P2P Lenders versus Banks:
Cream Skimming or Bottom Fishing?

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FIRST VERSION: January 31, 2017
THIS VERSION: May 1, 2019

Abstract

We derive three testable predictions from a bank-P2P lender model of competition: (i) P2P lending grows when some banks are faced with exogenously higher regulatory costs, (ii) P2P loans are riskier than bank loans; 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 loans and the consumer bank credit market in Germany and find empirical support. Overall, our analysis indicates the P2P lenders are bottom fishing, especially when regulatory shocks create a competitive disadvantage for some banks.

Keywords: P2P lending, bank lending, competition

JEL Classification: G21

I. Introduction

Motivation and Research Question: 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)),[1] with some theories emphasizing the value of deposit-taking and lending in the same institution.[2] Peer-to-peer (P2P) lending, which matches borrowers and lenders directly without reliance on deposits and eliminates an intermediating bank, has gained traction in recent years in Europe, the US and China (see, for example, Milne and Parboteeah (2016), Federal Reserve Bank of New York (2018) and Braggion, Manconi, and Zhu (2018)). The two largest P2P platforms in the US, Lending Club and Prosper, originated over \$44 billion and \$12 billion in loans respectively as of the last quarter of 2018. A report from PricewaterhouseCoopers (2015) noted that the origination volumes of US P2P lending platforms have grown an average of 84% per quarter since 2007. In the US mortgages market, fintech lenders have increased their market share from 5% to 15% in conforming mortgages and to 20% in Federal Housing Association mortgages during 2007-2015 (see, for example, Buchak, Matvos, Piskorski, and Seru (2018)). This increase in fintech and P2P lending is particularly interesting in light of the intertemporal behavior of new bank loans shown in *Figure 1*, which depicts the volume of new consumer loans in Germany provided by Auxmoney, the country's largest P2P platform, and by savings and cooperative banks. As is apparent, new bank loans are trending downward while new P2P loans are trending upward, although the absolute volume of bank lending far exceeds that of P2P lending.[3]

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[1] In these theories, banks either provide valuable screening to enhance investment efficiency (e.g., Coval and Thakor (2005) and Ramakrishnan and Thakor (1984)) or more effectively collect repayment from borrowers (e.g., Diamond (1984)). The growth of fintech raises the question of whether these advantages have declined.

[2] See, for example, Donaldson, Piacentino, and Thakor (2018). In their general equilibrium theory of banking, banks create *funding liquidity* with universal risk neutrality, wherein aggregate initial investment of the economy in real projects *exceeds* the entire endowment of the economy. Deposit-taking is necessary but *not* sufficient for bank liquidity creation. Rather the bank must accept deposits *and* make loans to create funding liquidity.

[3] Our focus is *not* on the *levels* of lending, but rather the *interaction* between P2P lending and bank lending. Nonetheless, as we discuss later, the volume of new lending by Auxmoney was about equal to that of a mid-sized bank in our sample by the end of 2018.

[Figure 1]

The commonly given explanations for the decline in bank lending relative to P2P lending have to do with advances in information technology – those that diminish the *relative* advantage of banks – and a heavier post-crisis regulatory burden on banks.[4]

Regardless of the underlying drivers and the observation that bank lending volume far exceeds P2P lending volume at present, these time series patterns raise interesting questions about the *nature* of the competition between P2P lending and (intermediated) bank lending. Under what circumstances do banks lose loans to P2P platforms? What are the risk characteristics of the loans that migrate from banks to P2P platforms? Are P2P platforms lending at higher or lower risk-adjusted interest rates than banks?

What We Do: Our main goal is to address these questions empirically. As motivation for the hypotheses we test, we develop a simple theoretical model of bank and P2P lending. Banks in this model are intermediaries between depositors and borrowers and thus finance loans with deposits and their own equity. Deposits provide valuable liquidity services to depositors.[5] The leverage on the bank's balance sheet creates a risk-shifting distortion that must be attenuated with sufficient bank equity. Each bank also has to incur a regulatory intermediation cost, which is the price of having access to profitability-enhancing deposits. In contrast, a P2P platform is a non-intermediated lender that finances its loans with money from investors. Following Philippon (2016), we view P2P loans as being all-equity financed – i.e., the platform has no leverage of its own. Access to leverage via rent-producing deposits is a key competitive advantage of banks in our model.

