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Sharing borrower information in a competitive credit market

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Abstract

We exploit detailed data on approved and rejected small business loans to assess the impact of the introduction of a credit registry in Bosnia and Herzegovina. Our findings are threefold. First, mandatory information sharing tightens lending at the extensive margin as more applications are rejected, particularly in areas with strong credit market competition. These rejections are based increasingly on hard information – especially positive borrower information from the new registry – and less on soft information. Second, lending standards also tighten at the intensive margin: the registry leads to smaller, shorter and more expensive loans. Third, the tightening of lending along both margins improves loan quality. Default rates go down, particularly in high-competition areas and for first time borrowers. This suggests that a reduction in adverse selection is an important channel through which information sharing affects loan quality.

Keywords: Information sharing, credit market competition, hazard models

JEL Classification Number: D04; D82; G21; G28

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1. Introduction

Agency problems in banking remain rife, especially in emerging markets where information asymmetries tend to be high, screening and monitoring costly and creditor rights weak. Finding novel ways to overcome these frictions is of first-order importance as lenders typically cannot apply risk-mitigation techniques – such as collateral (Bester, 1987) or contingency contracts (Bolton and Scharfstein, 1990) – that have been tried and tested in more benign lending environments. As a result, many borrowers continue to be credit rationed or charged high interest rates.

Various countries have recently introduced public credit registries in an attempt to improve the functioning of credit markets by requiring lenders to share borrower information. The empirical evidence on the effectiveness of such registries, in terms of greater access to credit and improved loan quality, remains limited and is mainly based on cross-country comparisons. This paper presents more direct evidence of what happens when lenders in a competitive credit market start to share borrower information. We focus on the introduction of a credit registry in which all lenders are required to participate. Evaluating the impact of such a regime change is challenging for at least two reasons. First, borrower information is typically only publicly available *after* a registry is introduced. Second, even if pre-registry data exist it remains difficult to identify the impact of information sharing if all banks and borrowers are similarly affected by the new regime.

To surmount these challenges, we use a unique contract-level data set consisting of the complete loan portfolio of a large lender in Bosnia and Herzegovina. Two features make our data particularly well suited to study the question at hand. First, we can exploit detailed information on the terms – amount, maturity, interest rate, collateral and performance – of all small-business loans that this lender granted through its branch network. Importantly, we have data from before and after the introduction of the credit registry and hence observe lending decisions by the same loan officers under different information-sharing regimes. Second, we also have information on all loan applications that this lender rejected and we know *why* they were rejected. We again have these data for the period before and after the introduction of the registry.

What makes our data even more valuable is the local context. Credit-market competition varies significantly across Bosnia and Herzegovina and we capture this variation through an objective competition measure (the number of local lenders) and a subjective measure based on loan officers' own perceptions. Based on existing theoretical work, we expect the impact of the credit registry to be stronger in geographical areas with more intense credit market competition. We therefore use a difference-in-differences framework to exploit the time variation in information sharing, cross-regional variation in competition, and cross-borrower variation in lending history. This strategy allows us to identify the impact of mandatory information sharing on rejection rates, lending conditions and loan quality.

We find that information sharing tightens lending at the extensive margin as more applications are rejected, in particular in competitive areas. These rejections are based increasingly on *hard* information – especially positive borrower information from the new registry. In contrast, the probability that a loan gets rejected due to soft information declines. Lending standards also tighten at the intensive margin: first time borrowers receive smaller, shorter and dearer loans for which they have to put up more collateral. Interestingly, with the registry in place repeat borrowers can now signal their quality to competing lenders. This forces the incumbent lender to offer better terms to repeat borrowers: they receive progressively larger, longer and cheaper loans. Lastly, the tightening of lending standards also results in higher loan quality, in particular in high-competition areas and for first time borrowers. This suggests that a reduction in adverse selection is an important channel through which information sharing affects loan quality. Various robustness and placebo tests confirm that the impacts we identify reflect the actual introduction of the credit registry and the associated sudden improvement in information sharing and not differences in economic conditions between branches, secular trends or model specification.

This paper contributes to the nascent literature on the mandatory sharing of "negative" and "positive" information in credit markets. Negative information refers to data on borrower defaults and arrears. Sharing this information helps lenders avoid low-quality borrowers and in turn incentivises borrowers to stay off the blacklist. Positive information includes data on applicants' outstanding loans and guarantees as well as their credit history (other than defaults and arrears). When lenders share positive information borrowers can gradually build up a valuable reputation as trustworthy borrowers.

Various theoretical contributions have explored how sharing these two types of information can alleviate moral hazard, adverse selection and over-borrowing. First, moral hazard may decline as borrowers no longer fear that their bank will extract rents from them by exploiting proprietary information (Padilla and Pagano, 1997). Hold-up problems due to informational lock-in (Sharpe, 1990; Rajan, 1992; von Thadden, 2004) diminish in particular for repeat borrowers. With a registry in place, defaulting borrowers also lose their reputation in the whole credit market and not just with their current lender (Hoff and Stiglitz, 1997). This further reduces moral hazard, in particular if banks only exchange negative information (Padilla and Pagano, 2000). Theory suggests that both mechanisms increase borrower discipline, improve loan quality and lead to more lending at lower interest rates.

Second, the availability of centralised credit data can reduce adverse selection and bring safe borrowers back into the market (Pagano and Jappelli, 1993).[1] While such improved screening boosts loan quality, the effect on the quantity of lending is ambiguous as more lending to safe borrowers may be offset by less lending to riskier clients.

[1] The effect may be even stronger when the sharing of hard borrower information encourages banks to invest more in soft, non-verifiable information to gain a competitive advantage (Karapetyan and Stacescu, 2014a).

Third, a credit registry can also prevent borrowers from taking loans from multiple banks ("double dipping") instead of applying for one single loan.[2] When borrowers can hide outstanding debt, each loan will be under-priced as new lenders ignore that their loan increases the default risk of existing debt. Sharing (positive) information about borrowers' other loans rules out such negative externalities and makes lenders more careful.[3] This may lead to fewer, smaller and more expensive loans with a better repayment record.

To sum up, the extant theoretical literature predicts an unambiguous positive effect of information sharing on loan quality while the impact on the quantity of lending is less clear-cut. Models that stress initial over-indebtedness predict a decline in lending, theories that focus on moral hazard suggest that lending increases and the effect of reduced adverse selection remains theoretically ambiguous.

Importantly, all these contributions suggest a stronger impact of information sharing in more competitive credit markets. When competition is high, moral hazard may be more salient because defaulting borrowers can easily move to another lender. Lender competition can also exacerbate adverse selection as investments in information acquisition fall (Hauswald and Marquez, 2006) and banks reallocate credit to captured borrowers of lower quality (Dell'Ariccia and Marquez, 2004). Over-borrowing is more likely to occur in high-competition markets too (Parlour and Rajan, 2001). For these reasons, the introduction of mandatory information sharing can be expected to "bite" most in competitive credit markets.[4]

On the empirical side, cross-country evidence suggests that information sharing is associated with less risk taking by banks (Houston et al., 2010; Büyükkarabacak and Valev, 2012), more lending to the private sector, fewer defaults and lower interest rates (Jappelli and Pagano, 1993; 2002). These effects appear to be stronger in developing countries (Djankov, McLiesh and Shleifer, 2007) and for opaque firms (Brown, Jappelli, and Pagano, 2009). However, cross-country studies only imperfectly control for confounding factors that might lead to a spurious correlation between information sharing and credit outcomes. Also, they typically do not analyse the mechanisms through which mandatory information sharing affects credit markets.

A small literature has therefore started to exploit contract-level information on the introduction of new credit registries, or changes in the coverage of existing registries, to more cleanly identify the impact of mandatory information sharing. Luoto, McIntosh and Wydick (2007) and de Janvry, McIntosh and Sadoulet (2010) analyse the staggered use of a registry

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[2] See Hoff and Stiglitz (1997), McIntosh and Wydick (2005) and Bennardo, Pagano and Piccolo (2015) for theory and McIntosh, de Janvry and Sadoulet (2005) for evidence from a Ugandan microfinance institution.

[3] Degryse, Ioannidou and von Schedvin (2012) use data from a Swedish bank to show that when a previously exclusive firm obtains a loan from another bank, the firm's initial bank decreases its internal limit, suggesting that information sharing allows lenders to condition their terms on loans from others. Cheng and Degryse (2010) provide similar evidence for the Chinese credit card market.

[4] This is also because *voluntary* information sharing is unlikely to emerge in competitive markets. See Pagano and Jappelli (1993) and Bouckaert and Degryse (2006) for theory and Brown and Zehnder (2010) for experimental evidence.

by the branches of a Guatemalan microfinance institution. They find an increase in loan performance, especially for borrowers that are aware of the existence of the registry. Doblas-Madrid and Minetti (2013) focus on the staggered entry of lenders into a credit registry for the US equipment-financing industry. Entry improved repayment for opaque firms but reduced loan size. In a similar vein, Hertzberg, Liberti and Paravisini (2011) show how lowering the reporting threshold of the Argentinian credit registry resulted in less lending to firms with multiple lending relationships due to improved lender coordination. Lastly, González-Uribe and Osorio (2014) explore the impact of *erasing* negative borrower information from a Columbian credit bureau. Wiping out this information allowed borrowers to attract larger and longer loans from new lenders. However, the quality of these new loans was significantly lower than those of similar borrowers whose credit history had not been reset.[5]

We contribute to this recent literature in at least two important ways. First, we use detailed information about local variation in lender competition as a source of identification. This allows us to test for the first time the theoretical prediction that mandatory information sharing is particularly beneficial in more competitive credit markets. Second, we have access to unique data on *why* individual loan applications were rejected before and after the introduction of the registry. We observe directly to what extent lenders use negative and positive borrower information when both types of information become publicly available. While this approach has clear strengths, it has some drawbacks as well. Our analysis is based on data from a single large bank in one particular country. While this may somewhat limit the external validity of our findings, we note that both the Bosnian market for small business loans and the credit registry we study are very similar to those in many other countries.

We proceed as follows. Section 2 provides background on our empirical setting, after which Sections 3 and 4 describe our data and identification strategy, respectively. Section 5 then presents our empirical results and Section 6 concludes.

[5] In a similar vein, Ioannidou and Ongena (2010) find that Bolivian firms switch banks once information about prior defaults is erased and their incumbent lender no longer holds them up.

2. Empirical setting

2.1. Small business lending in Bosnia and Herzegovina

Bosnia and Herzegovina emerged from the 1992-95 Yugoslav civil war with a badly damaged industrial infrastructure but a highly educated and entrepreneurial middle class (Demirgüç-Kunt, Klapper and Panos, 2010). To start a new business many entrepreneurs borrowed from a growing number of banks and microfinance institutions. When Bosnia and Herzegovina implemented its public credit registry in 2009, 17 banks and 12 microfinance institutions operated across the country. This competitive financial sector led to an expansion of domestic credit from 23.4 per cent of GDP in 2001 to 67.7 per cent of GDP in 2013.[6] An increasing number of small entrepreneurs took out several loans at the same time (Maurer and Pytkowska, 2011) and many loans were collateralised through personal guarantees by friends or family members. A registry for pledged movable assets only became operational in 2006.

There exists strong regional variation across Bosnia and Herzegovina in the competitiveness of the local market for small-business loans. For instance, in the city of Mostar a total of 23 branches of 12 different financial institutions provide small-business loans, whereas in Zivinice – a city of roughly similar population size – only 6 lenders operate 8 branches. This strong variation makes Bosnia and Herzegovina an interesting setting to study the interaction of mandatory information sharing and lender competition.

2.2. Information sharing in Bosnia and Herzegovina

While a private data-collection agency had been active in Bosnia and Herzegovina since 2000, most banks and microfinance institutions neither used it nor contributed information to it. Participation was voluntary and expensive and hence coverage was incomplete and ineffective. Lenders could therefore not check whether loan applicants had already borrowed from one or more competitors. As one manager of a large Bosnian financial institution succinctly put it: "Before the introduction of the credit registry, we were basically blind." Loan officers of competing lenders even actively disseminated *false* information about their borrowers. This suggests, in line with experimental evidence,[7] that coordination failures prevented the emergence of any voluntary information sharing among lenders.

In response to this institutional deficiency, the Bosnian central bank started to set up a public credit registry (Centralni Registar Kredita, CRK) in 2006. Yet it was only in July 2009 that participation became mandatory for all formal lenders, including microfinance institutions. This is also the month in which EKI, the Bosnian lender whose loan portfolio we analyse, started to provide information to the registry and began to use it. Stakeholder interviews suggest that the July 2009 registry introduction marked a sudden improvement in the

[6] Source: World Bank (http://data.worldbank.org/country/bosnia-and-herzegovina).
[7] *Ibid.* footnote 4.

available information about prospective borrowers. No other financial regulations were introduced in the second half of 2009.

