How Does P2P Lending Fit Into the Consumer Credit Market?

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Abstract

We develop a theoretical model to examine the interaction between bank lending and lending via peer-to-peer (P2P) lending platforms. The model predicts that: (i) banks prefer relationship lending loans over transaction loans and improve performance by avoiding transaction costs; (ii) transaction loans migrate to P2P lending platforms, so the emergence of P2P lending is correlated with a decline in bank lending; and (iii) the risk-adjusted interest rates on P2P loans are lower than those on bank loans. We confront these predictions with data on P2P lending and non-construction consumer bank credit market in Germany. The empirical findings support predictions of the model and indicate that riskier borrowers seeking transaction loans are the ones being served by P2P lending.

Keywords: P2P lending, financial intermediation, consumer credit

JEL Classification: D40, G21, G23, L86

1 Introduction

The contemporary theories of financial intermediation assign a pivotal role to banks as intermediaries between borrowers and savers (e.g. Coval and Thakor (2005), Diamond (1984), and Ramakrishnan and Thakor (1984)). Yet, peer-to-peer (P2P) lending, which matches directly borrowers and lenders and eliminates an intermediating bank, has gained traction in recent years in both Europe and U.S. (see, for example, Milne and Parboteeah (2016)). Lending Club and Prosper originated over $10 billion in loans in 2015 and firms that have gone public (e.g. Lending Club) are worth billions of dollars in market value. A report from PricewaterhouseCoopers (2015) noted that the origination volumes of U.S. P2P lending platforms have grown on average of 84% per quarter since 2007. While aggregate P2P lending volume is still only a relative small fraction of bank lending volume, its rapid grow in loan origination raises some fundamental questions about the *nature* of P2P lending and its *interaction* with bank lending.

First, what kind of loans are being originated by P2P lenders? That is, are these loans more or less risky than bank loans? Second, is P2P borrowing a more or less expensive source of finance in terms of a comparison of the risk-adjusted lender returns in P2P lending versus bank lending? Third, how does P2P lending affect volume and profitability of bank lending?

We address these questions theoretically and empirically. We begin by developing a simple adaption of the Holmstrom and Tirole (1997) and Mehran and Thakor (2011) bank monitoring models. There are both banks and P2P lenders in the model and two types of borrowers: relationship and transaction borrowers.[1] Relationship loans require bank monitoring to prevent inefficient asset substitution by borrowers, whereas transaction loans do not. Banks in their role as specialized intermediaries can monitor borrowers, but P2P investors cannot. Banks are able to earn rents on relationship loans – with pledgeability constraints limiting the extend of the rents – but lending on transaction loans are perfectly competitive. With this set-up, we derive the following results which serve as predictions for our empirical tests:

1. The loans made by P2P investors are riskier than bank loans, so bank loan portfolios will become less risky with the emergence of the P2P lending market;

2. The risk-adjusted interest rate on bank loan portfolio is higher than or equal to the risk-adjusted interest rate on P2P loans, and risk-adjusted interest rate on P2P loans will be the same as the rate these loans would get from banks;

[1] We use the terms "relationship loans" and "transaction loans" in the way they were defined by Boot and Thakor (2000).

3. Bank lending volume will decline with the emergence of the P2P lending market, but the average profitability of the bank loan portfolios will increase.

We confront these predictions with data on P2P and bank lending in Germany. The data on P2P lending are provided by Auxmoney, which is the largest and oldest P2P lending platform in Germany for consumer credit and data on bank lending are provided by the Deutsche Bundesbank. Because of differences between P2P and bank lending in terms of their origination, we compare the two data sets by controlling for risk and interest rate differences. In this way, we are able to set the same basis for our econometric estimates. Using German, rather than U.S., data has some advantages. First, the consumer lending market in the U.S. is very diffuse – it includes not only banks and P2P lending platforms, but also non-bank lenders like payday and title lenders. By contrast, consumer lending in Germany is primarily done by banks, and the Bundesbank provides good bank-level data. Second, in the U.S. P2P lending platforms do not serve subprime borrowers whereas in Germany there is no restriction on the borrower.[2] According to our study this is the share of the market that profits most from P2P lending. Third, in Germany there is access to banks' interest rates statistics, which permits a comparison of rates charged on bank loans and P2P loans. By contrast, we do not know the availability of this data in the U.S.

Our results can be summarized as follows. First, the loans made via P2P platforms are riskier than bank loans and carry higher interest rates than bank loans. Second, when adjusted for risk, P2P loan rates are actually less than or not significantly different to bank loans. Third, after controlling for interest rates for interest rates and risk differences, banks lending volume is negatively correlated with P2P lending lending volume but the average profitability of bank lending goes up. Our findings suggest that high-risk borrowers substitute bank loans with P2P loans. Thus, the empirical results are consistent with the predictions of the model. Fourth, the price elasticity of demand is higher for P2P loans than for bank loans. P2P loan demand appears to be driven primarily by loan interest rates – higher rates go with lower loan volume. Bank loan demand, by contrast, seems to be driven by not only loan interest rates but also other factors.

Our paper relates to the literature on P2P lending and on-line banking, which is till in its infancy. Although P2P lending, in its present form, is a relatively recent phenomenon that started in 2005 with the launch of Zopa, interest in research has been growing after Prosper (a competitor of Zopa) made its entire platform's data available in 2007; see, Ravina (2012) and Pope and Sydnor (2011). Some of the research has examined the extent to which observable attributes impact loans interest rates. Duarte et al. (2012)

[2]Lending Club and Prosper apply a minimum Fico score of 660 and 640, respectively, on borrowers. Subprime borrowers have typically scores below 600.

evaluate the impact of borrowers pictures on loan interest rates, Lin et al. (2013) evaluate the impact of friendship connections on interest rates, and Ravina (2012) evaluates the effect of beauty and skin color on interest rates.

Another strand of this literature examines the impact of information facilitation and institutional design on credit provision. Hildebrand et al. (2015) investigate to what extent the change from interest rate auctions to rates that are pre-determined by the website affects the amount of credit provided. Herzenstein et al. (2011) examine investor herding in determining which loan to fund.

Our work abstracts from the behavioral aspects of the P2P credit market. Instead, we offer a market perspective by analyzing the role of the P2P market vis-à-vis bank credit. In this sense, our work is related to Blaseg and Koetter (2015), who analyze why startups prefer equity crowdfinancing over bank credit.

The paper is organized as follows. Section 2 presents the theoretical model and the empirical predictions. Section 3.1 describes the data used for the empirical analysis. Section 3 reports the empirical results. Section 3.4 provides a robustness check by expanding our estimation in the context of internet consumers. Section 4 concludes.

2 Theoretical Background and Predictions

2.1 The Model

Consider an economy in which all agents are risk neutral. The riskless interest rate is zero. There are banks, a government regulator who provides deposit insurance, depositors and bank shareholders. There are three dates: $t = 0, 1, 2$. At $t = 0$, the bank invests \$2 in loans and securities. These assets pay off at $t = 2$. At $t = 1$, the bank may receive interim information about loan quality. The model presented below is closely related to that developed by Mehran and Thakor (2011).

Feasible Investments: The bank has a feasible investment set that consists of three assets: a portfolio of relationship loans, a portfolio of transaction loans, and a riskless asset (say a government bond).

If \$1 is invested in the portfolio of relationship loans, it pays off $X(m)$ to the bank at $t = 2$ if all the loans repay, where m is the monitoring done by the bank at $t = 0$, with $m \in [0, \bar{m}] \subset \mathbb{R}_+$, where $\mathbb{R}_+$ is the real line and $[0, \bar{m}]$. We assume $X' > 0$, and $X'' < 0$, $X(0) = 0$, with the Inada conditions $\lim_{m \to 0} X' = \infty$ and $\lim_{m \to \bar{m}} X' = 0$. The private cost of m to the bank is $V(m) \geq 0$, $V' > 0$, $V'' > 0$. Banks are relationship lending specialists who are experts in such monitoring relative to other lenders. This notion of bank monitoring is a reduced-form version of the set-up in Holmstrom and Tirole (1997) in that $X(m)$ is the borrower's pledgeable income from an efficient project that is available to repay the bank. This pledgeable income is increasing in m because greater monitoring increases the measure of the set of inefficient private-benefit projects the borrower can be prevented from investing in as the bank increases the borrower's repayment.[3] If the borrower chooses a private-benefit project, the bank receives no repayment because the project has no verifiable cash flow for the bank to claim. This notion of relationship banking, wherein bank monitoring enhances the borrower's project payoff and repayment to the bank, is also consistent with other papers on relationship banking (e.g., Boot and Thakor (2000); see Boot (2000) review). That is, higher bank monitoring leads to better project choices by relationship borrowers.