Main Results: The model yields the following results that serve as predictions that we test:

1. If some banks are subject to an exogenous increase in regulatory costs, and the un-

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[4]In the rest of the paper, we refer to bank and P2P lending as new loans provided by them in a certain period, not the actual stock of loans.

[5]In the context of the Merton and Thakor (2019) framework, we view these depositors as "customers" who receive liquidity services in addition to deposit interest, and shareholders as "investors" who care only about their expected pecuniary return.

affected banks are not sufficiently strong financially to replace the reduction in credit supply from the affected banks, banks in the aggregate will lose some loan market share to P2P lenders. This loss in market share is greater when the awareness of P2P lending is higher.

2. The loans made by P2P platforms are riskier than bank loans.

3. The risk-adjusted interest rates on P2P loans are lower than those on bank loans.

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 for consumer credit in Germany. Data on bank lending are provided by the Deutsche Bundesbank. That is, we focus on the impact of higher regulatory costs as well as the presence of P2P lenders on (i) *new* lending by banks and (ii) *new* loans by P2P lenders.

Because of differences in origination between P2P and bank lending, we compare the two datasets by examining risk and interest rate differences. Unlike previous studies, our database includes detailed information on interest rates for new loans as well as the risk profiles of P2P and bank loans. Using German rather than US data has some advantages.[6] First, the US consumer lending market is very heterogeneous – it includes not only banks and P2P lending platforms, but also nonbank 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, P2P lending platforms in the US do not serve subprime borrowers. Lending Club and Prosper apply minimum FICO score cutoffs of 660 and 640, respectively, to define credit-eligible borrowers; subprime borrowers typically have scores below 600.[7] In Germany, such restrictions do not exist, and subprime borrowers are also served by P2P lenders. Third, our data include interest rates on new loans, which permits a comparison of

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[6]Because we use German data, one may question the external validity of our analysis. However, our theoretical model is free of any specific institutional features of the German credit market, so our predictions are generally valid in any setting in which banks face regulatory costs that exceed those of P2P lenders and in which banks have a deposit-related funding advantage. Thus, we believe the external validity of our results is not a concern.

[7]This means P2P lending in the US will serve less risky borrowers by regulatory fiat, and may explain the findings of Chava, Paradkar, and Zhang (2018) and Di Maggio and Yao (2018).

rates charged on bank loans and P2P loans. Fourth, the German financial system is bank-based, in contrast to the market-based US system. This means our data permit us to focus more sharply on the impact of P2P lenders on banks in a setting in which banks dominate the credit market.

We focus on regional banks (i.e., savings banks (Sparkassen) and cooperative banks (Volksbanken)). In Germany, these banks have geographical restrictions, which permits a relatively clear analysis at the bank-state level. Moreover, their primary mandate is to provide credit for the local economy, which abstracts from other issues global banks might have and is closer to the bank described in our model. Therefore, Germany provides an excellent laboratory to investigate the competition between banks and P2P lending.

The predictions of the theory are supported by our empirical results. In order to provide causal evidence for our key result (Prediction 1), we use a quasi-natural experiment, in which capital requirements for some banks – and hence their regulatory costs – increased unexpectedly due to new regulation. The experiment we look at is the 2011 European Bank Authority (EBA) capital exercise, which occurred in October 2011, a few months after the 2011 stress test and subsequent failure of Dexia bank. The capital exercise required participant banks to reach and maintain a 9% core tier 1 capital ratio by the end of June 2012.[8] Two large Landesbanken in Germany had capital ratios below this threshold: NordLB and HELABA. Consequently, NordLB had to increase its capital as a percentage of total assets by 2.99% (from 6.01% to 9%) and HELABA had to increase its by 2.67% (from 6.33% to 9%). Both represented substantial increases. Landesbanken are also known as the "central bank" of savings banks and they are jointly owned by state governments and local savings banks. NordLB covers savings banks in Lower Saxony, Saxony-Anhalt, and Mecklenburg-Western Pomerania, whereas HELABA covers savings banks in Hesse and Thuringia.[9] We follow

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[8]In Germany, participant banks were: Deutsche Bank, Commerzbank, Landesbank Baden-Württemberg, DZ Bank, Bayerische Landesbank, Norddeutsche Landesbank, Hypo Real Estate Holding, WestLB, HSH Nordbank, Landesbank Hessen-Thüringen (HELABA), Landesbank, DekaBank, and WGZ Bank.

