)	-0.0300 (-1.61)	-0.0155 (-1.29)	-0.0330 (-1.56)	-0.0018 (-0.09)	-0.0091 (-0.28)
Applicant with exposure at the bank and other banks	-0.3127 (-1.43)	-0.6366 (-1.61)	-0.4806* (-1.92)	-0.8875** (-1.96)	-2.2905*** (-3.36)	-2.5879** (-2.44)
Post X Applicant with exposure at the bank and other banks	1.0446*** (8.28)	1.1777*** (4.92)	1.4997*** (9.52)	1.7046*** (5.70)	0.2398 (1.63)	0.3618 (1.49)
Post X Applicant with exposure at the bank and other banks X Size of total exposure	-0.0561*** (-6.33)	-0.0651*** (-3.90)	-0.0894*** (-8.03)	-0.1047*** (-5.00)	-0.0028 (-0.28)	-0.0087 (-0.52)
Applicant with exposure at other banks X Size of exposure at other banks	-0.0276* (-1.92)	-0.0571** (-2.28)	-0.0322** (-2.04)	-0.0575** (-2.09)	-0.1991*** (-3.41)	-0.2649*** (-2.94)
Applicant with exposure at the bank and other banks X Size of total exposure	-0.0113 (-0.69)	0.0228 (0.79)	-0.0269 (-1.49)	0.0117 (0.37)	0.2305*** (3.82)	0.2777*** (2.98)
Applicant with exposure at the bank X Size of exposure at the bank	0.0097 (0.56)	0.0363 (1.18)	0.0222 (1.13)	0.0561 (1.61)	0.2038*** (3.39)	0.2397** (2.57)
Log(Income)		0.0012 (0.16)		-0.0034 (-0.37)		0.0158* (1.77)
Bad credit history with the bank		-0.0603 (-0.38)		0.0000 (.)		-0.0172 (-0.19)
Bad credit history with other banks		0.0426 (0.59)				
Constant	1.3619*** (5.72)	1.9264*** (4.81)	1.4631*** (5.58)	2.1786*** (4.92)	1.4421* (1.79)	-1.5002 (-1.09)
Loan Applicant Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	370 592	159 958	324 551	141 065	46 041	18 893
R^2	0.9419	0.9465	0.9416	0.9458	0.9568	0.9687

*Notes: The table shows difference-in-differences regressions of the logarithm of loan amount as dependent variable. Only accepted loan applications (i.e., actual loans) by applicants with positive debt exposure at the time of submitting the application are included in the sample. The total number of loans given to applicants with positive outstanding debt exposure in the sample is 370,577, income data is available for a subset of 186,179 applicants. "Post" is a dummy variable taking the value of 1 if the loan application is made in the month of or subsequent to May 2012. The "Size of exposure at the bank, of exposure at other banks, or of total exposure" is the logarithm of the value of the applicant's debt exposure to the bank, other banks, or all banks where the applicant has outstanding credit. "Log(Income)" is the logarithm of the borrower's monthly income. "Bad credit history with the bank" is a dummy variable taking the value of 1 if the applicant has past delinquency with the bank where the application is submitted. "Bad credit history with other banks" is a dummy variable taking the value of 1 if the applicant has past delinquency with another bank. Regressions (1) and (2) are based on the full sample, regressions (3)-(4) are based on a subsample of loans given to applicants with no past delinquency, that is applicants with no delinquent loan during the past 5 years prior to the loan application, and regressions (5)-(6) are based on a subsample of loans given to applicants with past delinquency. The dependent variable Log(loan amount) is winsorized at 1st and 99th percentiles. All regressions include loan applicant and loan type fixed effects. The sample period is from February 2012 to October 2012. * p<0.1, ** p<0.05, *** p<0.01.*

Table 10.
Exposure heterogeneity, impact of bank competition on poaching, the intensive margin of lending, loan applicants with positive history