The relationship loans are risky. A random fraction $\gamma \in (0,1)$ of the loans will repay (assuming that the bank has monitored to ensure borrowers' choices of efficient projects) at $t = 2$, where $G(\cdot)$ is the probability distribution of γ as viewed at $t = 0$. At $t = 1$, the realization of γ becomes known to the bank and the regulator. At $t = 1$, after observing the realization of r, the bank also makes a second monitoring decision by choosing $e \in \{0,1\}$. We call this "maintenance monitoring", intended to ensure that there is no interim project-switching by the borrower that reduces the repayment to the bank. If the bank chooses $e = 1$, then the payment at $t = 2$ is $X(m)$ on all repaying loans. If the bank chooses $e = 0$, then the payment to the bank on repaying loans falls to 0 (for \$1 invested in the relationship loan portfolio). The private cost of e to the bank is We, where $W > 0$ is a constant.

Transaction loans do not involve any bank monitoring. That is, there is nothing special that the bank does relative to other lenders when it comes to these loans. This portfolio includes loans with perfectly correlated prospects, and the probability that a loan will repay is $\theta \in (0,1)$. \$1 invested in this portfolio promises to repay $\$R$ at $t = 2$. Because intermediation by the bank is unnecessary for these loans, we assume this is a perfectly competitive market and these borrowers can avail of peer-to-peer lending at competitive rates that yield lenders zero expected profits. Whether the transaction loan portfolio will default or repay will become known at $t = 1$ to the bank and the regulator.

The third investment option for the bank is the riskless asset. \$1 invested in this asset yields \$1 for sure at $t = 2$.

Each asset requires an investment of \$1, so with \$2 to invest, the bank can invest in

[3] Holmstrom and Tirole (1997) have only two inefficient private-benefit projects. Our specification assumes a continuum of such projects. So suppose the bank and the relationship borrower negotiate repayment of X. This repayment obligation makes the borrower prefer a set, say S_x, of private-benefit projects to the efficient project. A level of bank monitoring $m \geq m_x$ is needed to guarantee that the borrower chooses the efficient project. Thus $X(m)$ should be viewed as the repayment obligation that requires a monitoring of m by the bank. If X is changed, so must m. Thus, the bank endogenously chooses m, knowing that this choice will imply a maximum X that can be set on the loan.

only two out of the three assets at $t = 0$.

Bank Regulator: The government regulator provides complete deposit insurance. For simplicity, we normalize the insurance premium at zero. Regulation involves a cost $\Psi > 0$ of continuing the bank between $t = 1$ and $t = 2$; this may be a marginal administrative cost of regulating the bank. There may be a similar cost for the period between $t = 0$ and $t = 1$, but it plays no role in the analysis so we set it at zero. In addition to providing deposit insurance, the regulator decides at $t = 1$ whether to allow the bank to continue for a second period or shut it down. This decision has to be subgame perfect. If the bank is shut down at $t = 1$, the regulator recovers 0 on the relationship loan portfolio, \$1 on the riskless asset and the value of the transaction loan portfolio after it is known whether the loans will repay.

Bank Size and Capital Structure: For simplicity, we fix the bank's size at \$2 and take its capital structure as given; the bank funds itself with capital that is a fraction $c \in (0, 1)$ of the bank's total funding of \$2. The remaining fraction $1 - c$ is funded by (completely) insured deposits. We ignore refinancing risk by assuming that loans and deposits are maturity-matched, i.e., depositors are paid off at $t = 2$ along with shareholders.

Bank's Decision Variables: At $t = 0$, the bank chooses $m \in [0, \bar{m}]$ and at $t = 1$ it chooses $e \in \{0, 1\}$. Both the m and e choices are only privately observed by the bank and not by anyone else. The bank must also choose which two of the three assets to invest its \$2 in. The bank makes all its decisions to maximize the value of its equity.

Sequence of Events: At $t = 0$, the bank raises \$2 from its financiers, of which $2[1 - c]$ comes from depositors and $2c$ from shareholders. The bank decides which two of three assets to invest in: the relationship loan portfolio, the transaction loan portfolio and the riskless asset. Each asset requires a \$1 investment. After the bank has chosen its asset portfolio, it chooses its monitoring $m \in [0, \bar{m}]$. At $t = 1$, the bank and the regulator observe the realized value of γ and whether the transaction loan portfolio will repay or default at $t = 2$. The regulator determines whether to shut the bank down or let it continue for a second period. If allowed to continue, the bank chooses its maintenance monitoring $e \in \{0, 1\}$ for the second period. See Figure 1.

2.2 Analysis

We will analyze two cases separately. First, we will assume that the bank invests in the relationship loan portfolio and the riskless asset (Case I). Then we will assume that the bank invests in the relationship and transaction loan portfolios (Case II). Then we will compare the two cases.

Case I: We will use backwards induction for our analysis and begin with an examination of events at $t = 1$. Let m^* be the level of monitoring chosen by the bank at $t = 0$. Let $\tilde{m}^*$ be the level of monitoring the regulator believes the bank has chosen. The bank invested \$1 in the relationship loan portfolio at $t = 0$ and \$1 in the riskless asset.

Now let γ be the realization at t=1 of the fraction of relationship loans that will repay at t=2. The bank and the regulator observe γ, after which the bank computes the net wealth of its shareholders as:

$$\gamma X(m^*) + 1 - 2[1-c] - W \qquad \text{with } e = 1 \tag{1}$$

$$\max\{1 - 2[1-c], 0\} \qquad \text{with } e = 0 \tag{2}$$

To focus on the case of interest, we assume that the bank's deposit repayment, $2[1-c]$, satisfies:

$$2[1-c] > 1 \tag{3}$$

This is a reasonable restriction, given that c is typically in the 0.04 to 0.15 range. Thus, the incentive compatibility (IC) constraint for the bank to prefer $e = 1$ to $e = 0$ is:

$$\gamma X(m^*) + 1 - 2[1-c] - W \geq 0 \tag{4}$$

This allows us to solve for the critical value of γ, call it γ^*, that determines the bank's choice of e:

Lemma 1: There is a critical value of γ, defined as

$$\gamma^* = \frac{2[1-c] + W - 1}{X(m^*)} \tag{5}$$

such that the bank will choose $e = 1 \ \forall \ \gamma \geq \gamma^*$ and $e = 0 \ \forall \ \gamma < \gamma^*$, which is strictly decreasing in the bank's capital for any given m^* chosen at $t = 0$.
Proof: in Appendix.

Lemma 2: Assuming that $m^* > \tilde{m}^*$, the regulator will allow the bank to continue in the second period if $\gamma \geq \gamma_r^*$ and shut it down if $\gamma < \gamma_r^*$, where

$$\gamma_r^* = \frac{2[1-c] - 1 + W + \Psi}{X(\tilde{m}^*)} \tag{6}$$

with $\gamma_r^* > \gamma^*$.The regulator's cut-off is decreasing in bank capital.
Proof: in Appendix.

Since $\gamma_r^* > \gamma^*$, the regulator can be assured that when the bank is allowed to continue in the second period, it will choose $e = 1$. Moreover, because γ_r^* is strictly decreasing in bank capital, the probability of second-period continuation is higher for a bank that starts out with higher capital at $t = 0$.

We now move to $t = 0$ and solve for m^*. The bank solves:

$$\max_{m \in [0,\bar{m}]} \left\{ \int_{\gamma_r^*}^{1} \{\gamma X(m) + 1 - 2\,[1-c] - W\} dG(\gamma) - V(m) - 2c \right\} \tag{7}$$

This leads to one of the main results of this section.

Proposition 1: There is a unique interior solution to (7), represented by m^*. In a Nash equilibrium, $m^* = \tilde{m}^*$, and the bank is allowed to continue in the second period if $\gamma \geq \gamma_r^*$ at $t = 1$. If allowed to continue, the bank chooses $e = 1$.
Proof: in Appendix.