[9]In its 2012 Annual Report, NordLB describes its sources of capital to meet the higher requirements. They included the Association of Savings Banks in Lower Saxony; the Savings Banks Holding Association in Saxony-Anhalt; and the Special Purpose Holding Association of Savings Banks in Mecklenburg-Western

Puri, Rocholl, and Steffen (2011) and link the savings banks to their respective Landesbank. When a Landesbank is required to raise more capital, the savings banks of these states are also faced with higher regulatory costs due to their links with their Landesbank since much of the additional capital is provided by their local savings banks. This has two effects on the savings banks that work in the same direction to reduce lending by these banks. One effect is direct – these banks are using loanable funds to purchase equity in their Landesbanken rather than lending the money. The other effect is indirect – the equity investment increases the risk of the savings banks and requires a higher capital ratio, which *de facto* increases regulatory costs.

Thus, our empirical strategy is to test whether savings banks linked to NordLB and HELABA *vis-a-vis* other savings banks and cooperative banks decreased their lending after the capital exercise.[10] Moreover, we test (i) if P2P lending rose more in those states, and (ii) whether the P2P market share gain was larger when the *unaffected* banks in the region were financially weaker (lower capital ratios) and hence less capable of making up for the reduced credit supply from the affected banks.

The capital exercise is a useful shock because it is exogenous to P2P lending and any pre-shock actions of affected banks. We exploit this exogenous variation in the EBA bank selection rule and use a difference-in-differences (diff-in-diff) approach to identify the effect of the capital exercise on (i) overall bank lending in affected states, and (ii) Auxmoney lending activity in affected states.

We find that overall bank lending decreases in states where banks affected by the EBA exercise are present – affected banks reduced their lending more than unaffected banks in these states. Auxmoney also increased its lending in the treated states, and increased it by more if the *unaffected* banks in these states had low capital ratios.

Pomerania, State of Lower Saxony, State of Bremen. The form was cash injection and conversion of silent participations and other capital instruments.

[10]The impact of higher capital requirements on bank lending has been examined in numerous papers. See, for example, Gropp, Mosk, Ongena, and Wix (2018), who specifically examine the credit supply effect of the EBA exercise.

To gain further insight into the effect of P2P lending, we examine whether the decline in bank lending in the regions with treated banks was greater when borrower awareness of the availability of P2P lending was greater. We do this by examining the internet search behavior of consumers in the period preceding the capital exercise and document that Auxmoney experienced a larger increase in loan volume when consumers had searched more for the word "Auxmoney" prior to the capital shock – i.e., when there was greater pre-shock consumer awareness of Auxmoney.

Related Literature: Although P2P lending, in its present form, is a relatively recent phenomenon that started in 2005 with the launch of Zopa, research interest has been growing after Prosper (a competitor of Zopa) made its entire platform's data available in 2007; see, for example, Pope and Sydnor (2011), Lin, Prabhala, and Viswanathan (2013), and Morse (2015). Most of the investors are now hedge funds and large institutions.[11]

Also relevant is the young but growing literature on fintech, to which P2P lending represents one of the components. Examples are Philippon (2015, 2016), Greenwood and Scharfstein (2013), and Buchak, Matvos, Piskorski, and Seru (2018). Philippon (2015) documents that despite advances in financial technology, the cost of financial intermediation has remained relatively constant over time. Philippon (2016) argues that fintech can bring about efficiency-enhancing structural change in the financial services industry, but that political economy factors are likely to impede this. Greenwood and Scharfstein (2013) emphasize that the recent growth in the financial industry has been driven mainly by the growth of asset management and household credit, and those shadow banking activities, such as P2P lending, were significant facilitators of the increase of household credit. Buchak, Matvos, Piskorski, and Seru (2018) find that fintech firms set interest rates that are more predictive of ex-post default rates than rates set by banks for the US residential mortgage market, and suggest that this may reflect the superior ability of fintech lenders to analyze big data.[12]

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[11]Buchak, Matvos, Piskorski, and Seru (2018) point out that many of these institutions are the recipients of government safety nets, protection, and subsidies, which raises concerns about risk spillover implications.