The Bosnian credit registry requires lenders to submit a report every time a loan to a firm or private individual is disbursed, repaid in full, late or written off. The registry contains both negative information on past loan defaults and positive information on any other loans that a loan applicant has still outstanding. The registry also includes information on whether the borrower has a guarantor or is a guarantor themselves. Each borrower receives a credit score based on his or her current debt as well as past repayment performance. Information is comprehensive and dependable as the central bank checks its quality and consistency.

Banks are required to include a clause in each loan contract in which the borrower agrees to a credit check via the registry. Borrowers are therefore aware that their repayment performance will be recorded and shared with other banks. While submitting information to the registry is mandatory, checking the data is voluntary and subject to a small fee of BAM 0.15 (US$ 0.12). The registry receives on average about 240,000 requests a month.

2.3. The lender

We use data from EKI, one of the main providers of individual-liability micro and small-business loans in Bosnia. Founded in 1996, EKI lends through a network of 15 branches to around 34,000 borrowers across both parts of the country (the Republika Srpska and the Federation of Bosnia and Herzegovina). Borrowers are typically small firms that are relatively opaque as they are not monitored by the press or rating agencies and in most cases do not have audited accounts.

EKI loan officers act as sales agents who collect all loan applicant information, including from the credit registry, that is needed to make an initial lending decision. Loan officers fill out an electronic site-visit form with information on the borrower, his or her credit history and available collateral. These initial lending decisions are then discussed during a meeting of the branch-level loan committee on the basis of which the loan application is approved or rejected. Each branch employs on average 14 loan officers at any point in time.

3. Data

3.1. Loan applications and granted loans

We have access to all loan applications received by EKI during the period January 2007-December 2012 and all loans granted during June 2002-December 2012. Figure A1 in the Appendix summarises the loan applications (panel A) and approved loans (panel B) for the overlapping period January 2007-December 2012.[8] We also show the distribution of loans and applications across branches in high versus low-competition areas and, for approved loans, across new versus existing borrowers. For the loan applications, we know the age and gender of the applicant as well as the loan amount, loan purpose and term requested. Table 1 (panel A) shows that the median loan applicant was 41 years old and asked for a two-year loan of BAM 3,000 (US$ 2,160). About 60 per cent of the applicants were male.

The raw data show that the rejection rate almost doubled, from 8 to 15 per cent, after the introduction of the credit registry (the remainder of the loan applications was approved or, in a few cases, withdrawn by the applicant). A unique feature of our data is that we know exactly why each loan was rejected, as loan officers are required to enter the main motivation for rejecting a loan into the management information system. We split the various rejection reasons into those based on hard versus soft information or, alternatively, into those based on external versus internal information. Rejections based on hard information are those where loan applicants were dismissed because of their age, a low credit score (negative registry information), too much outstanding debt elsewhere (positive registry information), a bad credit history with EKI itself, weak financials or insufficient collateral. Rejections based on soft information are those where the loan officer had doubts about the applicant's character, received a bad recommendation from someone else, or where the loan purpose was unclear. Rejections due to internal information are based on information that EKI collected itself, either in the past or during the current screening. This includes information on the financial ratios of the borrower, the purpose of the loan, the character of the borrower and the available collateral. Rejections due to external information are those based on ("positive") information about applicants' outstanding debt elsewhere or ("negative") information about previous repayment problems. Both types of information became easily available with the introduction of the credit registry while they were generally unavailable before (as voluntary exchange of borrower information among lenders was virtually absent).

Panel A of Table 1 shows a clear shift in the rejection reasons once the credit registry is introduced: more (less) loans are rejected due to hard (soft) information. Loan officers start to rely more on external information, in particular positive information about outstanding loans elsewhere. This indicates that mandatory information sharing led to a significant change in loan officer behaviour.

[8] Tables A1 and A2 in the Appendix provide the exact variable definitions and data sources.

TABLE 1. Summary statistics

	[1] Mean pre-Credit registry	[2] Mean post-Credit registry	[3] Obs.	[4] Median	[5] St. dev.	[6] Min	[7] Max
Panel A: Extensive margin							
Dependent variables:							
Loan rejected	0.082	0.147***	210,044	0	0.322	0	1
Loan rejected: Hard information	0.038	0.123***	210,044	0	0.277	0	1
Loan rejected: Soft information	0.045	0.023***	210,044	0	0.180	0	1
Loan rejected: Internal information	0.064	0.058***	210,044	0	0.234	0	1
Loan rejected: External information (negative)	0.004	0.034***	210,044	0	0.141	0	1
Loan rejected: External information (positive)	0.014	0.054***	210,044	0	0.186	0	1
Independent variables:							
Loan amount (BAM)	3,814	3,303***	210,044	3,000	2,746	100	15,000
Loan term	27	24***	210,044	24	13	1	66
Applicant age	40	42***	210,044	41	12.33	17	82
Applicant male	0.58	0.61***	210,044	1	0.49	0	1
Panel B: Intensive margin							
Dependent variables:							
Loan amount (BAM)	3,564	3,173***	236,893	3,000	2,802	500	15,000
Loan term	23	23.170	236,893	19	11.365	6	60
Interest rate	18.540	21.210***	236,893	20.500	3.903	12	26
Collateral	2.301	2.414***	236,893	2	1.506	0	10
Problem loan	0.059	0.017***	236,893	0	0.208	0	1
Independent variables:							
Competition: 1-HHI	0.807	0.799***	236,893	0.806	0.068	0.556	0.898
Perceived competition	4.981	5.099***	234,185	5.5	1.1555	3	6.5
Loan/income ratio	3.186	2.975***	236,893	2.484	2.332	0.444	11.765
Borrower age	40	42***	236,893	40	12.094	20	68
Borrower male	0.593	0.612***	236,893	1	0.490	0	1
Borrower education	1.93	1.95***	236,893	3	0.392	2	4
Borrower monthly income (BAM)	1,212	1,159***	236,893	1,031	577	350	3,691
Borrower urban	0.39	0.33***	236,893	2	0.674	1	3
Stable income	0.863	0.831***	236,893	1	0.353	0	1
Loan immovable	0.081	0.010***	236,893	0	0.282	0	1
Loan movable	0.427	0.531***	236,893	0	0.498	0	1
Loan stock	0.408	0.181***	236,893	0	0.472	0	1
Loan household	0.071	0.142***	236,893	0	0.291	0	1
Personal collateral	0.248	0.319***	236,893	0	0.546	0	2
Social collateral	1.968	1.994	236,893	2	1.021	1	5
Third-party collateral	0.040	0.088	236,893	0	0.308	0	2
Loans/officer	21.42	17.66***	236,893	20	9.048	2	45
Branch growth (quarterly)	0.058	0.044***	236,131	0.023	0.265	-0.495	1.241

Notes: Panel A: Sample period is January 2007-December 2012. Panel B: Sample period is June 2002-December 2012. Asterisks refer to the p-value of a t-test of equality of means and *** indicates significance at the 1% level. Source: EKI.

For the more than 200,000 loans approved between June 2002 and December 2012, we have detailed contract-level information on their size, maturity, interest rate, collateral and purpose. We also have precise information on whether and when there was a late repayment, whether the loan was written off and, if so, how much principal and interest was recovered. We also know borrowers' income, education, gender, employment status and family size. Overall, we observe the complete borrowing history of over 130,000 unique borrowers and can therefore distinguish between new and returning borrowers. Lastly, we know the identity of the 458 different loan officers that granted loans in our dataset. The average loan officer approved 21 (18) loans per month before (after) the introduction of the credit registry.

Panel B of Table 1 shows that the median granted loan amount equals the median requested amount and is 2.5 times the average monthly household income of borrowers. The median maturity of granted loans (19 months) is below the median requested maturity (24 months). The annual nominal interest rate was 19 per cent.[9] Borrowers use the loans mainly for business purposes, with about half of all loans used to buy movable assets such as equipment and vehicles. A vast majority of loans is collateralised, typically by some form of personal collateral and/or one or several guarantors.

Our measure of loan quality is a dummy equal to "1" if loan repayment was, at least once, more than 30 days late. Of these late loans, 97 per cent end up in default and are subsequently written off. Before the introduction of the registry, 5.9 per cent of all loans defaulted. This percentage went down to 1.7 per cent once the registry was in place. For each non-performing loan we know when repayment problems started and we use this dynamic information in our hazard analysis (see Section 4).

3.2. Local credit-market competition

As will become clear in the next section, our identification strategy is predicated on the prior that mandatory information sharing has a stronger impact in competitive credit markets. We construct both an objective and a subjective proxy for the intensity of lender competition in each of the 15 localities where EKI operates. First, we calculate a Herfindahl-Hirschman index (HHI) where we express a lender's market share as the number of branches it operates in a locality. To do so we collect time-varying data on the distribution of branches across Bosnia and Herzegovina from various sources. We first conduct a survey where we ask loan officers of each branch to list their local competitors and cross-check this information with branch information from www.mixmarket.org, the second EBRD Banking Environment and Performance Survey (BEPS II) and lenders' annual reports. We then calculate an annual competition measure equal to $1\text{-}HHI_{bt}$ where b indicates the branch and t the year.[10]

Our second measure of local lender competition is based on loan officers' subjective perceptions. We use information from the aforementioned survey where loan officers in each branch were asked how much they agreed, on a scale from one to seven, with the following statement: "In the last ten years, there has been an increase in competitive pressure in my area of operation." This competition measure is time invariant, averaged by branch and ranges between 3 and 6.5.

[9] Annual consumer price inflation was 7 per cent in 2008 (source: World Bank, (http://data.worldbank.org/country/bosnia-and-herzegovina).

[10] $\mathrm{HHI_{bt}} = \sum_{i=1}^{N} s_{bti}^2$ where $s_{bti}^2 = \text{Number branches}_{bti}/\text{Total branches}_{bt}$ is the market share in terms of branches for lender i and N is the total number of lenders.

4. Identification and empirical methodology

4.1. Impact on the extensive and intensive lending margins

We exploit our detailed data to identify the effects of mandatory information sharing on the extensive and intensive lending margins and the subsequent performance of approved loans. In the first part of our analysis we apply a difference-in-differences framework to a dataset that spans the year before and the year after the introduction of the credit registry. We then analyse how the introduction affected lending outcomes differently depending on whether areas were more or less affected by mandatory information sharing. We regard loan applications and approved loans in high-competition areas as the affected or treated group and those in low-competition areas as the control group. For both the objective and the subjective competition measure we construct a dummy equal to one (zero) for areas with above (below) median competition levels.

A key identifying assumption of this diff-in-diff framework is that outcome variables would have developed similarly in the treatment and control group in case no credit registry had been introduced. More precisely, we assume that outcomes in both groups had followed a parallel path even if there were (time-invariant) level differences. Any trend differences that appear once mandatory information sharing is introduced can then be attributed to the registry. Figure A2 in the Appendix shows trends, conditional on borrower and loan characteristics, for four key outcome variables in the low versus high-competition areas around the July 2009 introduction of information sharing. In panels A and B, we observe that average loan amounts and terms developed very similarly in high versus low-competition areas. However, once information sharing is in place there is a sharp drop in loan size and maturity in both types of areas. Moreover, in the same month there is a sudden and sharp jump in the interest rate charged as well as the required collateral (panels C and D). We test more formally for parallel trends in Section 5 by running the baseline regression for a number of fictitious placebo events. Moreover, we show that our results are robust to controlling for any diverging trends between high and low-competition areas in our regression framework.

We first apply our diff-in-diff framework to measure the impact of information sharing on the extensive margin – the probability that loan applications get approved or rejected – and then on the intensive margin (loan amount, term, interest rate and collateral). To this end we analyse a pooled dataset consisting of all loan applications and all approved loans in the year before and the year after the introduction of the credit registry. We then explain the probability of rejection by a *Credit registry* dummy that identifies applications and loans after the introduction of the registry, a *Competition* variable that identifies the high-competition areas and the interaction between the two. *Competition* is a dummy variable that is one if local credit market competition is above the median level of competition as measured by 1 minus the HHI index. Our baseline pooled OLS regression model is therefore:

$$Y_{ibt} = \alpha_1 \cdot Info_t + \alpha_2 \cdot Comp_b + \beta \cdot I_{bt} + \gamma \cdot X_{ibt} + \varepsilon_{ibt} \tag{1}$$

Where Y_{ibt} is one of our outcome variables for loan or loan application i in branch b in month t; $Info_t$ is a dummy variable that is "one" for all observations in July 2009 and later, in other words the period when the credit registry was in place; $Comp_b$ is a dummy variable that is one for all loans and loan applications in high-competition branches; I_{bt} is an interaction term between $Info_t$ and $Comp_b$; X_{ibt} is a matrix of control variables and ε_{ibt} is the error term. We cluster the standard errors conservatively at the individual loan officer level. Results remain quantitatively and qualitatively unchanged when we do not cluster or cluster by branch.