Log(Loan amount)	Loan applicants living in	19 Regions + Budapest			19 Regions	19 Regions	
	By branch density	*Above median*	*Below median*	*Below 25th Pctile*		*Above median*	*Below median*
		(1)	(2)	(3)	(4)	(5)	(6)
Post X Applicant with exposure at the bank		1.8525***	2.6782***	2.3568***	2.1403***	1.6398***	2.6782***
		(4.05)	(5.13)	(3.10)	(5.90)	(3.25)	(5.13)
Post X Applicant with exposure at the bank X Size of exposure at the bank		-0.1148***	-0.1815***	-0.1643***	-0.1377***	-0.0968**	-0.1815***
		(-3.12)	(-4.33)	(-2.69)	(-4.72)	(-2.38)	(-4.33)
Applicant with exposure at other banks		-0.8980*	0.5749	1.0153	-0.3284	-1.3485**	0.5749
		(-1.73)	(0.97)	(1.17)	(-0.80)	(-2.36)	(0.97)
Post X Applicant with exposure at other banks		0.8534**	-0.0207	-0.9987	0.4498	0.7188	-0.0207
		(2.18)	(-0.05)	(-1.48)	(1.43)	(1.64)	(-0.05)
Post X Applicant with exposure at other banks X Size of exposure at other banks		-0.0525*	0.0011	0.0650	-0.0278	-0.0427	0.0011
		(-1.87)	(0.03)	(1.34)	(-1.23)	(-1.35)	(0.03)
Applicant with exposure at the bank and other banks		-1.1376*	-0.3822	-0.6552	-0.7634	-1.3088**	-0.3822
		(-1.91)	(-0.56)	(-0.65)	(-1.63)	(-2.01)	(-0.56)
Post X Applicant with exposure at the bank and other banks		1.6286***	1.7627***	1.7838**	1.6097***	1.4213***	1.7627***
		(4.04)	(3.84)	(2.52)	(5.12)	(3.31)	(3.84)
Post X Applicant with exposure at the bank and other banks X Size of exposure all banks		-0.1021***	-0.1061***	-0.1092**	-0.0979***	-0.0871***	-0.1061***
		(-3.61)	(-3.29)	(-2.20)	(-4.44)	(-2.89)	(-3.29)
Log(Income)		-0.0782**	-0.0080	0.0328	-0.0474*	-0.1006**	-0.0080
		(-2.21)	(-0.20)	(0.55)	(-1.69)	(-2.56)	(-0.20)
Applicant with exposure at other banks X Size of exposure at other banks		0.0057	-0.0144	-0.0318	-0.0057	0.0034	-0.0144
		(0.45)	(-1.00)	(-1.56)	(-0.58)	(0.25)	(-1.00)
Applicant with exposure at the bank and other banks X Size of exposure all banks		0.0547	-0.0587	-0.0912	0.0117	0.0942**	-0.0587
		(1.32)	(-1.25)	(-1.32)	(0.36)	(2.05)	(-1.25)
Applicant with exposure at the bank X Size of exposure at the bank		0.0803*	0.0129	0.0270	0.0479	0.0984*	0.0129
		(1.74)	(0.25)	(0.35)	(1.32)	(1.95)	(0.25)
Constant		1.8834***	2.4876***	1.1503	2.2506***	2.2616***	2.4876***
		(3.32)	(3.56)	(0.94)	(4.79)	(3.51)	(3.56)
Loan Applicant Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
N		78 265	62 830	28 707	122 783	59 953	62 830
R^2		0.9490	0.9404	0.9407	0.9433	0.9474	0.9404