[12] In the same spirit Vallee and Zeng (2018) focus on the investor side of P2P lending. Iyer, Khwaja, Luttmer, and Shue (2016) highlight the importance of soft information for borrower screening and Butler,

Our paper differs from this literature in various ways. First, we develop a theoretical model in which intermediation costs for banks and their role in providing liquidity services to depositors, bank leverage, and competition among banks and with P2P lenders all interact to generate predictions about the kinds of loans that will migrate from banks to P2P lending platforms. Second, we document – consistent with the predictions of the model – that when banks face higher regulatory costs, the riskiest bank loans migrate to P2P lenders first, causing both a decline in average risk in bank lending as well as a decline in overall bank lending, and that this happens more when the *unaffected* banks in the region are capital-constrained and consumers are more aware of P2P lending. Third, we also document that P2P loans have lower risk-adjusted interest rates than banks.[13]

A contemporaneous related paper is Tang (2018) which also examines whether P2P lending is a substitute for or complement to bank lending. Her framework predicts that when there is a negative shock to bank credit supply, whether the quality of the P2P borrower pool worsens or improves depends on whether bank and P2P lending are complements or substitutes. Using a change in US accounting rules for banks as a negative shock to bank credit supply, the paper shows that P2P lending in the US is a substitute for bank lending in that it serves inframarginal bank borrowers, but it is a complement for small loans. Apart from the obvious difference in German versus US data, there are three key differences between the two papers. First, we develop a theoretical model of bank capital structure which defines specific features of banks versus P2P lenders and derives endogenous bank and P2P lending choices that generate the predictions we test. Second, we use a different shock to bank capital that affected banks *heterogeneously*. This allows us to examine the impact of the shock on banks subgroups, aggregate bank lending, and on P2P lending, as well as the associated reallocation effects. Third, we focus on a different set of issues, including pricing

Cornaggia, and Gurun (2017) show that good access to local bank finance causes consumers who seek peer-to-peer loans to do so at lower interest rates. Hertzberg, Liberman, and Paravisini (2018) use P2P lending data to show that loan maturity can be used as screening device.

[13]The reason for this, in our theory, is different from the screening advantage for P2P lenders from the more effective analysis of big data suggested in Buchak, Matvos, Piskorski, and Seru (2018).

and default risk differences between banks and P2P platforms and the effect of mediating variables like bank capital and consumer awareness of P2P lending.

The rest of the paper is organized as follows. Section 2 presents the theoretical model. Section 3 describes the data. Section 4 presents the empirical findings. Section 5 concludes. All proofs are in the Appendix.

II.   Theory and Predictions

In this section, we develop a simple theoretical model that is primarily designed to generate testable predictions about how P2P lenders and banks compete and the implications of this for bank lending.

A.   The Model

Consider an economy in which all agents are risk neutral and the riskless rate is zero. There are banks, each of which has a borrower. For each borrower, there is always the possibility that a competing bank will arrive to bid for its business. For a competing bank, the cost of acquiring a borrower who is presently with another bank is $\widetilde{\alpha}_B$, that represents the cost of prying away a borrower who has a loan from the incumbent bank. The variable $\widetilde{\alpha}_B$ is composed of; (i) a random variable $\widetilde{\alpha} > 0$ and (ii) a deterministic function $b(s) \geq 0$ where "s" represents the strength of the incumbent's bank relationship with its borrower, that is, $\widetilde{\alpha}_B = \widetilde{\alpha} + b(s)$. We assume that $\frac{\partial b}{\partial s} \geq 0$, to indicate that the prying cost for a competitor increases as the strength of the incumbent bank's relationship with the borrower increases. The realization of $\widetilde{\alpha}$, which we shall refer to as α, becomes common knowledge at $t = 0$ before competition begins. Similarly, a P2P platform also faces a borrower acquisition cost $\widetilde{\alpha}_P$ in prying away a borrower from another bank, where $\widetilde{\alpha}_P \equiv \widetilde{\alpha} + b(s) + c(w)$, "$w$" represents awareness of P2P lending on the part of the borrowers and $\frac{\partial c}{\partial w} < 0$, with $\lim_{w \to \infty} c = 0$. We assume that $c(w) \geq 0$ and $\widetilde{\alpha}_B \geq \widetilde{\alpha}_P$.

The sequence of events is as follows. There are two dates: $t = 0, 1$. At $t = 0$, the bank has a borrower who needs a loan of $L > 0$. The winning bank contracts with the borrower to repay L_R at $t = 1$ in exchange for a loan of L at $t = 0$. Once L_R is determined, the bank defines its capital structure for financing the loan. At $t = 1$, the borrower's project (financed with the loan) either pays off or not. The loan is repaid in full if the project pays off, and it defaults if the project fails.