Our standard battery of covariates X_{ibt} includes loan-level control variables, such as dummies for various loan types, key borrower characteristics (such as age and gender) and a proxy for local economic activity. Since reliable conventional measures of local economic activity across Bosnia and Herzegovina do not exist, we use local night light data from 2003 to 2010 as proposed by Henderson, Storeygard and Weil (2011).

Our main parameter of interest is β: the additional impact of mandatory information sharing on loan outcomes in high-competition areas. Based on the prior that mandatory information sharing has a larger impact in more competitive credit markets, the interaction between the credit-registry dummy and the measure of local competition should be positive. To identify this interaction coefficient more cleanly, we also estimate:

$$Y_{ibt} = A_b + B_t + \beta \cdot I_{bt} + \gamma \cdot X_{ibt} + \varepsilon_{ibt} \tag{2}$$

Here A_b and B_t are branch and month fixed effects, respectively. An advantage of this specification is that we can control for omitted local variables through branch-level effects and for economy-wide shocks through month fixed effects. If information sharing matters more in high-competition branches, even after controlling for branch fixed effects, this is strong evidence that our results are not driven by omitted regional variables.

We also estimate this fixed-effects model with a separate time trend $time_t$ for high and low-competition areas. This allows us to control for possibly diverging trends in outcomes prior to the registry introduction (in violation of the parallel trends assumption discussed before). Equation (3) in effect provides an in-model correction, under the assumption that the trends are linear, for the case where the parallel trends assumption may not be fully satisfied (Angrist and Pischke, 2009):

$$Y_{ibt} = A_b + B_t + \beta \cdot I_{bt} + \gamma \cdot X_{ibt} + \delta_0 time_t + \delta_1 time_t * Comp_b + \varepsilon_{ibt} \quad (3)$$

In order to obtain unbiased estimates in our diff-in-diff setting, we need to ensure that we can attribute impacts to information sharing and not to differences between borrower groups due to non-random assignment across areas with different levels of lender competition. We therefore present a variant of Equation (1) where we use propensity score matching based on borrower and loan characteristics to assure that borrowers in high (treatment) and low (control) competition areas are comparable. By matching borrower and loan characteristics we also circumvent the issue of jointness of loan terms (Brick and Palia, 2007). Lastly, the introduction of mandatory information sharing may also have shifted the composition of the borrower pool. For that reason we need to make sure that we compare similar borrowers before and after the registry introduction. We therefore also undertake propensity score matching where we control for longitudinal changes in the applicant or borrower pool.

We match loans based on all available loan, borrower and local characteristics and calculate the propensity scores with nearest neighbour matching with replacement. There is very large common support with only less than 1 per cent of observations outside the support area. We then use the propensity scores as weights in a linear regression model where we exclude any variable that might be jointly determined with our dependent variables. We apply a double-robust estimator (Robins, 2000) since this yields unbiased estimates of the average treatment effect when either the propensity score matching model or the linear regression model is correctly specified.

4.2. Impact on loan quality

In the second part of our analysis, we wish to identify the impact of mandatory information sharing on repayment performance and loan quality. We especially want to investigate the impact of the credit registry in high-competition markets and for new borrowers. We do so by using a hazard model, where the hazard rate is defined as the probability of a borrower being late on their repayment at time *t* conditional on the fact that they repaid regularly up to that point. Hazard functions allow us to model not only whether a loan is going to default but also how the probability of default changes over time. This is particularly important as the underlying reasons to default might change over the life of the loan (that is, strategic default).[11]

The time between disbursement and the first instance of late (>30 days) repayment is our variable of interest when estimating the hazard rate. We do not use the write-off date as our default indicator because its timing depends more on the bank's discretion than on the borrower's default date. The hazard model allows us to compare the development of the

[11] See also Ongena and Smith (2001), Ioannidou, Ongena and Peydró (2014) and Jiménez, Ongena, Peydró and Saurina (2014) for recent applications of duration analysis in the empirical banking literature.

hazard rates before and after the introduction of mandatory information sharing and for first-time as well as repeat EKI borrowers. If mandatory information sharing indeed results in a better allocation of credit, then we expect a large drop in the hazard rate after the registry information and in particular in high-competition branches.

Aside from their economically intuitive interpretation, the main advantage of hazard models is their ability to deal with censoring. Censoring occurs when the loan is repaid or when the life of the loan extends beyond the sample period (right censoring). Given that most loans are repaid successfully, the effects of censoring in estimating the default probability will be particularly severe and not correcting for it will yield biased and inconsistent estimates in static probability models (Ongena and Smith, 2001). However, a semi-parametric model (Cox and Lewis, 1966; Cox, 1972), which makes no assumption about the form of the hazard function, is able to deal with right censoring as the log-likelihood function takes into account the ratio of completed versus non-completed loans. Left censoring can cause biased estimates as well, but it is not an issue in our case as we only observe new loans.

To estimate the baseline hazard, let *T* measure the amount of time (the "spell") before the first late repayment of the loan (the "switch"). The hazard function can be used to describe the distribution of *T* and is defined as:

$$h(t) = \lim_{\Delta t \to 0} \left\{ \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t} \right\} \tag{4}$$

The hazard function *h(t)* is the probability of repayment on a loan being late in time *t* conditional on regular repayments until then. Alternatively we can model the distribution of time until first late repayment as its survivor function:

$$S(t) = P(T \geq t) \tag{5}$$

The relationship between the survivor function and the hazard function is:

$$h(t) = \frac{-d \log S(t)}{dt} \tag{6}$$

Using the non-parametric Kaplan and Meier (1958) estimator we will plot the survival function for different groups of loans. This estimator is easily adjustable for right censoring.

Following Cox (1972), we estimate the effect of a set of potentially time-varying covariates Xt and the distributions of time to default with the proportional hazard model:

$$h(t) = \lim_{\Delta t \to 0} \left\{ \frac{P(t \leq T < t + \Delta t | T \geq t, X_t, \beta)}{\Delta t} \right\} = h_0(t) exp(\beta' X_t) \tag{7}$$

where h_0 represents the baseline hazard when all covariates are set to zero: $X=0$. Covariates shift the baseline hazard without affecting the underlying shape of the hazard function. The hazard rate for each individual with characteristics X_t is thus proportional to h_0. The partial effect of X_t on the log of the covariates hazard rate is represented by the estimated β coefficients. In the Cox (1972) semi-parametric approach the functional form of h_0 is not specified and the model uses the ranking of duration times to estimate the β parameters via maximum likelihood methods.

The Cox proportional hazard model relies on two assumptions. First, it assumes continuous time, as the presence of tied events in discrete time would make ranking impossible. Since late repayments are only observed at intervals, we deal with tied events with the approximation by Breslow (1974). Second, it assumes proportionality, which implies time fixed β coefficients. We relax this assumption by estimating a model where the effect of covariates X_t can change over the life of the loan.

We will check the robustness of our results to the functional form of the hazard rate by estimating two parametric specifications using the exponential and the Weibull distribution. The exponential distribution is easy to interpret and characterised by a constant hazard rate as the probability of late repayment is constant over time (Kiefer, 1988). The exponential distribution is a special case of the Weibull distribution when α is equal to 1. The Weibull distribution is expressed as:

$$h(t) = h\alpha t^{\alpha - 1} \tag{8}$$

The coefficient α is particularly interesting as it measures duration dependence. If $\alpha > 1$ the hazard rate increases with time (positive duration dependence), giving us an indication of the shape of the baseline hazard which is unobserved in the Cox specification.

5. Results

5.1. Information sharing and loan rejections

Table 2 provides estimation results, based on our difference-in-differences framework, to explain the probability that a loan application was rejected. In addition to the variables *Credit registry*, *Competition* and their interaction term, all specifications include our standard applicant and loan covariates. Columns 1 and 2 show the baseline specification, estimated with a logit and linear probability model, respectively. We provide the logit model as a benchmark but focus primarily on the linear model so that we can estimate the model using both time and fixed effects. An added advantage is that we can directly interpret the coefficients as marginal effects. A possible disadvantage of linear probability models is that fitted values might fall outside the 0,1 bounds. However, in our case more than 99 per cent of the linear predictions have a value that lies between zero and one.

TABLE 2. Information sharing and credit market competition: Extensive margin

Dependent variable →	Loan rejected					
	Logit	Linear probability model				
	[1]	[2]	[3]	[4]	[5]	[6]
Credit registry	0.409***	0.049***	0.048***	0.052***		
	(0.034)	(0.004)	(0.004)	(0.010)		
Competition	0.170***	0.018***		0.017***		
	(0.032)	(0.003)		(0.003)		
Credit registry*Competition	0.236***	0.040***	0.035***	0.041***	0.044***	0.047***
	(0.046)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)
No. of applications	63,891	63,893	63,893	63,893	63,893	63,893
Pseudo R-squared	0.022	0.019	0.036	0.028	0.043	0.043
Applicant covariates	Yes	Yes	Yes	Yes	Yes	Yes
Loan covariates	Yes	Yes	Yes	Yes	Yes	Yes
Branch fixed effects	No	No	Yes	No	Yes	Yes
Month fixed effects	No	No	No	Yes	Yes	Yes
Time trends	No	No	No	No	No	Yes

Notes: This table shows regression results to explain the probability that a loan application was rejected. Robust standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. A Hausman test rejected equivalence of random and fixed effects models. Before credit registry: June 2008-June 2009. During credit registry: July 2009-July 2010. All specifications include applicant covariates, loan size and type, and a time-varying night-light measure of local economic activity. Constant not shown. Competition: Dummy variable that is '1' if local credit market competition is above the median level of competition as measured by 1 minus the HHI index (where market shares are measured in number of branches). Table A2 in the Appendix contains all variable definitions.

We find that the introduction of the credit registry is associated with a large and statistically significant increase in the probability that a loan application gets rejected, all else equal. In the logit model in column 1, the marginal probability of rejection is equal to 4.8 percentage points and this is consistent with the magnitude of the linear probability effects reported in the subsequent columns. These range between 4.8 and 5.2 percentage points and in all cases the coefficients are significantly different from zero at the 1 per cent level.

In order to provide empirical support to our theoretical framework, we should find stronger effects of the introduction of the credit registry in high-competition areas. This is indeed the case as the interaction term of *Competition* and *Credit registry* has a positive and significant effect in all models. After the introduction of the credit registry, the rejection probability is 4 percentage points higher in high than in low-competition areas (9 versus 5 percentage points). In line with the theoretical literature outlined in Section 1, this suggests that mandatory information sharing is especially effective in competitive credit markets. The statistical and economic significance of this result survives when we add branch fixed effects (column 3), month fixed effects (column 4) or both (column 5). Including separate time trends for high and low-competition branches (column 6) does not alter the results either.

We also observe a significantly higher base probability of rejection in high-competition areas, since the marginal effect is close to 2 percentage points for the probit model and 1.8 percentage points for the linear probability model. These level effects of course disappear once we control for the time effect of the credit-registry introduction and for cross-sectional differences in competition with time and branch fixed effects in columns 5 and 6.

The finding that information sharing reduces the probability that a loan application is accepted, in particular in competitive areas, suggests that the newly available information makes loan officers more conservative. This is in line with theories that stress over-borrowing in competitive areas in the absence of information sharing (Parlour and Rajan, 2001).

In Table A3 in the Appendix we subject the baseline interaction effect between *Competition* and *Credit registry*, based on the linear probability model, to a number of robustness (columns 1-3) and placebo (columns 4-6) tests. In the first three columns, we vary the time window over which we estimate the effect of the registry introduction. Our regular window is one year before and one year after the introduction. In column 1 we use a shorter symmetric window of just one year in total (February 2009-February 2010). In column 2 we then use a wider window which comprises the period May 2008-December 2010 while in column 3 we use the widest window possible given the available data: January 2007-December 2012. In all cases the statistical and economic significance of the impact of the credit registry in high-competition areas is very similar to our base result in Table 2.

We provide placebo tests in columns 4 to 6 to carefully check whether our results are not driven by any secular trends that hitherto remained undetected. These tests are also a more formal way to test for the parallel trends assumption: since at the fictitious dates no credit registry was introduced, we should not detect any impact. In column 4 we show results for a placebo test where we move our two-year window one year forward. This means that we take the true treatment period as the control period and then assume that the treatment period only starts in July 2010. We basically assume that the credit registry was introduced a year later than it really was. In column 5 we show results for a placebo test where we move our two-year window one year backwards. We now take the true control period as the treatment period and assume that the credit registry was already introduced in July 2008, a year earlier than it really was. This placebo test is especially useful because it allows us to test whether we are not also picking up any impact of the 2007-09 global financial crisis.