*Notes: The table shows subsample estimations of difference-in-differences regressions of the logarithm of loan amount as dependent variable. Accepted loan applications by applicants with positive debt exposure are included in the sample (no negative history applicants). Subsamples are based on the total number of bank branches in the loan applicant's region. Applications by applicants with past delinquencies are not included in the sample. "Post" is a dummy variable taking the value of 1 if the loan application is made in the month of or subsequent to May 2012. The "Size of exposure at the bank, of exposure at other banks, or of total exposure" is the logarithm of the value of the applicant's debt exposure to the bank, other banks, or all banks where the applicant has outstanding credit. "Log(Income)" is the logarithm of the borrower's monthly income. "Bad credit history with the bank" is a dummy variable taking the value of 1 if the applicant has past delinquency with the bank where the application is submitted. "Bad credit history with other banks" is a dummy variable taking the value of 1 if the applicant has past delinquency with another bank. All regressions include loan applicant and loan type fixed effects. The sample period is from February 2012 to October 2012. The total number of bank branches in Budapest is 369, while the average number of bank branches in the 19 other counties is 96 (with minimum of 52 and maximum of 189). * p<0.1, ** p<0.05, *** p<0.01.*

Table 11.
Loan performance, loan applicants with positive history

Default on Loan in 6 Years	All Accepted Applications		Loan Applicants with No Past Delinquency		Loan Applicants with Past Delinquency	
	(1)	(2)	(3)	(4)	(5)	(6)
Post X Applicant with exposure at the bank	-0.0103***	-0.0201***	-0.0095***	-0.0225***	0.0196	0.0582**
	(-4.77)	(-5.57)	(-4.62)	(-6.50)	(1.18)	(2.01)
Applicant with exposure at other banks	-0.0110***	-0.0256***	-0.0131***	-0.0268***	-0.0053	0.0162
	(-4.54)	(-6.55)	(-5.62)	(-7.07)	(-0.33)	(0.60)
Post X Applicant with exposure at other banks	-0.0074***	-0.0083***	-0.0068***	-0.0069***	-0.0139*	-0.0339***
	(-4.51)	(-3.30)	(-4.26)	(-2.79)	(-1.77)	(-2.81)
Applicant with exposure at the bank and other banks	0.0053**	0.0018	0.0067***	0.0085**	-0.0202	-0.0047
	(2.10)	(0.44)	(2.71)	(2.11)	(-1.31)	(-0.18)
Post X Applicant with exposure at the bank and other banks	0.0032*	-0.0040	-0.0044**	-0.0149***	0.0246***	0.0378***
	(1.77)	(-1.43)	(-2.39)	(-5.05)	(4.25)	(4.05)
Log(Total Exposure)	0.0008***	-0.0050***	-0.0016***	-0.0055***	0.0031**	-0.0006
	(2.78)	(-10.92)	(-5.35)	(-12.03)	(2.53)	(-0.29)
Log(Income)		-0.0049***		-0.0044***		-0.0067***
		(-11.65)		(-10.29)		(-4.29)
Bad credit history with the bank		0.1649***				0.0537***
		(13.63)				(3.16)
Bad credit history with other banks		0.0734***				
		(28.55)				
Constant	0.0199***	0.1666***	0.0562***	0.1805***	-0.2038***	-0.1292***
	(3.26)	(16.31)	(9.34)	(17.72)	(-6.87)	(-2.63)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	370 592	159 958	324 551	141 065	46 041	18 893
R^2	0.0217	0.0323	0.0180	0.0242	0.0151	0.0228

*Notes: The table shows difference-in-differences regressions of the Default on Loan in 6 Years as dependent variable. Only accepted loan applications (i.e., actual loans) by applicants with positive debt exposure at the time of submitting the application are included in the sample. The total number of loans given to applicants with positive outstanding debt exposure in the sample is 370,577, income data is available for a subset of 186,179 applicants. "Post" is a dummy variable taking the value of 1 if the loan application is made in the month of or subsequent to May 2012. "Log(Income)" is the logarithm of the borrower's monthly income. "Bad credit history with the bank" is a dummy variable taking the value of 1 if the applicant has past delinquency with the bank where the application is submitted. "Bad credit history with other banks" is a dummy variable taking the value of 1 if the applicant has past delinquency with another bank. Regressions (1) and (2) are based on the full sample, regressions (3)-(4) are based on a subsample of loans given to applicants with no past delinquency, that is applicants with no delinquent loan during the past 5 years prior to the loan application, and regressions (5)-(6) are based on a subsample of loans given to applicants with past delinquency. The dependent variable Log(loan amount) is winsorized at 1st and 99th percentiles. All regressions include loan applicant and loan type fixed effects. The sample period is from February 2012 to October 2012. * p<0.1, ** p<0.05, *** p<0.01.*