Case II: Now the bank's portfolio consists of the relationship loan and the transaction loan. We begin once more by analyzing events at $t = 1$ first. Let γ be the realized value of the fraction of the relationship loan portfolio that will repay at $t = 2$ and suppose it is discovered that the transaction loan portfolio will repay. Then the bank's net payoff from choosing $e = 1$ is:

$$\gamma X(m) + R - 2\,[1-c] - W \tag{8}$$

and from choosing $e = 0$, it is:

$$\max\{R - 2\,[1-c]\,, 0\} \tag{9}$$

We will assume that:

$$R < 2\,[1-c] \tag{10}$$

Thus, the payoff to the bank's shareholders from choosing $e = 0$ is 0.

If it is discovered at $t = 1$ that the transaction loan portfolio will default at $t = 2$, then the bank's net payoff from choosing $e = 1$ is:

$$\gamma X(m) - 2\,[1-c] - W \tag{11}$$

We now have our next result.

Lemma 3: When it is discovered at $t = 1$ that the transaction loan portfolio will repay at $t = 2$, the bank will choose $e = 1$ over $e = 0$ if $\gamma \geq \gamma^0$ where

$$\gamma^0 = \frac{2[1-c] + W - R}{X(m^0)} \tag{12}$$

If it is discovered at $t = 1$ that the transaction loan portfolio will default at $t = 2$, then the bank will prefer $e = 1$ over $e = 0$ if $\gamma \geq \hat{\gamma}^0$, where

$$\hat{\gamma}^0 = \frac{2[1-c] + W}{X(m^0)} \tag{13}$$

Here, m^0 is the bank's monitoring choice at $t = 0$.
Proof: in Appendix.

Based on our earlier analysis, the following lemma is stated without proof.

Lemma 4: When it is discovered at t=1 that the transaction loan portfolio will repay at t=2, the bank will be allowed by the regulator to continue if $\gamma \geq \gamma_r^0$ where

$$\gamma_r^0 = \frac{2[1-c] + W - R + \Psi}{X(\tilde{m}^0)} \tag{14}$$

If it is discovered at $t = 1$ that the transaction loan portfolio will default at $t = 2$, then the bank will be allowed to continue if $\gamma \geq \hat{\gamma}_r^0$, where

$$\hat{\gamma}_r^0 = \frac{2[1-c] + W + \Psi}{X(\tilde{m}^0)} \tag{15}$$

Here, $\tilde{m}^0$ is the regulator's belief about the bank's monitoring choice at $t = 0$.
Proof: in Appendix.

We now move to t=0 and solve for the optimal monitoring m^0. The bank solves:

$$\max_{m \in [0,\bar{m}]} \Big\{ \theta \int_{\gamma_r^0}^{1} \{\gamma X(m) + R - 2[1-c] - W\} dG(\gamma) + \\ (1-\theta) \int_{\hat{\gamma}_r^0}^{1} \{\gamma X(m) - 2[1-c] - W\} dG(\gamma) - V(m) - 2c \Big\} \tag{16}$$

This leads to our final main result.

Proposition 2: There is a unique interior solution to (16), represented by m^0. In a Nash equilibrium, $m^0 = \tilde{m}^0$, and the bank is allowed to continue in the second period if $\gamma \geq \gamma_r^0$ in the case in which it is discovered at $t = 1$ that the transaction loans will repay, and it is allowed to continue in the second period if $\gamma \geq \gamma_r^0$ in the case in which it is discovered at $t = 1$ that the transaction loans will default. Moreover, the level of

monitoring of relationship loans by the bank is higher when the bank invests additionally in the riskless asset than when it invests additionally in transaction loans, i.e., $m^* > m^0$.
Proof: in Appendix.

Proposition 3: The bank's shareholder value with the riskless asset is higher than it is with the risky transaction loan. So the bank will prefer to combine the riskless asset with the relation loan.
Proof: in Appendix.

These results show that the bank monitors more and adds more value to its relationship loans when it avoids transaction loans in a market in which these loans are competitively priced. Since no special intermediation services are provided for these loans, they will migrate to the P2P lending market. A natural question is why banks were making these loans in the first place. In the absence of competition from the P2P market banks may have earned positive projects on these loans, so it may have made sense to include them in the portfolio but competition from the P2P market drives these profits to zero. This leads to the following corollaries:

Corollary 1: Transaction loans migrate to P2P platforms, bank loan portfolio become less risky, and aggregate bank lending declines.

Corollary 2: The risk-adjusted interest charged on the relationship loans banks make is higher than the risk-adjusted interest rate on P2P loans.

The model thus yields the following predictions.

1. Bank loan portfolios will become less risky with the emergence of the P2P lending market (Corollary 1).

2. The risk-adjusted interest rate on bank loans is higher than or equal to the risk-adjusted interest rates of P2P loans, and the risk-adjusted interest rates on P2P loans will be the same as the rates these loans would get from banks (Corollary 2).

3. Bank lending will decline with the emergence of the P2P lending market (Corollary 1).

4. Bank strictly prefers relationship loans to transaction loans (Corollary 1).

We proceed by confronting these model predictions with data on the German banking sector and P2P lending.

3 Empirical Evaluation

3.1 Data and Descriptive Statistics

The data sources used in our study are (i) Auxmoney for data on P2P lending; (ii) the Deutsche Bundesbank (Interest Rates Statistics) for data on bank lending; (iii) Schufa for data on credit ratings; (iv) the Deutsche Bundesbank (Balance Sheet Statistics) for data on loan loss provisions; (v) the Federal Statistical Office (Statistisches Bundesamt) for data on inflation, unemployment and GDP growth (interpolated quarterly), all by state;[4] (vi) Google Trends for data on Google search statistics.

Auxmoney is the oldest and largest P2P lending platform in Germany. According to its website, from the day it begun business in 2007 until late 2015 the total volume of credit provided was EUR 219 million in 39,090 projects, with an average nominal interest rate of 9.65%.

Auxmoney provided us two different data sets. The first includes all loans divided by cities between January 2010 and August 2014, with no maturity information. The second includes the average interest rate and the average credit rating represented by the Schufa score for each state per month.[5] For reasons of data confidentiality, Auxmoney only provides records with observations containing at least five loans. They also provide us with the statistics of the distribution of their loan maturities provided in the first data set as reported in Table 1.

[Table 1]

As Table 1 shows, the largest number of loans provided are the three-year loans, while one-year maturity loans make up the smallest number. On average, the large-size loans are the ones with the longer maturities. Loans range from EUR 11,487 for the five-year maturity to EUR 2,815 for the one-year maturity. In terms of total volume distribution, the largest loan volumes are from the four- and five-year maturities.

The Deutsche Bundesbank statistics used in this study are provided by two different datasets. The first is the Interest Rates Statistics (MIR, Bade and Beier (2016)), which gives the amounts and the interest rates per bank and per month applied to non-construction consumer credit lines (outstanding and new business) for different maturities (overdraft, up to one year, and more than one year). The statistics are composed of

[4]This data will be used as state–control variables in our estimations.

[5]Schufa is a German private credit bureau with 479 million records on 66.2 million natural persons. Schufa provides credit ratings for each person requesting a loan and Auxmoney provides the Schufa score of each credit application.

monthly observations between January 2011 and August 2014. The second is the data set from the Balance Sheet Statistics (BISTA, Beier et al. (2016)), which gives information on write–ups and write–downs, from which we derive the banks' loan loss provisions.

Our analysis is at the state level. The regional differentiation of bank loans is possible because of a feature of the German banking system: the presence of Sparkassen and Volksbanken. Sparkassen are geographically restricted banks with a legal mandate to provide bank services to all potential costumers.[6] Volksbanken are cooperative banks (also geographically restricted), whose costumers are actually members of an organizational structure that aims at credit facilitation. By focusing on those banks that are more readily comparable to Auxmoney, we therefore avoid the inclusion of large commercial banks or any non-regional banks. Thus, there are 105 banks in our sample, which hold loan portfolios of relatively small sizes.

Table 2 provides comparative descriptive statistics of the amount of P2P loans and the average bank total new loans per state with a distribution analysis of the banks new loans by size for each of the different maturities (overdraft, one-year loans, from one- to five-year loans).

[Table 2]

Table 2 shows that the average total volume of new loans granted by Auxmoney per state per month is EUR 109,089, which is far lower than the average total loan volume per month of the average total amount of new loans per bank per state, which is EUR 99,864,000.