Finally, in column 6 we randomly allocate branches to either high or low-competition status. We repeat this random allocation a thousand times and show the average result. The treatment period starts in July 2009, the actual date that the credit registry was introduced. In all three cases we find that our results disappear. This gives us additional confidence that the results in Table 2 are not spurious but indeed reflect a change in lending behaviour due to the introduction of the credit registry in July 2009.

In Table 3 we assess which type of information is responsible for the additional conservatism among loan officers after the introduction of the registry. We present multinomial logit regressions to explain the probability of loan rejection due to the use of various types of borrower information. The dependent variable is a categorical one and indicates whether a loan application was accepted (which we take as the base probability) or rejected on the basis of different types of information. We then estimate the effect of the introduction of the credit registry on rejections due to hard versus soft information (columns 1 and 2) or, in a separate multinomial set-up, due to internal information, negative external information or positive external information (columns 3-5).

The results in columns 1 and 2 show, in line with Table 2, that the introduction of mandatory information sharing led to a higher rejection probability and that this is especially so in high-competition areas. We now also observe directly that it is hard information that is responsible for this stricter screening by loan officers. In contrast, the probability that a loan gets rejected due to soft information goes down after the introduction of the registry, especially in low-competition areas. Note that there is a positive base effect of lender competition on the rejection probability due to hard information (column 1) but not due to soft information (column 2). This is in line with theories that stress that lending competition reduces banks' investments in generating and using soft information (Hauswald and Marquez, 2006).

In columns 3 to 5, we cut the data in a different way and compare rejections due to internal versus external information. The latter is split up in positive versus negative information, both of which became more easily available due to the registry. We find that after the registry introduction loan officers reject more loans on the basis of both internal and external information although the impact of external information is much stronger. In particular, column 5 shows a very strong increase in rejections due to positive information about applicants' debt elsewhere and this holds independent of the local competition level. The use of negative information (credit scores that contain information about applicants' past defaults) increases too, in particular in high-competition areas where adverse selection problems may be most severe.

TABLE 3. Types of borrower information and the likelihood of loan rejection

	Hard vs Soft Information		Internal vs External Information		
			Internal	*External information*	
Rejection reason →	*Hard*	*Soft*	*information*	*Negative*	*Positive*
	[1]	[2]	[3]	[4]	[5]
Credit registry	0.653***	-0.768***	0.205***	0.739***	1.254***
	(0.037)	(0.086)	(0.048)	(0.053)	(0.105)
High competition	0.222***	0.029	0.219***	-0.021	0.647***
	(0.037)	(0.059)	(0.043)	(0.057)	(0.108)
Credit registry*Competition	0.130**	0.814***	0.235***	0.285***	-0.041
	(0.051)	(0.112)	(0.065)	(0.077)	(0.132)
No. of applications	63,893			63,473	
Pseudo R-squared	0.026			0.032	
Applicant covariates	Yes	Yes	Yes	Yes	Yes
Loan covariates	Yes	Yes	Yes	Yes	Yes

Notes: This table presents multinomial logit regressions to explain the probability that a loan application was rejected due to the use of various types of borrower information. The base probability is that the application was accepted. Robust standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Before credit registry: June 2008-June 2009. During credit registry: July 2009-July 2010. All specifications include borrower covariates, loan size and type, and a time-varying night-light measure of local economic activity. Constant not shown. Competition: Dummy variable that is '1' if local credit market competition is above the median level of competition as measured by 1 minus the HHI index (where market shares are measured in number of branches). Table A2 in the Appendix contains all variable definitions.

5.2. Information sharing and loan conditions

We proceed by analysing the change in lending conditions around the credit registry introduction to gauge to what extent loan officers adjusted their lending on the intensive margin. The loan characteristics we consider are the *Loan amount*, *Loan term* (maturity), *Interest rate* and *Collateral* (which is the sum of posted personal, social and third-party collateral). In line with our identification strategy, we assess both the direct effect of the introduction of the registry as well as its interaction with *Competition*.

Table 4 reports the difference-in-differences results. Mandatory information sharing was accompanied by a *reduction* in both loan amounts and maturities and an increase in the interest rate charged and collateral required. All of these effects are statistically significant, stronger in competitive areas and hold when including our standard set of borrower and other covariates. The unreported covariate coefficients show that older, highly educated, higher-income and rural borrowers receive larger loans at lower interest rates.

These results also hold when we use propensity score matching to assure that borrowers in high (treatment) and low (control) competition areas are comparable (column 3) or when we match to correct for possible longitudinal changes in the borrower pool (column 4).[12] The same holds for adding month and branch fixed effects in column 5, which comes at the cost of not being able to estimate the level effects of *Credit registry* and *Competition*, and for adding separate time trends for high and low-competition branches (column 6). Finally, column 7 shows that our results do not change when we sort branches by competition level based on the subjective rather than the objective *Competition* measure.

After the introduction of the registry, the loan size drops by 19 per cent. In high-competition areas, the reduction is even more pronounced, averaging 25 per cent. The same pattern can be found looking at loan maturity, where loans are 13 per cent shorter overall (equivalent to 90 days) and 16.3 per cent shorter in high-competition areas (almost 120 days). Smaller loans do not lead to lower interest rates as they are 0.7 percentage points higher overall and 0.8 percentage points higher in competitive areas.[13] Gehrig and Stenbacka (2007) argue that information sharing generates a flatter inter-temporal structure of interest rates as banks see fewer benefits to establishing long-term lending relationships. In line with our results, their model suggests that information sharing increases the interest rates paid by new borrowers.

In a similar vein, collateralisation requirements go up after the introduction of the credit registry by 0.68 extra items pledged to each loan, in particular in high-competition areas where the number of required collateral items increases by 0.83. The increased reliance on collateral is in line with US evidence presented by Doblas-Madrid and Minetti (2013) and with theoretical work by Karapetyan and Stacescu (2014b) who show that information sharing and collateral may be complements as borrowers with a bad credit history are now more likely to face collateral requirements. In all, our results indicate clearly that the introduction of the credit registry led loan officers to significantly tighten their lending conditions on the intensive margin.

[12] When we compare new borrowers before and after the introduction of the registry along various observable characteristics, we do not find that they have changed much. Even where differences are statistically significant, they are minor in economics terms. This suggests that EKI did not react to the registry by shifting its lending to a different type of borrower.

[13] The positive impact of information sharing on interest rates is independent of whether we control for loan amount or not.

TABLE 4. Information sharing and credit market competition: Intensive margin

(A) Loan amount

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Credit registry	-0.185***	-0.103***	-0.125***	-0.025			
	(0.019)	(0.028)	(0.025)	(0.027)			
Competition		-0.039	0.028	-0.037			
		(0.024)	(0.025)	(0.025)			
Credit registry*Competition		-0.146***	-0.127***	-0.156***	-0.128***	-0.110***	-0.138***
		(0.033)	(0.031)	(0.033)	(0.031)	(0.029)	(0.029)
No. of loans	28,240	28,240	28,240	28,240	28,240	28,240	28,240
Adjusted R-squared	0.435	0.439	0.443	0.421	0.461	0.461	0.464

(B) Loan term

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Credit registry	-0.131***	-0.092***	-0.092***	-0.071***			
	(0.012)	(0.017)	(0.017)	(0.017)			
Competition		-0.043**	0.010	-0.043**			
		(0.017)	(0.017)	(0.017)			
Credit registry*Competition		-0.071***	-0.076***	-0.078***	-0.069***	-0.052**	-0.078***
		(0.022)	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)
No. of loans	28,240	28,240	28,240	28,240	28,240	28,240	28,240
Adjusted R-squared	0.332	0.337	0.339	0.313	0.356	0.356	0.357

(C) Interest rate

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Credit registry	0.685***	0.494***	0.498***	-0.117			
	(0.061)	(0.087)	(0.087)	(0.076)			
Competition		0.025	-0.207***	-0.003			
		(0.073)	(0.075)	(0.078)			
Credit registry*Competition		0.343***	0.381***	0.332***	0.389***	0.396***	0.343***
		(0.120)	(0.123)	(0.106)	(0.115)	(0.115)	(0.110)
No. of loans	28,240	28,240	28,240	28,240	28,240	28,240	28,240
Adjusted R-squared	0.241	0.243	0.247	0.202	0.275	0.275	0.275

(D) Collateral

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Credit registry	0.320***	0.117***	0.107**	0.140***			
	(0.041)	(0.044)	(0.043)	(0.046)			
Competition		0.225***	0.345***	0.275***			
		(0.049)	(0.058)	(0.058)			
Credit registry*Competition		0.357***	0.185***	0.281***	0.228***	0.200***	0.194***
		(0.065)	(0.068)	(0.069)	(0.054)	(0.050)	(0.061)
No. of loans	28,228	28,228	28,228	28,228	28,228	28,228	28,228
Adjusted R-squared	0.372	0.391	0.084	0.102	0.440	0.440	0.130
Month and branch fixed effects	No	No	No	No	Yes	Yes	Yes
Group-specific trend	No	No	No	No	No	Yes	Yes
Matching: Competition	No	No	Yes	No	No	No	No
Matching: Credit registry	No	No	No	Yes	No	No	No
Perceived competition	No	No	No	No	No	No	Yes

Notes: This table shows OLS regressions at the loan level to estimate the impact of the introduction of the credit registry on loan amount (Panel A); loan term (Panel B); interest rate (Panel C) and number of pledged collateral items (Panel D). Before credit registry: June 2008-June 2009. During credit registry: July 2009-July 2010. All specifications include a time-varying nigh-light measure of local economic activity. Constant not shown. Competition: Dummy variable that is '1' if local credit market competition is above the median level of competition as measured by 1 minus the HHI index where local market shares are measured in number of branches. Table A2 in the Appendix contains all variable definitions. Sample contains first-time EKI borrowers only. Standard errors are robust and clustered by loan officer. ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively.

In Appendix Tables A4 and A5 we report similar robustness and placebo tests as the ones we performed for the extensive lending margin. The same covariates as in Table 4 are included but not shown for reasons of brevity. We again find that our coefficient of interest is remarkably robust to broadening or widening the window around the *correct* starting date of the registry (Table A5). And, as before, our results disappear once we move the start of the treatment to a fictitious date one year earlier or one year later (Table A4). In additional unreported placebo tests we let the treatment period start in October 2010 for *Loan amount*, September 2006 for *Loan term* and February 2009 for *Interest rate*. These placebo start times are chosen on the basis of a Clemente-Montañés-Reyes unit-root test, which indicates a possible break point in that month for each dependent variable. We also perform a test where the placebo treatment starts in September 2008 – the collapse of Lehman Brothers – and ends with the introduction of the registry in July 2009. If we simply picked up a crisis effect, this should show up here. Throughout all these placebo tests, our original results disappear, suggesting that we indeed pick up the true registry effect and not another trend or break point such as the global financial crisis.

Table 5 compares the impact of information sharing on first time borrowers with that on repeat borrowers.[14] We estimate the evolution of subsequent loans for borrowers who successfully repaid their first loan. Using borrower-fixed effects we show that subsequent loans become progressively larger, longer, cheaper and require less collateral.[15] As the lender gathers information about the borrower, loan terms are relaxed to reward timely repayment.

What is particularly interesting, though, is that this effect becomes stronger for all of the loan terms after the introduction of the credit registry. This is reflected in the statistically significant coefficients for the interactions between the loan numbers and the *Credit registry* dummies. The implication is that while information sharing results in tighter loan terms for first time borrowers, it improves these terms for repeat borrowers. In the absence of information sharing, repeat borrowers that try to switch to a competing lender get pooled with low-quality firms and are therefore offered an unattractive interest rate (Sharpe, 1990). With information sharing, outside lenders can observe good borrower performance. This reduces the market power of the incumbent lender and boosts the bargaining power of reputable borrowers (Padilla and Pagano, 1997). This leads to better loan terms over the course of the lending relationship, in line with Petersen and Rajan (1995) and the aforementioned theoretical work of Gehrig and Stenbacka (2007).

[14] First-time clients are new to EKI but may have borrowed from other lenders in the past.

[15] The use of client-fixed effects implies that all one-time borrowers drop out of these regressions so that we compare first-time and repeat loans among a set of repeat borrowers.