Table 12.
Loan performance, one-time loan applicants with positive history

Default on loan in 6 years	All Accepted Applications		Loan Applicants with No Past Delinquency		Loan Applicants with Past Delinquency	
	(1)	(2)	(3)	(4)	(5)	(6)
Post X Applicant with exposure at the bank	-0.0361***	-0.0461***	-0.0337***	-0.0462***	-0.0411	-0.0484
	(-14.62)	(-12.12)	(-14.79)	(-13.08)	(-1.58)	(-1.20)
Applicant with exposure at other banks	-0.0312***	-0.0497***	-0.0339***	-0.0500***	-0.0405*	-0.0515
	(-11.25)	(-12.03)	(-13.08)	(-12.85)	(-1.65)	(-1.35)
Post X Applicant with exposure at other banks	-0.0126***	-0.0152***	-0.0085***	-0.0096***	-0.0549***	-0.0785***
	(-6.96)	(-5.91)	(-4.96)	(-3.89)	(-5.22)	(-5.39)
Applicant with exposure at the bank and other banks	0.0210***	0.0062	0.0104***	0.0017	0.0164	0.0012
	(6.86)	(1.37)	(3.58)	(0.39)	(0.67)	(0.03)
Post X Applicant with exposure at the bank and other banks	-0.0364***	-0.0381***	-0.0325***	-0.0362***	-0.0633***	-0.0476***
	(-15.34)	(-11.34)	(-13.72)	(-10.75)	(-6.64)	(-3.46)
Log(Total Exposure)	0.0004	-0.0051***	-0.0020***	-0.0056***	0.0037**	0.0022
	(1.11)	(-10.79)	(-6.42)	(-12.19)	(2.04)	(0.85)
Log(Income)		-0.0012***		-0.0008***		-0.0028***
		(-6.36)		(-4.46)		(-3.55)
Bad credit history with the bank		0.1900***				0.0446**
		(16.22)				(2.32)
Bad credit history with other banks		0.1008***				
		(32.91)				
Constant	0.0509***	0.1519***	0.0843***	0.1659***	-0.0750*	-0.0154
	(7.68)	(16.20)	(13.26)	(18.33)	(-1.86)	(-0.26)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	236 757	122 110	213 725	110 046	23 032	12 064
R^2	0.0432	0.0639	0.0328	0.0428	0.0212	0.0305

*Notes: The table shows difference-in-differences regressions of the Default on Loan in 6 Years as dependent variable. Only accepted loan applications (i.e., actual loans) by one-time applicants with positive debt exposure at the time of submitting the application are included in the sample. The total number of loans given to applicants with positive outstanding debt exposure in the sample is 236,757, income data is available for a subset of 122,110 applicants. "Post" is a dummy variable taking the value of 1 if the loan application is made in the month of or subsequent to May 2012. "Log(Income)" is the logarithm of the borrower's monthly income. "Bad credit history with the bank" is a dummy variable taking the value of 1 if the applicant has past delinquency with the bank where the application is submitted. "Bad credit history with other banks" is a dummy variable taking the value of 1 if the applicant has past delinquency with another bank. Regressions (1) and (2) are based on the full sample, regressions (3)-(4) are based on a subsample of loans given to applicants with no past delinquency, that is applicants with no delinquent loan during the past 5 years prior to the loan application, and regressions (5)-(6) are based on a subsample of loans given to applicants with past delinquency. The dependent variable Log(loan amount) is winsorized at 1st and 99th percentiles. All regressions include bank and loan type fixed effects. The sample period is from February 2012 to October 2012. * p<0.1, ** p<0.05, *** p<0.01.*