Intermediation Cost: In exchange for being given access to deposit funding (D), banks must abide by regulations and agree to be supervised by regulatory authorities. Without specifying the details of these regulations, we stipulate that the "regulatory cost of intermediation" to the bank due to this is $K > 0$. We assume that the social cost of bank failure is $\Omega(D) > 0$, which is increasing and convex in D.[14] The desire to minimize this cost can cause the regulator to supervise banks, impose capital requirements, etc., and this can generate a regulatory cost K for banks. Note that banks will not internalize Ω in their capital structure or lending decisions.

Loan Types: There are two good loans of varying risk: g and G. The g loan is associated with a borrower whose project pays off $\widehat{x}$ with probability (w.p.) $q \in (0, 1)$ and 0 w.p. $1 - q$. The maximum *pledgeable* cash flow that this borrower has to repay the loan is $x \in (0, \widehat{x}]$. The G loan is associated with a borrower whose project pays off $\widehat{x}$ w.p. p and 0 w.p. $1 - p$. The maximum *pledgeable* cash flow to repay the loan is x for this borrower as well. The payoffs on G and g are random variables. Whether the bank has g or G is exogenously specified for now.[15] In the cross-section of banks, some banks have g and some have G. Regardless whether the bank has g or G, it has the option to unobservably invest in a loan instead, call it B, that generates a private benefit of $\Pi > 0$ for the bank insiders (this is the manager who is also the inside equityholder) but no contractible payoff for outside financiers – i.e., the depositors[16]. This moral hazard in lending is similar to that in Holmstrom and Tirole

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[14]The assumption that $\Omega(D)$ is increasing in D is in Merton and Thakor (2019).

[15]Later we will discuss what happens if the bank has both G and g.

[16]There are many ways to think about this loan. For example, it could be a loan to a family member or a friend.

(1997). Further, banks' specialization in monitoring (e.g. Holmstrom and Tirole (1997))
and screening (e.g. Ramakrishnan and Thakor (1984)) their borrowers may give them an
advantage over P2P lenders in controlling borrower risk. To reflect this, we assume that the
repayment probabilities of G and g for a P2P lender are $\bar{p}$ and $\bar{q}$ respectively, with:

$$p \geq \bar{p} > q \geq \bar{q}; \quad \frac{p}{\bar{p}} = \frac{q}{\bar{q}} \tag{1}$$

$$\Pi < L < qx - K \tag{2}$$

This means that both g and G are socially efficient, whereas B is not.[17] The competitive
structure of the loan market is similar to that in Holmstrom and Tirole (1997) in which
the incumbent bank can set the borrowers' repayment, L_R^i, on loan $i \in \{g, G\}$ equal to
the *pledgeable* cash flow, x, on the project. However, if a competing bank arrives, then
the loan repayment will have to be set to match that offered by the competing bank – i.e.,
$L_R^i = \min\{x, \widehat{L}_R^i\}$, where $i \in \{g, G\}$ and $\widehat{L}_R^i$ is the loan repayment the incumbent bank must
offer when there is a competing bank for loan i.

The Bank's Financing Choices: The bank can finance the loan with any combination
of deposits and (inside) equity. Let E denote (inside) equity[18] raised at $t = 0$ and D denote
deposits raised at $t = 0$, to finance loan $i \in \{g, G\}$. Then

$$D^i + E^i = L \tag{3}$$

Let $D^i = \bar{D}^i$ if no competing bank arrives and $D^i = \widehat{D}^i$ if a competing bank arrives.
Deposits are uninsured. Since the bank's capital structure decisions are made at $t = 0$ after
the terms of lending are known, depositors can set the bank's repayment at $t = 1$, D_R^i,

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[17]Assuming $\frac{p}{\bar{p}} = \frac{q}{\bar{q}}$ just means that the disadvantage faced by P2P lenders vis-a-vis banks is the same for
g and G loans.

[18]We are not addressing in this context the agency problem between managers and equity holders, and we
simply assume that they are the same.

$i \in \{g, G\}$, after observing these terms. All corresponding values for the competing bank will be designated with a tilde – i.e., $\widetilde{D}^i$, $\widetilde{D}^i_R$, $\widetilde{L}^i_R$, $i \in \{g, G\}$. See *Table I* for a summary of the notation that we use in the model.