TABLE 5. Information sharing, credit market competition and repeat lending

Dependent variable →	Amount granted	Term granted	Interest rate	Collateral
	[1]	[2]	[3]	[4]
Credit registry	-0.251***	-0.191***	1.036***	0.621***
	(0.021)	(0.016)	(0.077)	(0.038)
Credit registry*Competition	-0.073***	-0.041***	-0.008	0.271***
	(0.013)	(0.010)	(0.051)	(0.028)
2^{nd} loan	0.345***	0.284***	-1.045***	0.028
	(0.013)	(0.010)	(0.049)	(0.026)
3^{rd} loan	0.583***	0.475***	-1.720***	0.043
	(0.023)	(0.018)	(0.081)	(0.044)
4^{th} loan	0.774***	0.662***	-2.346***	0.076
	(0.034)	(0.028)	(0.118)	(0.061)
5^{th} loan	0.953***	0.858***	-2.919***	0.181**
	(0.045)	(0.038)	(0.161)	(0.081)
6^{th} loan	1.167***	1.026***	-3.377***	0.175*
	(0.059)	(0.049)	(0.215)	(0.103)
7^{th} loan	1.316***	1.242***	-4.208***	0.303**
	(0.079)	(0.068)	(0.292)	(0.130)
2^{nd} loan*Credit registry	0.051**	0.026	-0.115	-0.494***
	(0.021)	(0.016)	(0.076)	(0.037)
3^{rd} loan*Credit registry	0.104***	0.070***	-0.411***	-0.576***
	(0.026)	(0.021)	(0.097)	(0.049)
4^{th} loan*Credit registry	0.120***	0.070***	-0.348***	-0.564***
	(0.033)	(0.027)	(0.117)	(0.058)
5^{th} loan*Credit registry	0.138***	0.077**	-0.410***	-0.641***
	(0.040)	(0.033)	(0.146)	(0.071)
6^{th} loan*Credit registry	0.066	0.097**	-0.417**	-0.574***
	(0.049)	(0.041)	(0.186)	(0.088)
7^{th} loan*Credit registry	0.114	0.072	-0.169	-0.666***
	(0.070)	(0.060)	(0.263)	(0.113)
Branch controls	Yes	Yes	Yes	Yes
Client fixed effects	Yes	Yes	Yes	Yes
No. of loans	81,883	81,883	81,883	81,883
R-squared	0.317	0.303	0.121	0.303

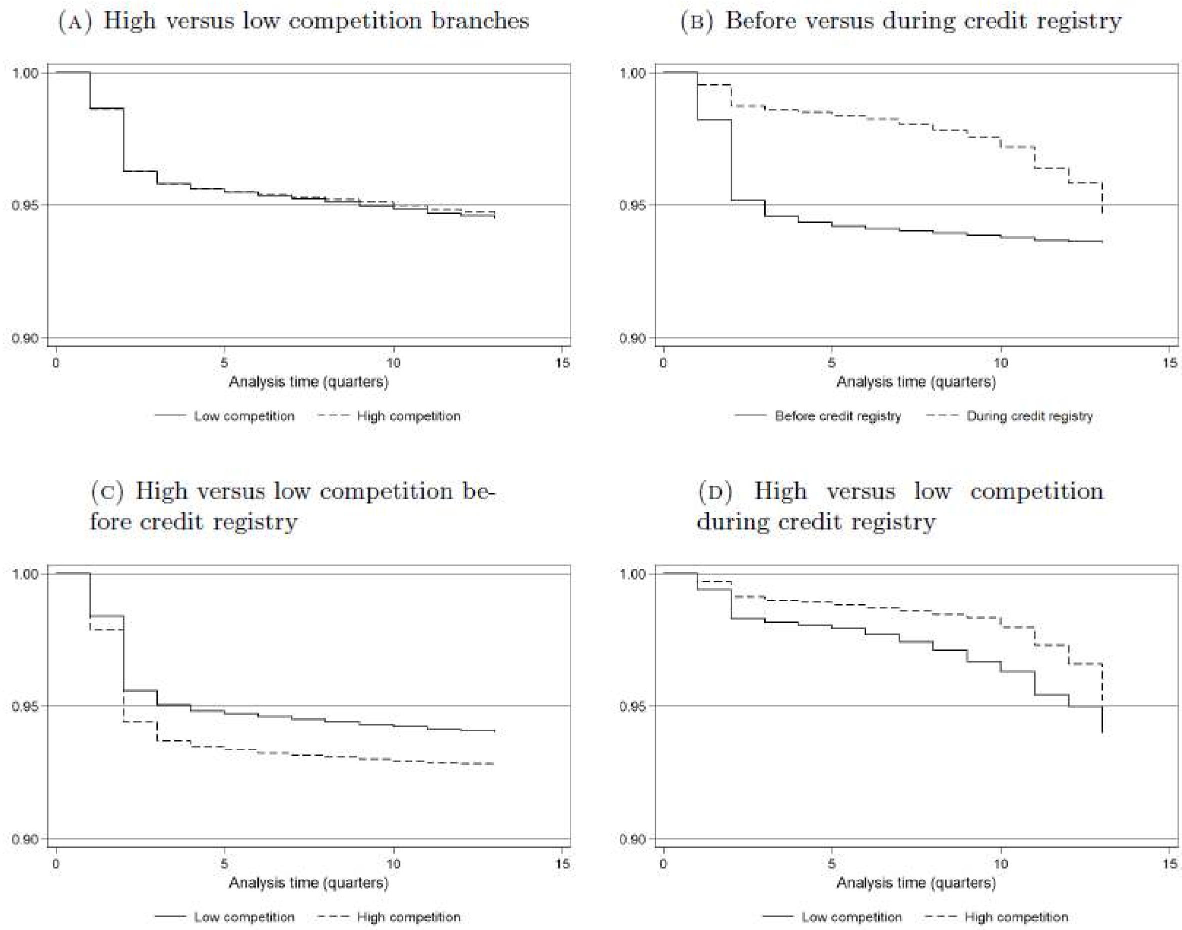
Notes: This table shows client fixed effect regressions to estimate the impact of the introduction of the Bosnian credit registry and credit history on log of loan amount granted [1]; log of loan term granted [2]; interest rate [3] and total number of collateral contracts [4] across branches that experience varying degrees of credit market competition. Robust standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Sample only includes repeat clients. Before credit registry: June 2008-June 2009. During credit registry: July 2009-July 2010. All specifications include a time-varying night-light measure of local economic activity and control dummies for product type. Constant not shown. Local competition: Dummy variable that is '1' if local credit market competition is above the median level of competition as measured by 1 minus the HHI index (where local market shares are measured in number of branches). Table A2 in the Appendix contains all variable definitions.

Interestingly, supplementary (unreported) regressions indicate that the additional increase (decrease) in loan amount (interest rate) for repeat borrowers after the introduction of the registry was mainly observed in high-competition areas. This suggests that in areas where more lenders are present and competition is stronger, information sharing opens up more outside options to formerly captive borrowers and, as a result, the impact of information sharing on repeat borrowers is higher in such competitive credit markets.

5.3. Information sharing and loan quality: non-parametric results

Figure 1 provides a first non-parametric look at our data on loan quality in the form of a Kaplan-Meier survival analysis over the period June 2002 to December 2012. The graphs show how the probability that a borrower has not (yet) defaulted on her loan changes over time (horizontal axis, in quarters). At the time of disbursement (*t=0*) the probability of survival is by definition 1 but then gradually erodes over time. In effect, the graph thus shows the inverse of the cumulative default probability. Panel A compares, for the whole sample period, the survival probability of borrowers in the branches that face below median competition with those that are confronted with an above median level of competition. The key point to take away from this panel is the minimal difference in the survival behaviour among borrowers in high versus low-competition areas. The difference between both curves is statistically insignificant as shown by a logrank test (p-value=0.60).

FIGURE 1. Information sharing, credit market competition and loan quality: Kaplan-Meier survival analysis



Notes: These four graphs show Kaplan-Meier survival estimates over the sample period June 2002-December 2012. Logrank test statistics for differences between the curves:
Panel A: $\chi^2(1) = 0.27$ (*p-value*$= 0.60$). Panel B: $\chi^2(1) = 1667.53$ (*p-value*$= 0.00$).
Panel C: $\chi^2(1) = 113.72$ (*p-value*$= 0.00$); Panel D: $\chi^2(1) = 106.89$ (*p-value*$= 0.00$).

In panel B, we start to compare the survival behaviour of loans granted before and after the introduction of the credit registry. In this context, right censoring will affect disproportionately the more recent group of loans. The correct hazard rate is then calculated as the ratio of loans that have defaulted at time *t* over the remaining loans (Ongena and

Smith, 2001). Without correcting for right censoring, the hazard rate would be calculated as the ratio of all loans dropping from the dataset over remaining loans. Panel B reveals a substantial difference in repayment behaviour as loans granted with the credit registry in place have a significantly higher survival probability compared with loans approved without mandatory information sharing. This is the first piece of evidence we bring to bear that points to a positive impact of information sharing on loan quality.

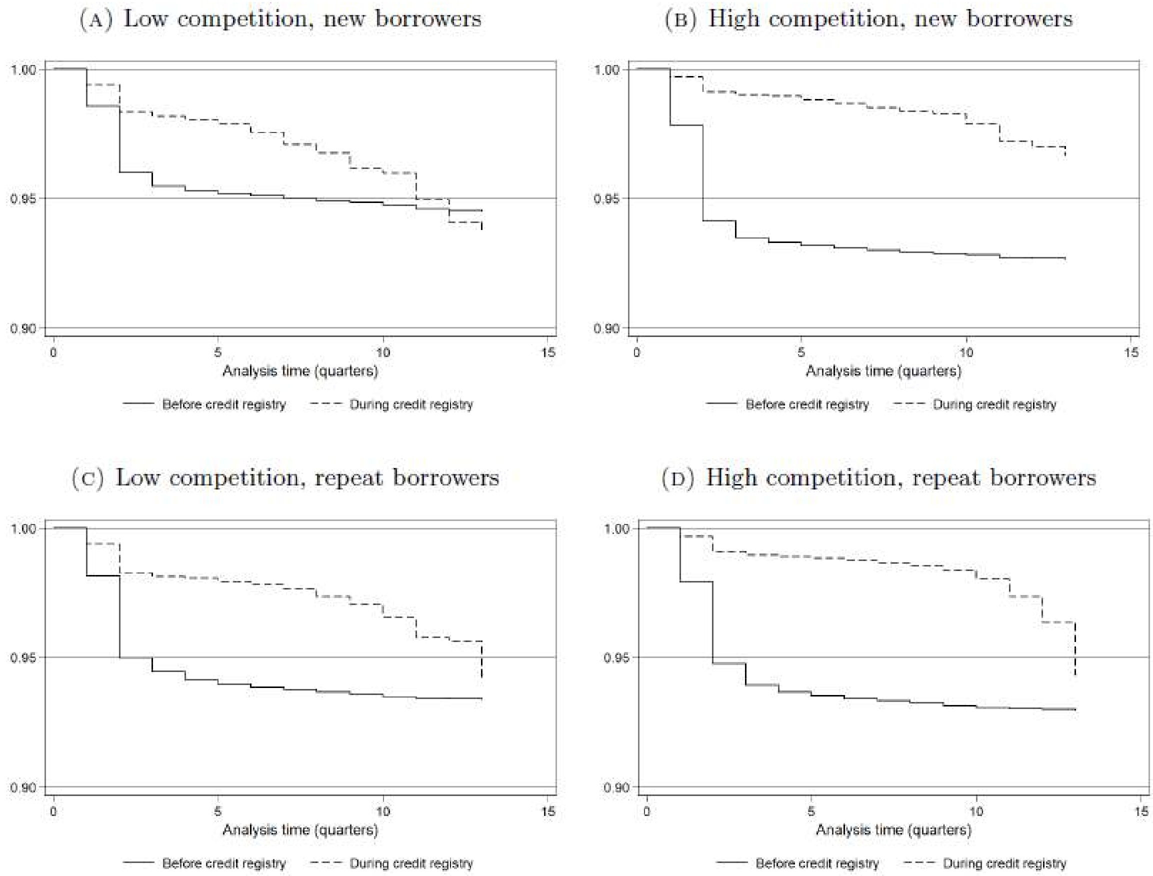
A striking aspect of panel B is that the difference between both loan types already emerges during the first quarters after loan disbursement. Indeed, the probability of a loan not being late in the first six months after disbursement increases from 94.6 percentage points before the credit registry introduction to 98.6 percentage points afterwards. Over time this difference declines but stays statistically and economically significant.

Panels C and D look at the interaction of mandatory information sharing and local credit market competition. Panel C shows that without information sharing repayment rates are significantly worse in high-competition areas (the p-value of a logrank test is 0.00). However, we observe the opposite after the registry introduction (panel D, p-value=0.00). Repayment behaviour now becomes even slightly better in high-competition areas (and this is what drove the lack of an overall difference over the whole sample period in panel A). The difference is one (two) percentage points after 12 (24) months and remains significant throughout the sample period. This effect is economically meaningful as it amounts to a third of the average default rate in the period before mandatory information sharing.

In Figure 2 we take this analysis one step further and now distinguish between first time borrowers (clients that had never borrowed from EKI) and repeat borrowers. On the one hand, we expect the impact of the credit registry to be concentrated among new borrowers as the information asymmetry between bank and prospective borrower is largest. On the other hand, to the extent that the registry (also) had an impact on borrower behaviour, we also expect an improvement in repayment behaviour among repeat borrowers as these now realise that a default will "cost" them more in terms of foregone future borrowing opportunities. As before, we also slice our data by competition level, leading to the four panels in Figure 2.