Table 3 reports the descriptive statistics of the interest rates applied to new loans by banks and P2P during the period January 2011 to August 2014 and a t-test on the difference of the variables.

[Table 3]

The average interest rates across banks and states are 11.18%, 2.99% and 4.59% for overdraft, $[0, 1]y$ loans and $]1, 5]y$ loans, respectively. During the same period, the average interest rate applied for P2P loans is 12.75%. Interest rates on P2P loans are significantly higher than $[0, 1]y$ loans and $]1, 5]y$ loans, but not from overdraft.

[6] For further details on the Sparkassen structure, see Puri et al. (2011).

As Table 3 shows, on average, overdraft interest rates are higher than the other interest rates. In particular, the spread between the average interest rate on overdraft and the average interest rate on $[0, 1]y$ loans is due to (1) the cost of liquidity provision which is provided "on demand" for overdraft; (2) the different risk profile of the borrowers. A comparison of the interest rates charged by banks and by P2P lenders indicates higher P2P lending rates except for overdraft.

Since we use data across different German states, we also verify whether the consumer credit loans are proportionally distributed in each state. If credit provision is concentrated in one or only a few specific regions, our analysis will be biased. Figure 2 shows the geographical distribution of credit provision among German states for both the banking sector and P2P lending. Each individual dark bar represents the share of bank credit provided in a specific state in relation to the total amount of bank credit provided in all states (in our sample of banks). Similarly, each single light-colored bar represents the share of P2P credit provided in a specific land in relation to the total amount of P2P credit provided in all states. Although the amount of credit is unevenly distributed among states, Figure 2 shows that bank and P2P loans are proportionally distributed among themselves and across states. To conclude, Figure 2 shows that for some lands (Brandenburg, Saarland and Thuringia) there is no information on Sparkassen credit. Those three states are therefore excluded from our sample.

In our analysis we consider also several control variables. For each land we consider three control variables: inflation, GDP growth and unemployment.

Moreover, given that P2P lending is largely related to internet diffusions, we add as other control varibles the Google hits on credit-specific keywords. We consider specifically the Google hits for the words: 'Finanzierung" (funding), "Kredit" (loan), and "Auxmoney" for each German state for the period January 2011 to August 2014.

Google Trends provides a monthly or weekly time series of the volumes of Google hits for each selected keyword. Therefore, in order to have comparable volumes at different points in time, we aggregate the weekly time series to the month resolution. By default, for each time series, Google Trends normalizes the volumes to their highest value, which is set equal to 100, and all the other values are related to it with a precision of one. This normalization allows for comparisons of time series within the same German state but not across them. The results of our analysis are shown in Table 4. Note that, the summary statistics are based on 12 German states instead of 16. Brandenburg, Bremen, Saarland and Thuringia are excluded because the volumes of the Google searches, although pooled at the state level, are negligible and do not display enough variation.

[Table 4]

3.2 Riskness of Loan Portfolios and Risk-Adjusted Interest Rates

In light of the presented model, we analyze how P2P lending complements the German non-construction consumer credit market. As Table 2 shows, the largest P2P lending platform in Germany intermediates less credit than a small sized bank. Thus, at the current stage, the challenge of this exercise is to present evidence supporting the model even if the size of P2P lending is negligible from the banking sector perspective.

We address the empirical predictions of the model presented in Section 2 in terms of specific empirical hypotheses. Prediction 1 can be tested indirectly. In fact, if bank loans are less risky than P2P loans and P2P lending compete with banks in the credit market then prediction 2 holds if:

Hypothesis 1: *Bank loans are less risky than P2P loans.*

Prediction 2 refers to the risk adjusted interest rate, a variable that our data allows us to calculate. Prediction 2 therefore can be tested directly with the following hypothesis:

Hypothesis 2: *The risk-adjusted interest rate on bank loan portfolio is higher or equal to the risk-adjusted interest rates of P2P loans.*

With the first hypothesis, we aim to test whether bank loans are less risky than P2P loans. In order to investigate this hypothesis, we need to measure the risk of the P2P loans in a way that permits a comparison to the risk of bank loans: probability of default.

Auxmoney provides the credit rating of its loans based on Schufa score. Banks also have access to the Schufa scores of their clients, but this information is kept confidential. The only proxy we have for loan riskiness from the Deutsche Bundesbank data is the loan loss provision. Whenever banks expect a loan not to perform (normally, when it is 90 days overdue), banks take the precaution of writing them down from their balance sheet and creating a provision which is set aside as an allowance. Similarly, a loan can be written up if it was expected to default but was paid in the end. In the BISTA of the Deutsche Bundesbank, loans are written up/down in full regardless of their recovery rate; see e.g., Memmel et al. (2015).

We use this information to proxy banks loan issuance default probability π^b defined as write–up and write–down over outstanding loans:

$$\pi^{b,i}_{l,t} = \frac{writeupdown^{b,i}_{s,t}}{outstanding^{b,i}_{s,t}} \,, \tag{17}$$

For comparability reasons we measure the default probabilities of the borrowers by using the Schufa score data. From the Schufa scores we proxy the default probabilities by using the transformation table provided by Korczak and Wilken (2010); see the Appendix. In this way we were able to match the Schufa scores and loan default probabilities.

The results are summarized in Table 5, which reports the credit risks summary statistics of bank and P2P loans in terms of the borrowers' default probabilities and a formal test of the risk difference between P2P loans and the three categories of non-construction consumer loans.

[Table 5]

As Table 5 shows, on average, P2P borrowers have a default probability of 7.27%. This is much bigger than the 0.12%, 0.14% and 0.05% for borrowers of overdraft, $[0, 1]y$ and $]1, 5]y$ loans, respectively. The risk differences are statistically significant at the 5% confidence level. This suggests that bank borrowers are very different from P2P borrowers. The former are less risky.

Table 5 reports also our test of *Hypothesis 1*. As the table shows, P2P loans are substantially more risky than all the other bank loans, independently on the maturity of the loans. The test statistic rejects the null hypothesis at the 1% level.

In order to test Hypothesis 2, we analyze the interest rates charged by both P2P (i^{P2P}) and banks (i^b), and calculate the risk-adjusted interest rate as:

$$1 + r^h = (1 - \pi^h) \times (1 + i^h) + \pi^h \times RR^h \ , \qquad (18)$$

where r is the risk-adjusted interest rate, i is the risky rate, π is the probability of default and RR is the recovery rate, h equals $P2P$ when it represents $P2P$ lending and equals b when it represents banks. Table 6 reports the summary statistics of the risk-adjusted interest rates for both bank loans and P2P loans.

[Table 6]

Table 6 shows that if P2P loan interest rates are adjusted by risk, they are largely in line with those charged by banks for one- to five-year maturities. There is a big difference between the risk-adjusted interest rates on overdraft and P2P loans, but it stems from differences in borrower characteristics: P2P lends to borrowers excluded by banks from their loan portfolio.

Table 6 reports also the results of the formal statistical test, where the null hypothesis is that there is no statistical difference between the risk adjusted rate of bank loans and P2P loans. Table 6 shows that the null hypothesis cannot be rejected at the 10% confidence level for bank loans with a maturity of $[0, 1]y$ and $]1, 5]y$. The null hypothesis is rejected at the 10% confidence level for overdraft loans versus P2P loans.

3.3 Relation between P2P Lending and Bank Credit Provision

Prediction 3 states that bank lending decline with the emergence of P2P lending. This prediction indicates that there is a negative relationship between P2P and bank loans. We investigate this prediction first by looking to row data, i.e. the trend in the last 5 years of the amount of new loans issued by banks and the one issued by P2P. Figure 3 reports the amount of P2P loans with the amount of bank loans.

[Figure 3]

Figure 3 shows that while bank lending either remains constant or follows a downward trend, P2P lending follows a clear upward trend. On the other hand, P2P lending volume is largely volatile, indicating the market is evolving. This figure serves as anecdotal evidence that credit provision of both sources are negatively related.