Appendix

Table A.1.
Group and variable definitions

Groups	Definition
No-info loan applicants	Have no outstanding debt exposure or previous credit history at any bank.
Loan applicants with exposure at the bank	Loan applicants with outstanding debt exclusively with the bank where the loan application is made.
Loan applicants with exposure at other banks	Loan applicants with outstanding debt from creditors other than the bank where the application is made.
Loan applicants with exposure at the bank & other banks	Loan applicants who have outstanding debt at the bank where the application is made and at least one other bank
Variables	**Definition**
Post	=1 if the loan application is made in or subsequent to May 2012, =0 otherwise.
Log(Income)	Is the logarithm of the borrower's monthly income.
Log(Total debt exposure)	Is the value of the applicant's total debt exposure taking into account all banks where the applicant has outstanding credit.
Bad credit history with the bank	= 1 if the applicant has past delinquency with the bank where the application is submitted, =0 otherwise.
Bad credit history with other banks	= 1 if the applicant has past delinquency with another bank, =0 otherwise.

Notes: Group and variable definitions of commonly used groups and variables.

Table 2.A.
Loan performance, Loan applicants with positive history, subsamples based on DTI ratios

Default on Loan in 6 years	All Applications			Applicants with No Past Delinquency		
	Full Sample (Model 2, Table 11)	Applicant w above median DTI ratio	Applicant w below median DTI ratio	Full Sample (Model 4, Table 11)	Applicant w above median DTI ratio	Applicant w below median DTI ratio
	(1)	(2)	(3)	(4)	(5)	(6)
Post X Applicant with exposure at the bank	-0.0201***	-0.0115	-0.0254***	-0.0225***	-0.0122*	-0.0291***
	(-5.57)	(-1.58)	(-6.24)	(-6.50)	(-1.79)	(-7.28)
Applicant with exposure at other banks	-0.0256***	-0.0177**	-0.0263***	-0.0268***	-0.0208***	-0.0274***
	(-6.55)	(-2.43)	(-5.56)	(-7.07)	(-3.03)	(-5.83)
Post X Applicant with exposure at other banks	-0.0083***	-0.0091**	-0.0101***	-0.0069***	-0.0074**	-0.0085**
	(-3.30)	(-2.47)	(-2.94)	(-2.79)	(-2.04)	(-2.47)
Applicant with exposure at the bank and other banks	0.0018	0.0157**	-0.0063	0.0085**	0.0236***	-0.0033
	(0.44)	(2.16)	(-1.17)	(2.11)	(3.41)	(-0.61)
Post X Applicant with exposure at the bank and other banks	-0.0040	-0.0078**	-0.0043	-0.0149***	-0.0205***	-0.0117**
	(-1.43)	(-2.11)	(-0.95)	(-5.05)	(-5.37)	(-2.44)
Log(Total Exposure)	-0.0050***	-0.0110***	-0.0014	-0.0055***	-0.0121***	-0.0011
	(-10.92)	(-10.28)	(-1.55)	(-12.03)	(-11.20)	(-1.30)
Log(Income)	-0.0049***	-0.0199***	-0.0427***	-0.0044***	-0.0164***	-0.0439***
	(-11.65)	(-14.11)	(-24.43)	(-10.29)	(-11.41)	(-25.06)
Bad credit history with the bank	0.1649***	0.1818***	0.1119***			
	(13.63)	(12.10)	(5.16)			
Bad credit history with other banks	0.0734***	0.0807***	0.0552***			
	(28.55)	(23.91)	(13.12)			
Constant	0.1666***	0.4101***	0.6244***	0.1805***	0.4063***	0.6423***
	(16.31)	(21.21)	(20.69)	(17.72)	(21.06)	(21.34)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	159 958	74 457	82 754	141 065	61 776	76 921
R^2	0.0323	0.0418	0.0386	0.0242	0.0294	0.0360