In panels A and B we first focus on new borrowers. Compared with the two top panels in Figure 1 there is now a striking difference. The impact of the credit registry introduction is much larger for new borrowers, suggesting that the registry mainly "worked" through the bank side. Comparing the low-competition areas (panel A) with the high-competition areas (panel B) we see clearly that the difference between both survival functions is widest and most persistent in the high-competition areas, exactly as theory would suggest. It is in these highly competitive areas, where adverse selection problems are rife, that the registry has the most bite and loan officers put the hitherto unavailable borrower information to the best use. In these areas the survival probability for new borrowers after 12 months increased from 92.5 to 97.5 per cent.

FIGURE 2. Information sharing, credit market competition and loan quality for new vs. repeat borrowers: Kaplan-Meier survival analysis



Notes: These four graphs show Kaplan-Meier survival estimates over the sample period June 2002-December 2012. Logrank test statistics for differences between the curves:
Panel A: $\chi^2(1) = 723.77$ (*p-value*= 0.00). Panel B: $\chi^2(1) = 392.57$ (*p-value*= 0.00).
Panel C: $\chi^2(1) = 630.53$ (*p-value*= 0.00). Panel D: $\chi^2(1) = 130.52$ (*p-value*= 0.00).

In panels C and D we present a similar comparison but now for repeat borrowers. Independent of the level of competition, we see that the registry introduction is accompanied by an upward shift of the survival function: at each point in time repeat borrowers are less likely to default, suggesting that mandatory information sharing also increased borrower discipline. However, while in both graphs the differences between the "before" and "after" graphs are statistically significant (p-value is 0.00 in both cases), the difference is relatively small and declines over time. The main impact of the introduction of the credit registry therefore appears to come from a better selection of borrowers.

5.4. Information sharing and loan quality: (semi-)parametric results

In Table 6 we proceed by providing semi-parametric and parametric evidence on the impact of mandatory information sharing on loan quality. As discussed in Section 4.2, an important advantage of hazard models – where the hazard rate is the probability of a borrower defaulting at time *t* conditional on having repaid regularly up to that point – is that they deal properly with right censoring. A second advantage is that the specifications in Table 6 allow us to control for a battery of borrower and loan covariates. We stratify by branch so that the form of the underlying hazard function varies across branches (the coefficients of the remaining covariates are assumed to be constant across strata). Hence we do not need to assume a particular form of interaction between the stratifying covariates and time.

In columns 1-4 we present the results of a semi-parametric Cox proportional hazard model while columns 5 and 6 show equivalent specifications using a parametric exponential and Weibull model, respectively. In the first column we limit our sample to loans to first time borrowers, whereas in the following columns we use all loans and include a First loan dummy. We then interact this dummy with Credit registry to test whether the impact of mandatory information sharing was larger for first time borrowers (as Figure 2 suggests).

The results in the first three rows of Table 6 show that the registry introduction is associated with a statistically significant reduction in the hazard rate. Importantly, this effect is almost twice as high in high-competition areas, in line with Figure 1 and the literature that we discussed before. The second line shows that the level of bank competition as such does not have an impact on the hazard rate, analogous to panel C of Figure 1.

In the lower part of the table we show the estimated coefficients for our control variables. These have the expected sign and in most cases display a statistically significant relationship with the hazard rate. For instance, we find that older and more educated borrowers pose less risk while longer and larger loans tend to have higher repayment risks, all else equal.

As expected, columns 2-6 show that the interaction term between First loan and the Credit registry dummy is significantly negative, indicating that the registry reduced default risk in particular for first time borrowers, who are still relatively opaque. The coefficient for First loan itself is negative but not significantly different from zero.

In column 4, we relax the proportionality assumption of the Cox model and allow the effect of the covariates to change over the life of the loan. This is accomplished by estimating another set of coefficients that change linearly over time since disbursement (not reported). We find that even without a proportionality assumption the model yields practically identical estimates. The Weibull model in column 6 produces an Ln(alpha) of -0.645, meaning that the hazard rate decreases with time. This indicates that a substantial part of the borrower risk is "front loaded". Finally, the exponential model in column 5 is a special case of the Weibull distribution where alpha is equal to 1.

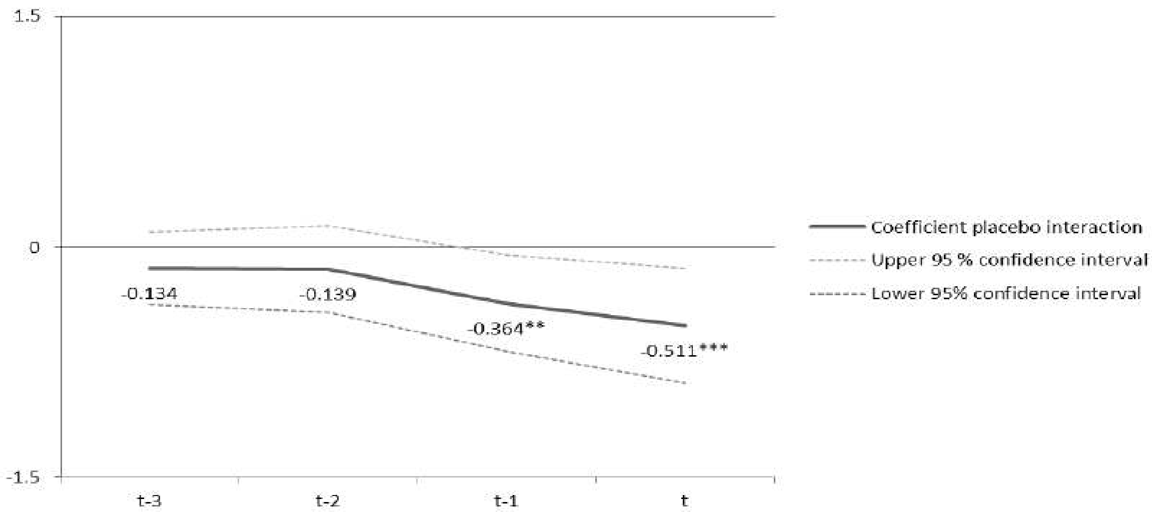
TABLE 6. Information sharing, credit market competition and loan quality: Hazard analysis.

Functional form	Cox				Exponential	Weibull
	[1]	[2]	[3]	[4]	[5]	[6]
Credit registry	-0.860***	-0.577***	-0.507***	-0.486***	-0.856***	-0.532***
	(0.127)	(0.078)	(0.091)	(0.083)	(0.105)	(0.080)
Competition	-0.230	-0.175	-0.178	-0.188	-0.035	-0.182
	(0.169)	(0.170)	(0.171)	(0.186)	(0.141)	(0.178)
Credit registry*Comp.	-0.467***	-0.511***	-0.556***	-0.496***	-0.739***	-0.501***
	(0.170)	(0.117)	(0.126)	(0.126)	(0.151)	(0.121)
Borrower education	-0.224***	-0.263***	-0.253***	-0.270***	-0.250***	-0.267***
	(0.052)	(0.038)	(0.041)	(0.042)	(0.042)	(0.040)
Borrower age	-0.014***	-0.014***	-0.014***	-0.015***	-0.014***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Borrower male	0.075**	-0.001	-0.008	-0.016	-0.020	-0.009
	(0.030)	(0.021)	(0.021)	(0.023)	(0.025)	(0.022)
Urban borrower	-0.009	0.025	0.033	0.028	0.048	0.025
	(0.046)	(0.040)	(0.045)	(0.044)	(0.042)	(0.042)
Stable income	-0.135***	-0.044	-0.079	-0.013	0.034	-0.028
	(0.051)	(0.051)	(0.050)	(0.054)	(0.083)	(0.053)
Interest rate	0.035***	0.028***	0.024***	0.040***	-0.002	0.034***
	(0.009)	(0.007)	(0.007)	(0.007)	(0.009)	(0.007)
Loan maturity	0.015***	0.023***	0.023***	0.005*	0.028***	0.015***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Loan/income ratio	0.042***	0.025***	0.032***	0.027***	0.028***	0.026***
	(0.009)	(0.007)	(0.008)	(0.008)	(0.009)	(0.007)
First loan		-0.012	-0.009	-0.057*	0.042	-0.036
		(0.030)	(0.033)	(0.033)	(0.036)	(0.031)
Credit registry*First loan		-0.201**	-0.230**	-0.201**	-0.197	-0.198**
		(0.096)	(0.107)	(0.101)	(0.144)	(0.099)
Ln(Alpha)						-0.645***
						(0.023)
No. of loans	101,883	185,934	162,746	185,934	185,934	185,934
LiTS controls	No	No	Yes	No	No	No
Branch stratification	Yes	Yes	No	No	Yes	Yes
Loan sample	First	All	All	All	All	All
Log-likelihood ratio	-45,728	-92,204	-102,917	-119,697	-52,650	-49,605
Proportionality	Yes	Yes	Yes	No	na	na

Notes: This table shows the results of Cox proportional hazard models in column [1] to [3], a Cox non-proportional hazard model in [4], a parametric exponential hazard model in [5] and a parametric Weibull hazard model in [6]. The dependent variable is the hazard rate, the probability that a loan i is defaulted on in a given month t given that default did not occur earlier. A default event occurs when a borrower is at least 30 days late in making a payment and the loan was eventually written off. Sample period: June 2002-December 2010. We restrict the sample to first-time borrowers in columns [1]-[3]. Credit registry is a dummy variable that is '1' if the credit registry was in place in a given month, zero otherwise. Competition: Dummy variable that is '1' if local credit market competition is above the median level of competition as measured by 1 minus the HHI index (where local market shares are measured in number of branches). In column [4] we relax the proportionality assumption and allow time-varying coefficients. All specifications include a time-varying nigh-light measure of local economic activity and controls for collateral use. Robust standard errors are clustered by loan officer and appear in parentheses. ***, **, * correspond to the 1%, 5%, and 10% significance level, respectively. Table A2 in the Appendix contains all variable definitions.

In Figure 3 we undertake a further placebo analysis to check that we pick up the introduction of the credit registry and not some secular trend. The graph shows the coefficient estimates and a 95 per cent confidence interval for the interaction term *Credit registry**Competition* as used in column 2 of Table 6. The value at time *t* shows the coefficient when using the actual timing of the registry introduction. The values at *t-1*, *t-2*, and so on indicate the estimates when introducing the registry 1 quarter, 2 quarters, and so on, earlier than the real date. This shows that when we artificially bring the registry introduction forward, the placebo impact is quickly reduced in size and essentially becomes zero two quarters before the actual introduction date. We conclude that our measurement of the impact of the registry indeed captures the shift in information-sharing regime and not an ongoing longer-term trend.

FIGURE 3. Cox proportional hazard model: Placebo test



Notes: This graph shows the odds ratio estimates (and a 95% confidence interval) for the interaction term *Creditregistry**Competition* as used in column 2 of Table 6. The value at t shows the coefficient when using the actual timing of the credit registry introduction. The values at $t-1$, $t-2$, etc. show the coefficient estimates when introducing the credit registry 1 quarter, 2 quarters, etc. earlier than the real introduction date.

In Appendix Table A7, we provide further evidence on the robustness of these findings by estimating similar models while allowing covariates to change over the life of the loan. In order to include time-varying covariates we modify the structure of our dataset so that each loan has multiple observations equal to the number of periods between disbursement and either repayment or default (Singer and Willett, 1993). In this way the hazard rate does not only depend on the loan and borrower characteristics at the time of disbursement, but also on a set of other variables – including the introduction of the credit registry – that may change during the life of the loan. The results in Table A7 are fully in line with those in Table 6: default risk is lower once the registry is introduced and this holds in particular in more competitive areas and for first time borrowers.

Finally, Table A8 shows that our results are also robust to adding additional interaction terms between *Credit registry* and other locality level covariates. We perform this exercise to confirm that our interaction term really picks up local competition and not other locality characteristics that might explain why certain localities benefited more from the credit registry introduction. We construct these new locality level variables using the second wave of the EBRD-World Bank Life in Transition Survey (LiTS II), a nationally representative household survey administered in 2010. We calculate the mean monthly food spending of households in a locality; the percentage of households that own a computer; the percentage of households that have a bank account; the percentage of households that can be classified as risk takers based on LiTS II; the percentage of household heads that are employed; the percentage of orthodox Christian households; the percentage of unemployment in the canton and the cantonal GDP. Overall, there are few significant differences between high and low-competition localities along these dimensions (Appendix Table A6).

If the introduction of the credit registry affected lending outcomes more in highly competitive areas, then the coefficient of *Credit registry**Competition* should remain negative and significant while the coefficient for the interaction term with each LiTS variable should be insignificant. The first line of Table A8 shows that our baseline interaction result is indeed robust to the inclusion of these various LiTS-based interaction terms.