As previously described, the size of P2P lending in Germany is too small to have an significant impact on the banking sector in terms of credit provision volume and profitability. However, if the P2P credit provision is negatively correlated with bank credit then our prediction holds indirectly. Therefore, we we test the following hypothesis:

Hypothesis III: *There is a negative relationship between the provision of banks and P2P loans.*

To test Hypothesis III we draw inference on how lending by P2P platforms relate to bank lending. We examine market cross-effects by estimating how bank and P2P loans volume correlate and thereby controlling for interest rates and risk difference. The control variables are chosen according to Stiglitz and Weiss (1981) and Freixas and Rochet (2008). That is we investigate the following system of equations:

$$\begin{cases} K^{P2P} = f\left(i^{P2P}, \pi^{P2P}; K^b, i^b, \pi^b\right) \\ K^b = f\left(i^b, \pi^b; K^{P2P}, i^{P2P}, \pi^{P2P}\right) \end{cases} \tag{19}$$

where K^h are the loan volume, i^h is the interest rate charged, π^h is the risk profile of borrowers. h equals $P2P$ when it represents P2P lending and equals b when it represents banks.

Empirically, we estimate the following system:

$$\begin{cases} \mathrm{Log}[K^{P2P}_{l,t}] = \alpha^{P2P}_0 + \alpha^{P2P}_1 i^{P2P}_{l,t-1} + \alpha^{P2P}_2 (i^{P2P}_{l,t-1} - i^{b}_{t-1}) + \alpha^{P2P}_3 \pi^{P2P}_{l,t-1} + \alpha^{P2P}_4 (\pi^{P2P}_{l,t-1} - \pi^{b}_{l,t-1}) \\ +\alpha^{P2P}_5 \mathrm{Log}[K^{b}_{l,t-1}] + \alpha^{P2P}_6 \Gamma + u_{l,t-1} \\ \mathrm{Log}[K^{b}_{l,t}] = \alpha^{b}_0 + \alpha^{b}_1 i^{b}_{t-1} + \alpha^{b}_2 (i^{b}_{t-1} - i^{P2P}_{l,t-1}) + \alpha^{b}_3 \pi^{b}_{l,t-1} + \alpha^{b}_4 (\pi^{b}_{l,t-1} - \pi^{P2P}_{l,t-1}) + \alpha^{b}_5 \mathrm{Log}[K^{P2P}_{l,t-1}] \\ +\alpha^{b}_6 \Gamma + u_{l,t-1} \end{cases} \tag{20}$$

where l denotes the state and t denotes the month. The dependent variable $\mathrm{Log}[K^{h}_{l,t}]$ is the log of the loan volume per state per month of Auxmoney when h corresponds to P2P and banks when h is equal to b. The other main regressors are the nominal interest rate charged and the default probability. Furthermore, the equation includes a constant, α^{h}_0, a vector of control variables, Γ, state fixed effect, δ_l, and a random error term, $u^{h}_{l,t}$.

By estimating the system of equation above we can test Hypothesis III looking to the coefficients α^{P2P}_4 and α^{b}_4, if they are negative and statistically different than zero the hypothesis is accepted.

To investigate Hypothesis III we perform a panel regression of the simultaneous Equations (19). The results are reported in Table 7. In order to perform this panel regression we consolidate all the bank loans into one reference variable for the banking sector.

[Table 7]

The first two columns of Table 7 show the regression of P2P lending volumes on its explanatory variables, the following two columns present the ones of the banking sector. The variables of our main interest are K^{b} in the first two columns and K^{P2P} in the following two columns. In other words, we are interested on the relation of credit provision between P2P platforms and banks after controlling for interest rate and risk difference. We find a clear negative and significant relation on the P2P side, i.e. the more credit banks provide the less credit P2P platforms originate and vice versa. However, the converse is not true. The coefficient of K^{P2P} on the third and fourth columns are not significant. This result may be due to the fact that P2P lending is relatively small compared to the banking sector (see Table 2), so its volume influence on the banking sector is still small.

Thus, we partially confirm Hypothesis III that there is a negative relation between the provision of banks and P2P loans.

Prediction 4 states that banks prefer relationship loans to transaction loans. With the data we have it is difficult to distinguish whether bank loans are relationship or transaction loans. However, we can investigate whether bank loans are indeed different from P2P loans in terms of their sensitiveness to the interest rate charged.

As described in the model, transaction loans are a full competitive market, i.e. any additional unit of credit provision comes from an additional unit of credit demand. Thus, an increase in interest rates reduces the demand and the amount of credit provision is also lower. As contrast, the market for relationship loans is scarce on the supply side: only banks can provide these loans. With relationship loans banks provide loans to customers that they have enough soft information and believe they will repay. Therefore, we argue that transaction loans have a negative elasticity to interest rates and relationship loans either do not respond to changes in interest rate or they have a positive relationship. We therefore test the following hypothesis:

Hypothesis IV: *P2P loans and bank loans are different type of loans because the elasticity of loan provision to changes in interest rates have different signs.*

The panel regression described in Equation 20 allows us to investigate also this hypothesis by looking to the coefficients α_1^{P2P} and α_1^b, if they are negative and positive, respectively, and statistically different than zero the hypothesis is accepted.

Table 7 shows that the coefficient α_1^{P2P}, is significant and negative as predicted by Hypothesis IV and in line with a competitive market on the supply side. The coefficient α_1^b, is significant and positive for bank loans, again suggesting that the bottleneck of credit provision in the banking sector is on the supply side.

In summary, although, we cannot formally test the fourth prediction of our model that banks strictly prefer relationship loans, our estimation shows that banks loan portfolio are different from P2P lending. P2P loan amount responds negatively to interest rates and therefore is demand driven characterized by a competitive market on the supply side.

3.4 Robustness: P2P Loans and the Digital Economy

In this section, we aim to investigate whether the results presented in the previous section could be related to some possible counterfactual effects. An alternative explanation for the raise in P2P lending popularity is the increased sympathy for new technologies. In other words, customers might demand P2P loans not because they are searching for a new source of transaction loans but because they want to experience a new form of credit provision and this sympathy is different across states and through time. In order to disentangle both effects we expand Eq. (19) as follows:

$$K^{P2P} = f\Big(i^{P2P}, \pi^{P2P}, K^b, i^b, \pi^b, D^{P2P}\Big), \tag{21}$$

where D^{P2P} is an "innovation factor" variable that aims at capturing the general interest of borrowers and lenders in new forms of internet-driven direct credit supply in order to check whether our results are affected by this omitted variable.

In order to capture this type of demand, we measure the frequency with credit-specific keywords as "Finanzierung" (funding), "Kredit" (loan), and "Auxmoney". For this purpose we use Google Trends, a web facility based on Google Search that shows how often a particular search term is entered in the search engine relative to the total search volume across various regions of the world, and in various languages.

The choice of the keywords is based on two criteria. First, the keywords should intuitively be related to the online consumer credit market. Second, the correlation among the keywords' queries should be small. Statistics on the terms googled are reported in Table 4.

Table 4 shows that there is a significant variability among states and through time of the "hit" of the different words we have considered, indicating heterogeneity of interest.

We also investigate the correlation among the "hits" of these variables. Table 8 presents the correlation among the Google variables.

[Table 8]

According to Table 8, the correlation among the four keywords is indeed very low. It is very difficult to indicate whether the hits of these words are highly related to investors or borrowers. However, we could expect that the word "Finanzierung" (funding) refers more to investors and "Kredit" (loan), to borrowers' interest. The word "Auxmoney", on the other hand, could be referred to the interest of both investors and borrowers.

Table 9 indicates that the results regarding loan elasticity to interest rates and the substituting relationship between banks and Auxmoney loans are confirmed.

The Google trend variables we considered are only significant for loan volumes of Auxmoney and not for lending banks. This is in line with what we expect: the majority of bank customers are not interested in finding bank loan opportunities on the internet (at least, so far). Instead, these variables are significant for Auxmoney loan volume. We find that the number of hits of the variable "Finanzierung" is significant and positively related to Auxmoney credit provision, which means that the interest for finding financing opportunities is related to larger volumes of Auxmoney loans. In contrast, the large amount of interest associated with the hits for "Kredit" is correlated with a smaller amount of loans. This result could be explained by the fact that when the number of people looking for credit grows larger, adverse selection problems are elevated.

The hits for "Auxmoney", on the other hand, are not correlated with a larger volume of loans, indicating little connection between the interest in these platforms and the actual providers of credit. However, it should be noted that these are just proxy variables that capture several dimensions of the behaviors of investors and creditors.

[Table 9]

Table 9 indicates that the results regarding loan elasticity to interest rates and the substituting relationship between banks and Auxmoney loans are confirmed. The table also shows that bank lending is not affected by these variables, as expected.