*Notes: The table shows difference-in-differences regressions of the Default on Loan in 6 Years as dependent variable. Only accepted loan applications (i.e., actual loans) by applicants with positive debt exposure at the time of submitting the application are included in the sample. The total number of loans given to applicants with positive outstanding debt exposure in the sample is 370,577, income data is available for a subset of 186,179 applicants. "Post" is a dummy variable taking the value of 1 if the loan application is made in the month of or subsequent to May 2012. "Log(Income)" is the logarithm of the borrower's monthly income. "Bad credit history with the bank" is a dummy variable taking the value of 1 if the applicant has past delinquency with the bank where the application is submitted. "Bad credit history with other banks" is a dummy variable taking the value of 1 if the applicant has past delinquency with another bank. Regressions (1) and (2) are based on the full sample, regressions (3)-(4) are based on a subsample of loans given to applicants with no past delinquency, that is applicants with no delinquent loan during the past 5 years prior to the loan application, and regressions (5)-(6) are based on a subsample of loans given to applicants with past delinquency. The dependent variable Log(loan amount) is winsorized at 1st and 99th percentiles. All regressions include loan applicant and loan type fixed effects. The sample period is from February 2012 to October 2012. * p<0.1, ** p<0.05, *** p<0.01.*

Table A.3.
Placebo test, step 1, probit regression

	Probability of acceptance
Log(monthly income)	0.0055***
	(2.79)
Year of Birth	0.0036***
	(12.37)
Applicant's Sex	0.0575***
	(7.79)
Applicant is unemployed	-0.1357***
	(-5.00)
Applicant was unemployed in the 5 months pre-application	-0.1071
	(-6.85)
Applicant is in public work program	0.3253***
	(3.44)
Applicant was in public work program in the 5 months pre-application	-0.2257***
	(-4.98)
Applicant has missing employment record	6.3055
	(0.08)
Applicant had missing employment record in the 5 months pre-application	0.0286***
	(4.14)
Applicant lives in Budapest	-0.0173**
	(-2.08)
Has bad credit history with the bank	-0.7356***
	(-60.77)
Has bad credit history with other banks	-0.8747***
	(-18.37)
Constant	-15.1426
	(-0.20)
Bank Fixed Effects	Yes
Occupation dummy	Yes
Employment type	Yes
Hours worked	Yes
Month dummy	Yes
N	223 642
Pseudo R^2	0.2285

Notes: The table shows coefficient estimates from probit regressions of the probability of acceptance on a sample of 223,642 loan applications made in the period from February 2012 to May 2012. The regressions include bank fixed effects. Occupation dummy indicates one of the following occupation category: manager, professional, technician, clerk, commercial employee, agricultural employee, industrial worker, machine operator, elementary worker, no employment. Employment dummy refers to one of the following employment status: employee, public employee, contract worker, self-employment, public servant, farmer, armed forces. "Hours worked" indicate one of the following categories: 1-9 hours, part-time, full-time, more than full hours. "Query month" refers to dummy variables indicating February, March, or April 2012.

Table A.4.
Placebo test, step 2, linear regression

Predicted probability of acceptance	All loan applications in February 2011-October 2011	
		(2)
Post	-0.02589***	-0.0189***
	(-22.16)	(16.55)
Log(Income)		0.0002
		(1.25)
Individual with earlier delinquency with this bank		-0.3708***
		(-52.54)
Earlier delinquency with other bank		-0.2370***
		(-59.41)
Constant	0.5039***	0.5449***
	(586.06)	(25.20)
Loan Applicant Fixed Effects	Yes	Yes
N	273 588	273 588
R^2	0.8889	0.8952

Notes: The table shows estimates from an OLS regression on predicted probabilites of loan acceptance as dependent variable, for the sample of loan applications made in the period February 2011 and October 2011. Acceptance probabilities are predicted based on estimates from the probit regression in table X. "Post" is a dummy variable taking the value of 1 if the loan application is made in or subsequent to May 2011. Definitions of remaining explanatory variables are the same as in Table 4. The total number of loan applications during the given sample period is 268 486. Regressions include applicant fixed effects.