6. Conclusions

Various countries have recently introduced credit registries – or are in the process of doing so. Many emerging markets regard registries that collect, consolidate and distribute reliable borrower information as a means to overcome weak creditor protection and inadequate bankruptcy laws. Many advanced countries consider new or improved credit registries as part of the policy response to the global financial crisis. In Europe, for instance, these discussions have focused on efforts to consolidate national credit registry data within a European central credit registry (IIF, 2013).

Are credit registries a useful component of a country's financial infrastructure? To help answer that question we present direct evidence of what happens when lenders are required to start sharing borrower information. Our analysis exploits unique data of a large small-business lender in a middle-income country. We have access to detailed information on the terms – amount, maturity, interest rate, collateral and performance – of all approved loans and on all rejected loan applications. We also know *why* loan applications were rejected. Using these data, we document how mandatory information sharing makes loan officers lend more conservatively at both the extensive and intensive margins. This impact is particularly pronounced for first time borrowers and in more competitive credit markets. Our data also reveal that the increased conservatism is mainly due to the availability of positive credit-registry information, which provides loan officers with a complete picture of the indebtedness of loan applicants. Loan quality increases considerably and this is especially the case in high-competition areas.

At first sight, the increase in rejection rates and associated reduction in lending appears at odds with cross-country evidence that shows a positive correlation between information sharing and banking sector depth. Our view is that both observations are not inconsistent. In particular, our identification strategy exploits data on the change in lending behaviour during a narrow time window around the change in information-sharing regime. This identification allows us to precisely estimate whether and how mandatory information sharing affects lending behaviour. In line with comparable loan-level evidence presented by Doblas-Madrid and Minetti (2013) we find no immediate loosening of lending standards. Indeed, the short-term impact is to tighten standards as the newly available information leads to a reassessment of borrowers' total indebtedness. This is also in line with recent theoretical work by Gehrig and Stenbacka (2007) who predict that information sharing may reduce lending and increase interest rates for first time borrowers without a credit history.

In the longer term, however, the improved functioning of the credit market can be expected to contribute to credit expansion. Indeed, our data already show how the increased transparency in the credit market allows well-behaved repeat borrowers to increase their borrowing limits and enjoy better loan conditions. Overall, our findings therefore illustrate how mandatory information sharing can help loan officers to make better informed credit decisions and to match loan offers more precisely with applicants' repayment capacity.

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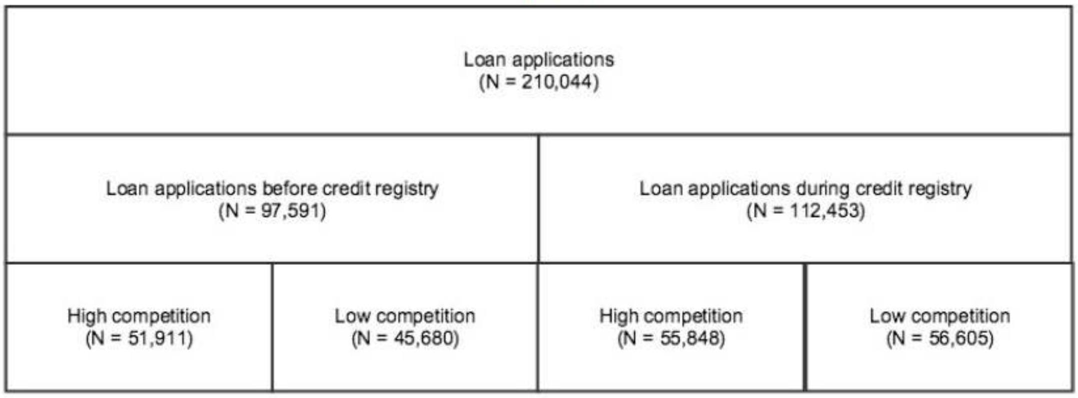
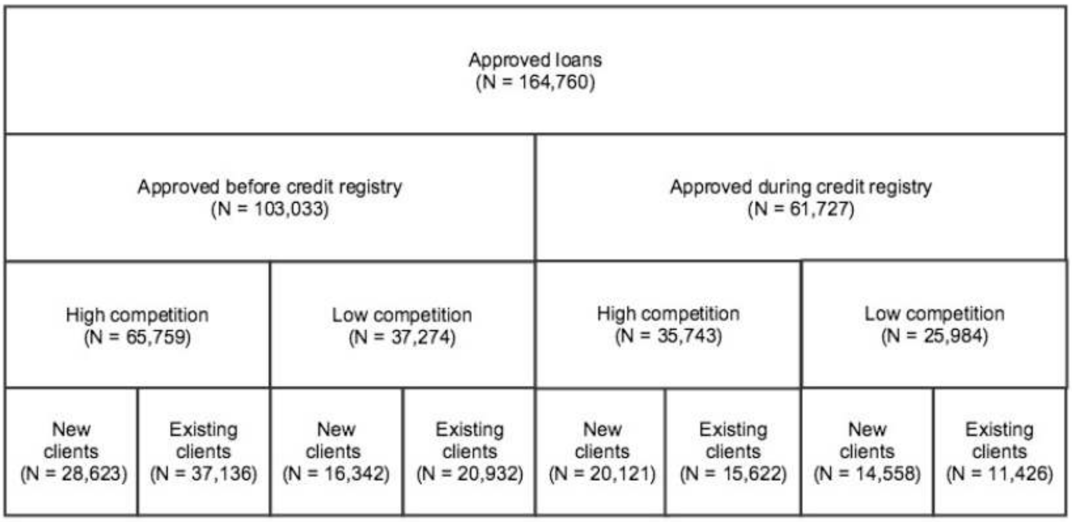
Appendix

Figure A1. Data structure

Panel A



Panel B



Notes: This figure summarizes the data structure for the overlapping sample of loan applications and loan portfolio (January 2007-December 2012). In the loan performance analysis a longer sample stretching back to June 2002 is used. Out of the total number of applications, 20,627 were withdrawn by the borrower before a decision was taken or the loan disbursed.

TABLE A1. Variable definitions and data sources: Extensive margin

Dependent variables:	Definition	Source	Unit
Loan rejected	Dummy=1 if loan application is rejected.	EKI	Dummy
Loan rejected: Hard information	Dummy=1 if loan application is rejected because of borrower age, low credit score in the registry, too many outstanding loans elsewhere, previous late or non-repayment with EKI, bad financial ratios or insufficient collateral.	EKI	Dummy
Loan rejected: Soft information	Dummy=1 if loan application is rejected because of a bad recommendation from someone else, because the purpose of the loan was unclear, or because the loan officer had doubts about certain character traits of the applicant.	EKI	Dummy
Loan rejected: Internal information	Dummy=1 if loan application is rejected because of information that the lender has in its own systems or has collected itself: information on financial ratios of the borrower, the purpose of the loan; the character of the client, and the available collateral.	EKI	Dummy
Loan rejected: External information (negative)	Dummy=1 if loan application is rejected because of a low credit score in the registry.	EKI	Dummy
Loan rejected: External information (positive)	Dummy=1 if loan application is rejected because of too many outstanding loans with competing lenders.	EKI	Dummy
Independent variables:			
Amount requested	Requested amount by the loan applicant.	EKI	BAM
Loan term requested	Requested term by the loan applicant.	EKI	Months
Applicant age	Age of the applicant.	EKI	Years
Applicant male	Dummy=1 if applicant male; 0 otherwise.	EKI	Dummy

Notes: BAM is Bosnian Convertible Marka.

TABLE A2. Variable definitions and data sources: Intensive margin

Dependent variables:	Definition	Source	Unit
Loan amount	Loan amount at time of disbursement.	EKI	BAM
Loan term	Length (tenor) of the loan at time of disbursement.	EKI	Months
Interest rate	Annual nominal interest rate on the loan.	EKI	%
Collateral	Total number of collateral items pledged.	EKI	Discrete
Problem loan	Dummy=1 if borrower was at any time at least 30 days late in making a payment.	EKI	Dummy
Independent variables:			
Credit registry	Dummy=1 for all quarters after and including July 2009 (time of CRK introduction); 0 otherwise.	Central Bank of Bosnia	Dummy
Competition: 1-HHI	1 minus HHI index. The (time-varying) HHI index ranges between [0, 1] and measures microcredit market concentration in the locality where an EKI branch is based. Market shares are expressed as number of branches.	BEPS, MIX, Annual reports	[0, 1]
Competition: Survey	Competition intensity as perceived by the two most senior loan officers in each branch. Average score on a 7-point Likert scale to the question: Over the past ten years, I think that other microcredit providers have increased their competitiveness in my area.	Loan officer survey	0.5 increments
Loan/income ratio	Loan amount at time of disbursement divided by monthly borrower income. Income includes primary plus secondary income.	EKI	Ratio
Borrower age	Borrower age.	EKI	Years
Borrower male	Dummy= 1 if borrower is male; 0 otherwise.	EKI	Dummy
Borrower education	1 = None, 2 = Primary, 3 = Secondary, 4 = Tertiary (College/University/Post Graduate).	EKI	1 to 4
Borrower income	Total annual borrower income (primary plus secondary income source).	EKI	BAM
Urban borrower	0 = Rural; 1 = Urban.	EKI	Dummy
Stable income	0 = unemployed or casually employed; 1 = stable employment (agricultural producer; full-time employed; own business; part-time employed) or pension.	EKI	Dummy
Loan immovable	Loan purpose = Purchase immovable assets (land and/or buildings).	EKI	Dummy
Loan movable	Loan purpose = Purchase movable assets (equipment, fixed assets, vehicles).	EKI	Dummy
Loan stock	Loan purpose = Purchase of stock (merchandise, raw material, working capital, agricultural inputs, livestock for reproduction, seedlings for orchards).	EKI	Dummy
Loan household	Loan purpose = Private (non-business related) expenses for the household.	EKI	Dummy
Personal collateral	Number of personal collateral pledges for each loan (includes mortgages, administrative bans on the borrower's salary and pledges of movable assets).	EKI	Discrete
Social collateral	Number of social collateral pledges for each loan (includes total and partial guarantees provided by family and friends of the borrower).	EKI	Discrete
Third-party collateral	Number of third party collateral pledges for each loan (includes checks or bills of exchange issued by a guarantor company).	EKI	Discrete
Stock index	Bosnia Investment Index (May 28th 2002=1).	Sarajevo Stock Exchange	Index
Local GDP	Time varying measure of local economic activity as proxied by the night-light intensity (derived from satellite images) in the locality where an EKI branch is based. Scale ranges from 0 to 63 where higher values indicate higher light intensity.	National Geophysical Datacenter; Henderson et al. (2011)	[0, 63]
Loans/officer	Monthly number of loans per loan officer.	EKI	Loans
Branch growth	Quarterly growth in total new lending volume (flow) per branch.	EKI	%

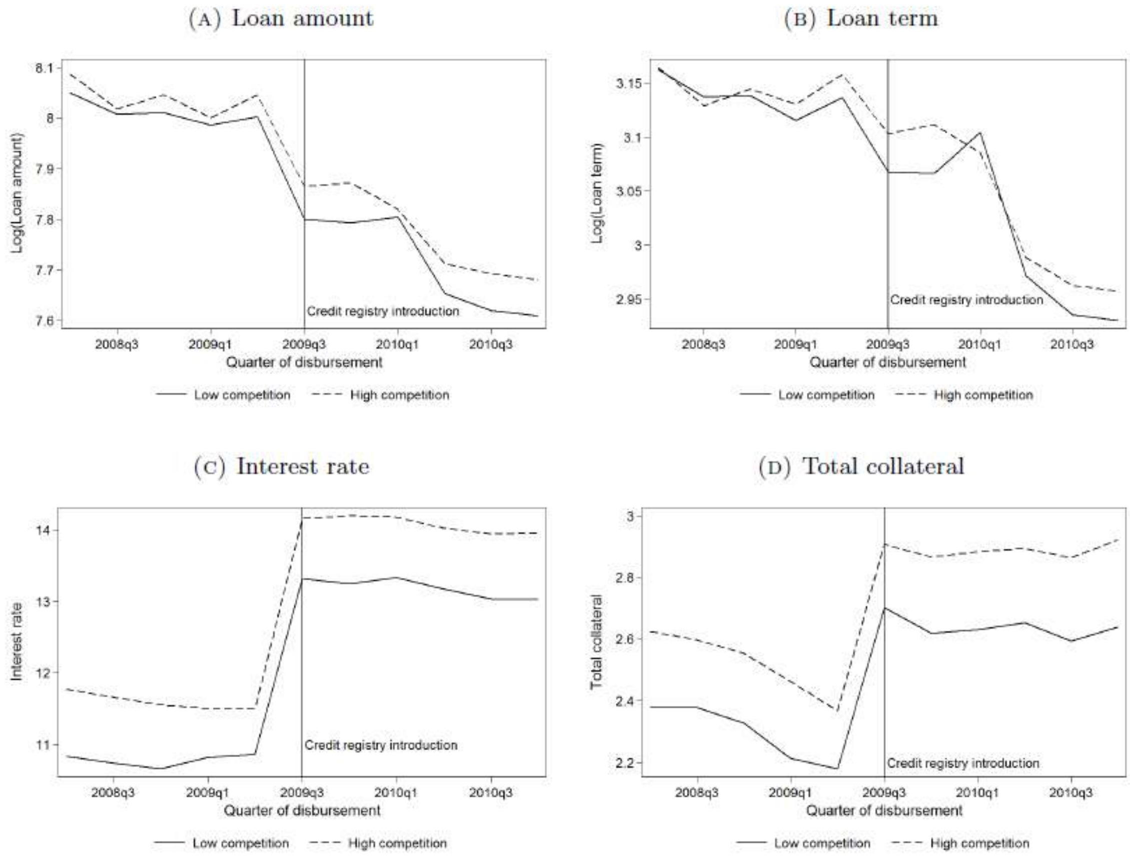
Notes: BAM is Bosnian Convertible Marka. BEPS is the EBRD Banking Environment and Performance Survey. MIX: www.mixmarket.org/.