4 Conclusion

This paper studies the impact of P2P lending on the credit market outcomes. We develop a theoretical model in which bank and P2P lending coexist and we test its prediction.

In the empirical analysis we investigate the testable hypothesis that arises from the empirical prediction of the model and highlight that Auxmoney, the largest P2P loan provider in Germany, is charging interest rates that are higher than those of banks, but that the borrowers are more risky that the banks' borrowers. However, if we control for risk, the risk-adjusted interest rate is in line with the interest rate charged by banks or even lower. Moreover, if we look at the distributions of loans of Auxmoney and their dynamics, we find that Auxmoney is lending relatively more where and when banks are lending less. Combining these two elements – riskiness and geographical distribution – we could conclude that Auxmoney is serving borrowers largely not served by banks, as predicted by our theory.

The immediate question raised is why banks are not serving these costumers. If credit was like any other good, one would expect that if prices increase together with risk there should still be actors willing to provide it. However, as our theoretical model predicts, the institutionalization of credit provision for these risky small loans are not the target for banks, because banks have a relative advantage in relationship loans.

Appendices

Proof Lemma 1: Treating (4) as an equality and solving for γ^* yields (5). Holding m^* fixed, we see that

$$\frac{\partial \gamma^*}{\partial c} = \frac{-2c}{X(m^*)} < 0$$

The regulator solves a different problem. Conditional on a choice of $e = 1$ by the bank, the net benefit of allowing the bank to continue is:

$$\gamma X(\tilde{m}^*) + 1 - 2[1-c] - W - \Psi \tag{22}$$

If the regulator shuts down the bank, then the bank has no choice of e, so the net benefit is:

$$1 - 2[1-c] \tag{23}$$

Two constraints must be satisfied for the regulator to allow the bank to continue in the second period:

Positive continuation payoff:

$$\gamma X(\tilde{m}^*) + 1 - 2[1-c] - W - \Psi \geq 0 \tag{24}$$

Domination of continuation over shut-down:

$$\gamma X(\tilde{m}^*) + 1 - 2[1-c] - W - \Psi \geq 1 - 2[1-c] \tag{25}$$

Let γ_r^* be the value of γ that solves (24) as an equality and $\tilde{\gamma}_r^*$ be the value of γ that solves (25) as an equality. Thus, we have:

$$\gamma_r^* = \frac{2[1-c] - 1 + W + \Psi}{X(\tilde{m}^*)} \tag{26}$$

and

$$\tilde{\gamma}_r^* = \frac{W + \Psi}{X(\tilde{m}^*)} \tag{27}$$

Since $2[1-c]-1>0$, it follows that $\gamma_r^* > \tilde{\gamma}_r^*$. Thus, (24) is the binding constraint.

Proof Lemma 2: It is clear that if $\gamma \geq \gamma_r^*$ both the positive-continuation-payoff constraint and the domination-of- continuation-over-shut-down constraint will be satisfied. So the bank will be allowed to continue if $\gamma \geq \gamma_r^*$. Comparing (6) and (5), it is clear that $\gamma_r^* > \gamma^*$. Moreover, it is clear from (6) that $\partial\gamma_r^*/\partial c < 0$.

Proof Proposition 1: The first-order condition (FOC) corresponding to (7) is:

$$\int_{\gamma_r^*}^{1} \gamma X'(m) dG(\gamma) - V'(m) = 0 \tag{28}$$

where we don't differentiate with respect to γ_r^* because it is the regulator's hurdle rate that depends on the regulator's belief about the bank's choice of m and cannot be affected by the actual choice. The second-order condition (SOC) is

$$\int_{\gamma_r^*}^{1} \gamma X''(m) dG(\gamma) - V''(m) < 0 \tag{29}$$

It is clearly satisfied since $X'' < 0$ and $V'' > 0$. Thus, m^* is unique and the Inada conditions guarantee it is in the interior.

In a Nash equilibrium, the regulator's belief about m^* must be correct, so $m^* = \tilde{m}^*$. When the bank is allowed to continue, it is true that $\gamma \geq \gamma_r^*$. Since $\gamma_r^* > \gamma^*$, the bank chooses e=1 when it is allowed to continue.

Proof Lemma 3: γ^0 solves $\gamma^0 X(m) + R - 2[1-c] - W = 0$, which yields (12). Moreover, γ^0 solves $\gamma^0 X(m) - 2[1-c] - W = 0$, which yields (13).

Proof Proposition 2: The FOC corresponding to (16) is:

$$\theta \int_{\gamma_r^0}^{1} \gamma X' dG(\gamma) + [1-\theta] \int_{\hat{\gamma}_r^0}^{1} \gamma X' dG(\gamma) - V' = 0 \tag{30}$$

and the SOC is:

$$\theta \int_{\gamma_r^0}^{1} \gamma X'' dG(\gamma) + [1-\theta] \int_{\hat{\gamma}_r^0}^{1} \gamma X'' dG(\gamma) - V'' < 0 \tag{31}$$

IT is easy to see that (31) holds since $X'' < 0$ and $V'' > 0$. Moreover, $m^0 > \tilde{m}^0$ must hold in a Nash equilibrium.

All that remains to be proved is that $m^* > m^0$. Write the FOC in (30) as

$$\theta\varphi(\gamma_r^0, m^0) + [1-\theta]\varphi(\hat{\gamma}_r^0, m^0) = 0 \tag{32}$$

It is easy to verify that $\varphi(\gamma_r)$ is concave in γ_r. Thus, it follows that

$$\varphi(\theta\gamma_r^0 + [1-\theta]\hat{\gamma}_r^0, m^0) > \theta\varphi(\gamma_r^0, m^0) + [1-\theta]\varphi(\hat{\gamma}_r^0, m^0) = 0 \tag{33}$$

But since the transaction loan market is perfectly competitive, we have $\theta R = 1$. Thus, substituting $\theta R = 1$ in (14) and (15) gives:

$$\begin{aligned} \theta\gamma_r^0 + [1-\theta]\hat{\gamma}_r^0 &= \frac{2[1-c] + W + \psi - 1}{X(m^0)} \\ &= \frac{1 - 2c + W + \psi}{X(m^0)} \end{aligned} \tag{34}$$

Going back to (6), write

$$\gamma_r^*(m^0) = \frac{1 - 2c + W + \psi}{X(m^0)} \tag{35}$$

Then it follows from (33) that

$$\begin{aligned} \varphi(\theta\gamma_r^0 + [1-\theta]\hat{\gamma}_r^0, m^0) &= \varphi(\gamma_r^*(m^0), m^0) \\ &> 0 \\ &= \varphi(\gamma_r^*, m^*) \qquad \text{(from the FOC(28))} \end{aligned}$$

Given the concavity of φ in γ_r^*, it follows that $m^* > m^0$.

Proof Proposition 3: The proof follows immediately from the above proposition whose proof shows that with the riskless asset the bank's shareholder value function is strictly increasing at the relationship loan monitoring level that is optimal with the transaction loan. Since both the riskless asset and the transaction loan portfolio yield the same expected profit for the bank, the result follows.

Rating	Score	% of the pop.	Default prob.
A	672-1000	ca 20%	0.88%
B	569-671	ca 20%	1.85%
C	520-568	ca 10%	2.72%
D	466-519	ca 10%	3.69%
E	406-465	ca 10%	4.81%
F	336-405	ca 10%	6.25%
G	243-335	ca 10%	8.77%
H	175-242	ca 5%	12.95%
I	137-174	ca 2%	16.64%
K	112-136	ca 1%	19.78%
L	79-111	ca 1%	24.27%
M	0-78	ca 1%	37.83%

Table A: Schufa score and default probabilities. Schufa scores for different credit qualities and equivalent default probability measures. The higher the score, the lower the default probability. Source: Korczak and Wilken (2010).

A Figures

Sequence of Events

t=0

- Bank raises $2c$ from shareholders and $2[1-c]$ from insured depositors.
- Bank determines how to invest the \$2.
- Bank chooses m and sets the repayment $X(m)$ on the relatiokship loan portfolio.

t=1

- Realized γ is observed.
- Regulator decides whether to allow the bank to continue for the second period.
- Bank chooses e.

t=2

- All payoffs realized.
- Depositors paid by bank and/or deposit insurer.

Figure 1: Sequence of events of the model.

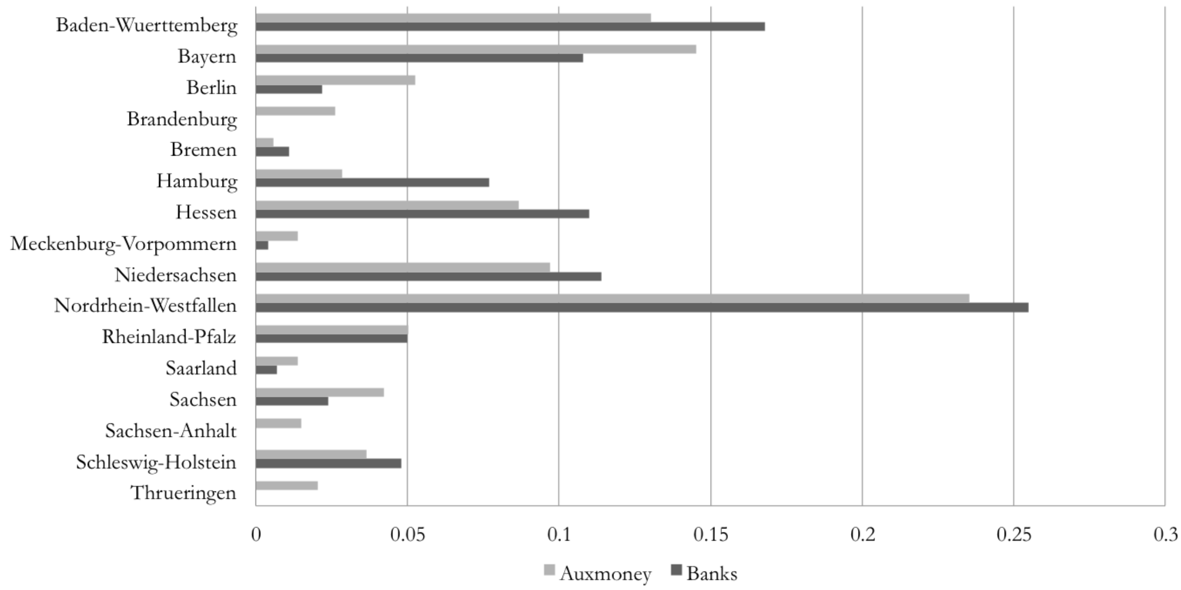

Figure 2: Share of credit provision by state in our sample. Source: Research Data ans Service Center (RDSC) of the Deutsche Bundesbank and Auxmoney, sample period January 2011 until August 2014.

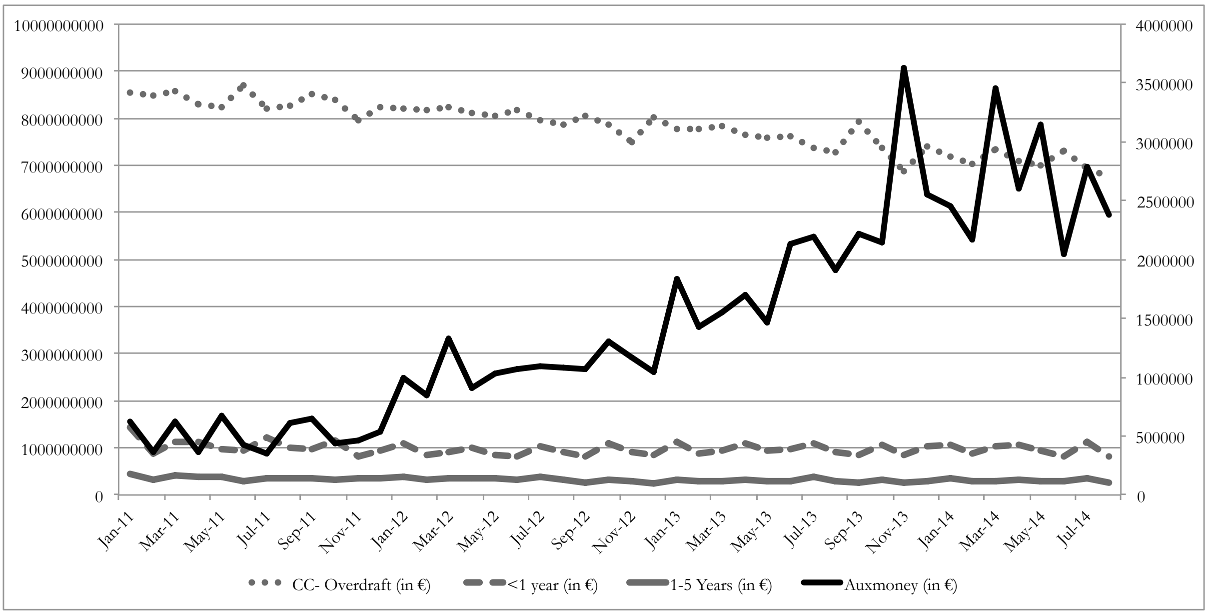

Figure 3: Provision of non-construction consumer loans by maturity structure. Auxmoney represents credit provided through the Auxmoney P2P platform (right axis), CC-Overdraft represent credit provision through overdraft in the banks in our sample, ¡1 year represent credit provision with maturity below one year in our sample, 1 to 5 years represent credit provision with maturity between one and five years in our sample (left axis). Source: Research Data ans Service Center (RDSC) of the Deutsche Bundesbank and Auxmoney, sample period January 2011 until August 2014.

B Tables

Maturity	# Loans	Volume
12	1,310	3,688,350
24	2533	9,221,550
36	3,292	15,813,900
48	2,084	16,356,700
60	1,405	16,140,600

Table 1: Distribution of Auxmoney loans per maturity.Source: Research Data ans Service Center (RDSC) of the Deutsche Bundesbank and Auxmoney, sample period January 2011 until August 2014.

	Banks				Auxmoney
	K^o	K^z	K^m	K^b	K^{P2P}
Mean	75,284,990	9,436,381	3,177,000	99,864,000	109,089
Std. Error	60,801,525	26,663,760	2,737,000	76,210,000	119,543
25^{th} pcl	38,023,000	1,206,000	1,436,000	65,357,000	27,500
50^{th} pcl	60,280,000	3,099,000	2,566,500	78,324,000	71,200
75^{th} pcl	92,530,500	7,656,500	3,990,500	103,093,000	141,550
# Obs	4664	4664	4664	4664	397

Table 2: Lending amounts, K, (in Euro) by bank, month and state, where the index o stands for overdraft, z stands for $[0,1]y$ loans, m stands for $]1,5]y$ loans. Source: Research Data ans Service Center (RDSC) of the Deutsche Bundesbank and Auxmoney, sample period January 2011 until August 2014.

	Banks				Auxmoney
	i^o	i^z	i^m	i^b	i^{P2P}
Mean	11.18	2.99	4.59	10.07	12.75
Std Error	1.08	0.98	0.84	1.08	0.83
Min	8.72	1.23	2.01	7.26	10.33
25^{th} pcl	10.37	2.35	3.98	9.32	12.2
50^{th} pcl	11.3	2.83	4.56	10.01	12.75
75^{th} pcl	12.01	3.33	5.08	10.91	13.36
Max	13.2	8.13	6.75	12.62	14.47
# Obs	572	572	572	572	397

	T-test
$i^o - i^{P2P}$	-1.70
$i^z - i^{P2P}$	-9.89***
$i^m - i^{P2P}$	-8.09***
$i^b - i^{P2P}$	-2.75**

Table 3: Banks' and Auxmoney interest rates, i, (in %) by month and state, where the index o stands for overdraft, z stands for $[0,1]y$ loans, m stands for $]1,5]y$ loans. T-test gives whether the difference of the two variables are significantly different from zero. ***, **, and * represent significance at the 1%, 5% and 10%, respectively. Source: Research Data ans Service Center (RDSC) of the Deutsche Bundesbank and Auxmoney, sample period January 2011 until August 2014.

	Google Trends		
	Finanzierung	Kredit	Auxmoney
Mean	67.42	61.26	32.84
Std Error	9.3	7.76	27.5
Min	39.5	0	0
25^{th} pcl	61.45	61.45	32
50^{th} pcl	67.4	61.5	35
75^{th} pcl	74	66.45	51.5
Max	90.75	82.4	100
# Obs	440	484	440

Table 4: Descriptive statisitcs for Google Trends for the words *Finanzierung*, *Kredit* and *Auxmoney* downloaded on October 16 2014. Google Trend data is normalized to 100 to the highest value. Source: Research Data ans Service Center (RDSC) of the Deutsche Bundesbank and Auxmoney, sample period January 2011 until August 2014.