Table A3. Extensive margin: Robustness and placebo tests

	Robustness tests			Placebo tests		
	Narrow window	Broad window	Broadest window	Post is pre	Pre is post	Random assignment
	[1]	[2]	[3]	[4]	[5]	[6]
Credit registry*Competition	0.030***	0.047***	0.054***	0.006	0.007	0.000
	(0.011)	(0.007)	(0.006)	(0.008)	(0.006)	(0.001)
Applicant covariates	Yes	Yes	Yes	Yes	Yes	Yes
Loan covariates	Yes	Yes	Yes	Yes	Yes	Yes
No. of applications	29,829	96,215	183,066	54,022	79,769	69,427
Adjusted R-squared	0.037	0.045	0.046	0.040	0.052	0.041

Notes: Columns [1], [2] and [3] show robustness tests of our main results as reported in Table 2. In columns [1] we use a shorter time window February 2009-February 2010. In column [2] the window is May 2008-December 2010. In column [3] we use the largest possible window January 2007-December 2012. Columns [4], [5] and [6] show placebo tests of our main results as reported in Table 2. In columns [4] and [5] we move the two-year window one year forward and backward, respectively. In column [6], we randomly allocate branches to either high or low competition status. We repeat this random allocation a thousand times and show the average result. The treatment period starts in July 2009. Credit registry is a dummy variable that is '1' if the credit registry was in place in a given month, zero otherwise. Competition: Dummy variable that is '1' if local credit market competition is above the median level of competition as measured by 1 minus the HHI index (where local market shares are measured in number of branches). Dummies for the introduction of the credit registry and for high competition are included but not shown. Robust standard errors are clustered by loan officer and appear in parentheses. ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively. Table A2 in the Appendix contains all variable definitions. The same borrower and loan covariates as in Table 2 are included but not shown.

Figure A2. Information sharing, credit market competition: Parallel trends



Notes: Conditional trends over the sample period January 2008-December 2010. Loan terms have been regressed on client and loan characteristics. The fitted values from these regressions are shown for high versus low competition areas in the graphs above.

Table A4. Intensive margin: Placebo tests

Dependent variable →	Loan amount			Loan term		
	Post is pre	Pre is post	Random allocation	Post is pre	Pre is post	Random allocation
	[1]	[2]	[3]	[4]	[5]	[6]
Post CRK*Competition	0.010	-0.046	0.000	-0.007	-0.022	0.000
	(0.040)	(0.030)	(0.000)	(0.034)	(0.020)	(0.000)
Borrower covariates	Yes	Yes	Yes	Yes	Yes	Yes
Local econ. control	Yes	Yes	Yes	Yes	Yes	Yes
No. of loans	12,627	38,407	28,240	12,626	38,407	28,240
Adjusted R-squared	0.380	0.459	0.007	0.247	0.357	0.006
Dependent variable →	**Interest rate**			**Collateral**		
	Post is pre	Pre is post	Random allocation	Post is pre	Pre is post	Random allocation
	[1]	[2]	[3]	[4]	[5]	[6]
Post CRK*Competition	-0.093	0.028	0.000	0.105	0.024	0.000
	(0.134)	(0.094)	(0.000)	(0.064)	(0.075)	(0.001)
Borrower covariates	Yes	Yes	Yes	Yes	Yes	Yes
Local econ. control	Yes	Yes	Yes	Yes	Yes	Yes
No. of loans	12,626	38,407	28,240	12,627	38,407	28,240
Adjusted R-squared	0.194	0.255	0.004	0.449	0.414	0.007

Notes: This table shows loan level estimates for weighted least squares models where the dependent variables are: loan amount, loan term, interest rate and total collateral contracts. In columns [1] and [4] we show results for a placebo test where we move the two-year window one year forward while in columns [2] and [5] we move the two-year window one year backward. In columns [3] and [6] we randomise the allocation to high and low competition branches over 1,000 trials. Post CRK is a dummy variable that is '1' if the CRK was in place in a given month, zero otherwise. Competition: Dummy variable that is '1' if local credit market competition is above the median level of competition as measured by 1 minus the HHI index (where local market shares are measured in number of branches). Robust standard errors are clustered by loan officer and appear in parentheses. ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively. Table A2 in the Appendix contains all variable definitions. The same borrower and loan covariates as in Table 4 are included but not shown.

TABLE A5. Intensive margin: Robustness tests

Dependent variable →	Loan amount			Loan term		
	Narrow window	Broad window	Broadest window	Narrow window	Broad window	Broadest window
	[1]	[2]	[3]	[4]	[5]	[6]
Post CRK*Competition	-0.133***	-0.132***	-0.101***	-0.063**	-0.080***	-0.048***
	(0.042)	(0.031)	(0.027)	(0.022)	(0.033)	(0.019)
Borrower covariates	Yes	Yes	Yes	Yes	Yes	Yes
Local econ. control	Yes	Yes	No	Yes	Yes	No
No. of loans	11,842	33,965	88,623	11,842	33,965	88,623
Adjusted R-squared	0.452	0.447	0.391	0.333	0.340	0.271

Dependent variable →	Interest rate			Collateral		
	Narrow window	Broad window	Broadest window	Narrow window	Broad window	Broadest window
	[1]	[2]	[3]	[4]	[5]	[6]
Post CRK*Competition	0.492***	0.358***	0.146	0.223***	0.236***	0.237***
	(0.123)	(0.114)	(0.094)	(0.064)	(0.060)	(0.073)
Borrower covariates	Yes	Yes	Yes	Yes	Yes	Yes
Local econ. control	Yes	Yes	No	Yes	Yes	No
No. of loans	11,842	33,965	88,623	11,842	33,965	88,623
Adjusted R-squared	0.231	0.268	0.266	0.451	0.431	0.382

Notes: This table shows robustness tests of our main results as reported in Table 4. In columns [1] and [4] we use a shorter time window February 2009-February 2010. In columns [2] and [5] the window is May 2008-December 2010. In columns [3] and [6] we use the widest possible window May 2006-December 2012. Credit registry is a dummy variable that is '1' if the credit registry was in place in a given month; '0' otherwise. Competition: Dummy variable that is '1' if local credit market competition is above the median level of competition as measured by 1 minus the HHI index (where local market shares are measured in number of branches). Robust standard errors are clustered by loan officer and appear in parentheses. ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively. Table A2 in the Appendix contains all variable definitions. The same borrower and loan covariates as in Table 4 are included but not shown.

TABLE A6. High vs. low competition areas: Means comparison of socio-economic characteristics

	Low competition areas	High competition areas
	[1]	[2]
Food spending	349.72	388.67
Percentage owns a computer	30.47	61.30**
Percentage bank account	42.99	54.30
Percentage risk takers	60.30	57.31
Percentage employed	28.94	42.59
Percentage orthodox	30.50	28.03
Crisis impact	2.33	2.19
Cantonal unemployment	0.46	0.46
Cantonal GDP	3,189	3,305

Notes: Sample period is June 2002-December 2010. Asterisks refer to p-value of t-test of equality of means. ** corresponds to the 5% level of significance. Source: EBRD-World Bank Life in Transition Survey (2010).

TABLE A7. Information sharing and loan quality: Hazard model extensions and alternative specifications

Functional form	Cox proportional		Exponential		Weibull	
Time structure	Time-varying predictors					
	[1]	[2]	[3]	[4]	[5]	[6]
Credit registry*competition	-0.301**	-0.247**	-0.268*	-0.203**	-0.264*	-0.200*
	(0.153)	(0.101)	(0.156)	(0.102)	(0.154)	(0.102)
Credit registry	-1.332***	-1.230***	-0.789***	-0.732***	-0.922***	-0.856***
	(0.115)	(0.080)	(0.118)	(0.083)	(0.117)	(0.082)
Competition	-0.056*	-0.102***	-0.049	-0.096***	-0.069**	-0.119***
	(0.030)	(0.022)	(0.034)	(0.025)	(0.033)	(0.024)
First loan		0.683***		0.665***		0.684***
		(0.022)		(0.024)		(0.024)
Credit registry*First loan		-0.329***		-0.219***		-0.244***
		(0.076)		(0.081)		(0.080)
Alpha					0.624***	0.633***
					(0.009)	(0.007)
No. of obs.	356,131	1,119,122	356,131	1,119,122	356,131	1,119,122
Log-likelihood ratio	-49,419	-101,919	-20,653	-41,799	-20,115	-40,842

Notes: This table shows the results of (semi-)parametric hazard models. The dependent variable is the hazard rate: the probability that a loan i is defaulted on in month t given that default did not occur earlier. A default event occurs when a borrower is at least 30 days late in making a payment and the loan was eventually written off. The same controls as in Table 6 and a constant are included but not shown. Sample period: June 2002-December 2010. We restrict the sample to new customers in columns [1], [3], and [5]. Credit registry is a dummy variable that is '1' if the credit registry was in place in a given quarter; '0' otherwise. Competition: Dummy variable that is '1' if local credit market competition is above the median level of competition as measured by 1 minus the HHI index where local market shares are measured in number of branches. Robust standard errors in parentheses. ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively. Table A2 in the Appendix contains all variable definitions.

TABLE A8. Information sharing, credit market competition and loan quality: Robustness tests

Local factor →	Mean food spending	Percentage owns a computer	Percentage bank account	Percentage risk takers	Percentage employed	Percentage orthodox	Cantonal unemployment	Cantonal GDP
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Credit registry* Competition	-0.644***	-0.517**	-0.450**	-0.524***	-0.556***	-0.602***	-0.524***	-0.431**
	(0.201)	(0.220)	(0.197)	(0.200)	(0.209)	(0.194)	(0.184)	(0.187)
Credit registry* Local factor	0.002	-0.001	-0.003	0.009	0.001	-0.002	0.799	-0.000
	(0.002)	(0.004)	(0.005)	(0.006)	(0.006)	(0.002)	(1.226)	(0.000)
Credit registry	-1.575**	-0.984***	-0.892***	-1.554***	-1.038***	-0.970***	-1.502***	-1.089***
	(0.699)	(0.208)	(0.274)	(0.335)	(0.249)	(0.174)	(0.527)	(0.315)
Local factor	0.000	-0.001	-0.003	0.003	-0.005	-0.005**	1.341	0.000
	(0.001)	(0.003)	(0.004)	(0.004)	(0.005)	(0.002)	(0.932)	(0.000)
Borrower covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	104,732	104,732	104,732	104,732	104,732	104,732	100,505	84,914
No. of branches	14	14	14	14	14	14	14	14
Log-Likelihood ratio	-53,770	-53,771	-53,762	-53,757	-53,756	-53,681	-57,727	-55,026

Notes: This table shows the results of a Cox proportional hazard model where the dependent variable is the hazard rate, the probability that a loan i is defaulted on in month t given that default did not occur earlier. A default event occurs when a borrower is at least 30 days late in making a payment and the loan was eventually written off. Sample period: June 2002-December 2010. We restrict the sample to first-time borrowers. Credit registry is a dummy variable that is '1' if the Credit registry was in place in a given month; '0' otherwise. Local factor: Dummy from Life in Transition Survey that is '1' if local factor is above median level. Competition: Dummy variable that is '1' if local credit market competition is above the median level of competition as measured by 1 minus the HHI index (where local market shares are measured in number of branches). Robust standard errors are clustered by loan officer and appear in parentheses. ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively. Table A2 in the Appendix contains all variable definitions. The same borrower and loan covariates as in Table 6 are included but not shown.