	Banks				Auxmoney
	π^o	π^z	π^m	π^b	π^{P2P}
Mean	0.12	0.14	0.05	0.12	7.27
Std Error	0.12	0.23	0.33	0.15	3.10
Min	-0.11	-1.51	-2.82	-0.67	0.88
25^{th} pcl	0.05	0.05	0.01	0.05	6.25
50^{th} pcl	0.1	0.12	0.03	0.10	6.25
75^{th} pcl	0.16	0.21	0.06	0.16	8.77
Max	0.85	1.86	3.07	0.91	24.27
# Obs	572	572	572	572	397

	T-test
$\pi^o - \pi^{P2P}$	-7.17**
$\pi^z - \pi^{P2P}$	-7.12**
$\pi^m - \pi^{P2P}$	-7.24**
$\pi^b - \pi^{P2P}$	-7.16**

Table 5: Risk, default probability, π, (in %) by month and state, where the index o stands for overdraft, z stands for $[0,1]y$ loans, m stands for $]1,5]y$ loans. Risk of Auxmoney clients derived from Schufa score and of banks' clients from loan loss provision llp. Schufa score transformation table is reported in the Appendix. T-test gives whether the difference of the two variables are significantly different from zero. ***, **, and * represent significance at the 1%, 5% and 10%, respectively. Source: Research Data ans Service Center (RDSC) of the Deutsche Bundesbank and Auxmoney, sample period January 2011 until August 2014.

	Banks				Auxmoney
	r^o	r^z	r^m	r^b	r^{P2P}
Mean	11.05	2.85	4.54	10.05	4.55
Std Error	1.07	0.96	0.91	1.06	3.32
Min	8.6	0.51	1.69	7.51	-14.55
25^{th} pcl	10.29	2.21	3.89	9.28	2.96
50^{th} pcl	11.18	2.64	4.54	10.02	5.19
75^{th} pcl	11.86	3.22	5.02	10.90	6.48
Max	13.12	7.93	8.3	12.63	12.61
# Obs	572	572	572		397

	T-test
$r^o - r^{P2P}$	6.40*
$r^z - r^{P2P}$	-1.84
$r^m - r^{P2P}$	0.10
$r^b - r^{P2P}$	5.35

Table 6: Risk-adjusted interest rate, r, in (%), by month and state, where the index o stands for overdraft, z stands for $[0,1]y$ loans, m stands for $]1,5]y$ loans. T-test gives whether the difference of the two variables are significantly different from zero. ***, **, and * represent significance at the 1%, 5% and 10%, respectively. Source: own calculations.

	log(K_t)			
	P2P		Banks	
	(I)	(II)	(III)	(IV)
i^{P2P}_{t-1}	-0.3435***	-0.4002***		
	(0.0659)	(0.0378)		
$i^{P2P}_{t-1} - i^{b}_{t-1}$	0.2957***	0.3772***		
	(0.0834)	(0.0418)		
π^{P2P}_{t-1}	-0.1507	0.1041		
	(0.2414)	(0.2985)		
$\pi^{P2P}_{t-1} - \pi^{b}_{t-1}$	0.1389	-0.1134		
	(0.2515)	(0.3010)		
i^{b}_{t-1}			0.0467***	0.0474***
			(0.0094)	(0.0098)
$i^{b}_{t-1} - i^{P2P}_{t-1}$			0.0029	0.0048
			(0.0043)	(0.0046)
π^{b}_{t-1}			0.0126	0.0056
			(0.0242)	(0.0224)
$\pi^{b}_{t-1} - \pi^{P2P}$			-0.0002	-0.0002
			(0.0005)	(0.0003)
$\log(K^{P2P}_{t-1})$	0.2811**	0.1637*	-0.0064	0.0011
	(0.0920)	(0.0832)	(0.0077)	(0.0052)
$\log(K^{b}_{t-1})$	-3.988***	-4.318***	0.5346***	0.6042***
	(0.6114)	(0.6781)	(0.0744)	(0.0531)
State controls	No	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes
R^2	0.6789	0.7363	0.997	0.9976
State	11	9	11	9
# Obs	365	313	365	313
Autocorrelation	0.000	0.000	0.000	0.000

Table 7: Comparison of P2P lending against Reference Rate for the banking sector. Panel data estimation with fixed effects and standard errors clustered by state. Dependent variable: estimations (I) and (II) log of credit provision by Auxmoney, estimations (III) and (IV) log of credit provision by banks. i_t is the interest rate, π_t is the risk measure and K_{t-1} the lagged credit provision. (***) represents significance at the 1% level, (**) at the 5% level, and (*) at the 10% level, standard errors in (). State controls include CPI, rent price index, GDP and employment. All explanatory variables are lagged. Risk measured in default probability (%). Autocorrelation gives the p-value for Wooldridge (2002, 2008) test for autocorrelation in panel data, where H_0 is autocorrelation.

	Finanzierung	Kredit	Auxmoney
Finanzierung	1		
Kredit	0.306	1	
Auxmoney	0.26	0.258	1

Table 8: Correlation Google Trend variables. Note the correlation of the downloaded variables and the correlation the searches may differ since they are normalized at different basis.

	log(K_t)			
	P2P		Banks	
	(I)	(II)	(III)	(IV)
i^{P2P}_{t-1}	-0.3507***	-0.4102***		
	(0.0707)	(0.0367)		
$i^{P2P}_{t-1} - i^b_{t-1}$	0.3095***	0.3995***		
	(0.0844)	(0.0335)		
π^{P2P}_{t-1}	-0.1204	0.1561		
	(0.2283)	(0.2847)		
$\pi^{P2P}_{t-1} - \pi^b_{t-1}$	0.1045	-0.1693		
	(0.2381)	(0.2860)		
i^b_{t-1}			0.0465***	0.0465***
			(0.0090)	(0.0095)
$i^b_{t-1} - i^{P2P}_{t-1}$			0.0028	0.0047
			(0.0043)	(0.0045)
π^b_{t-1}			0.0136	0.0056
			(0.0248)	(0.0220)
$\pi^b_{t-1} - \pi^{P2P}_{t-1}$			-0.0002	-0.0001
			(0.0005)	(0.0003)
$\log(K^{P2P}_{t-1})$	0.304***	0.1968**	-0.0056	0.0014
	(0.0934)	(0.0834)	(0.0076)	(0.0049)
$\log(K^b_{t-1})$	-3.907***	-4.115***	0.5434***	0.6164***
	(0.788)	(0.6810)	(0.0801)	(0.0620)
Hits(Finanzierung)$_{t-1}$	1.434**	1.514**	0.0211	0.0755
	(0.5763)	(0.4877)	(0.0594)	(0.0581)
Hits(Kredit)$_{t-1}$	-1.7829**	-2.433***	0.0072	0.08769
	(0.6928)	(0.55854)	(0.0631)	(0.0503)
Hits(Auxmoney)$_{t-1}$	0.3487	-0.0055	0.0042	0.0121
	(0.2367)	(0.1083)	(0.0237)	(0.0244)
State Controls	No	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes
R^2	0.6852	0.7435	0.997	0.9976
State	11	9	11	9
# Obs	365	313	365	313
Autocorrelation	0.000	0.000	0.000	0.000

Table 9: Comparison of P2P lending against Reference Rate for the banking sector and Google Search for Market Variables. Panel data estimation with fixed effects and standard errors clustered by state. Dependent variable: estimations (I) and (II) log of credit provision by Auxmoney, estimations (III) and (IV) log of credit provision by banks. i_t is the interest rate, π_t is the risk measure and $\log(K_{t-1})$ the lagged credit provision, Hits(Finanzierung), Hits(Kredit) and Hits(Auxmoney) are the percentage chnge in the search for these words at Google.(***) represents significance at the 1% level,(**) at the 5% level, and (*) at the 10% level, standard errors in (). State controls include CPI, rent price index, GDP and employment. All explanatory variables are lagged. Risk measured in default probability (%). Autocorrelation gives the p-value for Wooldridge (2002, 2008) test for autocorrelation in panel data, where H_0 is autocorrelation.

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