[Table I]

Liquidity Value of Deposits: Depositors derive a liquidity benefit of $\gamma > 0$ per dollar of deposits if the bank does not default. There is now an extensive literature on the microfoundations of this assumption.[19]

P2P Platforms: A P2P lending platform is a non-intermediated form of lending that links investors directly to borrowers via the platform. As Philippon (2015) points out, this is non-leveraged lending since the platform itself has no leverage and the claims of investors are direct (equity) claims on the loan cash flow. This has three implications. First, there is no asset-substitution moral hazard in terms of the platform unobservably investing in B.[20] Second, the platform does not have access to deposits, so all its financing comes from investors (not "customers"). Third, the platform does not incur the intermediation cost K that a bank incurs. All external providers of finance – depositors and investors – are competitive price-takers and thus their claims are priced to give them an expected return of zero (the riskless rate). The platform owner's compensation consits of various fees, one of which is a fraction of the borrower's repayment that goes to the platform owner, with the rest being paid to shareholders. Therefore, it is essentially an equity claim, whose value the platform owner seeks to maximize.[21]

The time line describing the sequence of events is summarized in *Figure 2*.

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[19]For example, Merton and Thakor (2019) view bank depositors as "customers" who receive nonpecuniary service benefits from which they derive positive utility; these are benefits that do not accrue to the investors in the bank. Diamond and Dybvig (1983) view the liquidity benefits as being synonymous with consumption smoothing. Donaldson, Piacentino, and Thakor (2018) view these as stemming from a wealth-safeguarding advantage possessed by the bank.

[20]In our model, the bank would never invest in B if it was all-equity financed.

[21]We do not address the incentive problem the P2P platform might have due to its fee compensation based on the volume of the loans (an aspect addressed by Balyuk and Davydenko (2019)). Introducing this element will strengthen our results, since the P2P platform will have an incentive to increase loan volume by making even riskier loans.

[Figure 2]

Discussion In a nutshell, the incumbent bank has three advantages over competing P2P lenders: (i) it is a relationship lender and thus competing lenders face a cost to pry away the bank's borrowers, (ii) it may have superior monitoring and screening capabilities, and (iii) it can raise financing via deposits at a lower cost than P2P lenders. Advantages (i) and (ii) are reflected in α_P, $\bar{p}$ and $\bar{q}$ and (iii) is reflected in γ. The incumbent bank also faces a cost disadvantage, which is the intermediation cost K that the P2P lender does not face.

B. Analysis

We will first consider the case in which there are no P2P lenders, so there is only interbank competition. We will show that in this case, no bank will lose its borrowers to another bank, so the main effect of interbank competition is to reduce loan prices. In what follows, we do not impose a regulatory capital requirement on banks, but we later discuss the effect of imposing such a requirement.

We begin by establishing the first best, in which the lender's project choice is observable and can be contracted upon. Thus, the B project is never chosen. The first best essentially solves the following $\max_{i \in \{g,G\}} \{V_i(D_i^*) - [1 - S_i]\Omega(D_i^*)\}$, where $V_i(D_i^*) = S_i[L_R^i - D_R^i] - E$ and D_i^* is the solution to $D_i^* \in \arg\max_D \{V_i(D_i) - [1 - S_i]\Omega(D_i^*)\}$, subject to $S_i[L_R^i - D_R^i] - E - K \geq 0$ and the deposit pricing constraint $D^i = S_i[D_R^i + \gamma D^i]$. Here $S_i = p$ if $i = G$ and $S_i = q$ if $i = g$.

In the second best, the bank ignores the social cost Ω and solves the following problem at $t = 0$ if it has G:

$$\max_D p[L_R^G - D_R^G] - E \tag{4}$$

subject to:

$$p[L_R^G - D_R^G] - E - K \geq 0 \tag{5}$$

$$p[L_R^G - D_R^G] \geq \Pi \tag{6}$$

$$D^G = p[D_R^G + \gamma D^G] \tag{7}$$

$$D^G + E^G = L \tag{8}$$

The objective function in (4) is the net present value (NPV) to the bank's shareholders, who are choosing their capital structure at $t = 0$ to maximize this NPV. (5) is the bank's participation constraint, (6) is the incentive comparability (IC) constraint to ensure that the bank prefers G to B, (7) is the depositors' pricing constraint that links the amount of deposits raised at $t = 0$ to the deposit repayment obligation at $t = 2$, and (8) is simply the bank's balance sheet identity. If the bank has g, then we simply replace p by q and D_R^G by D_R^g.

To focus on the cases of interest, we now impose the following restrictions on the exogenous parameters:

$$\frac{\Pi + L[1 - p\gamma]}{p} > x > \max\left\{\frac{\Pi + L[1 - \bar{p}\gamma] - [\Pi - \{\alpha_P + K\}][1 - \bar{p}\gamma]}{\bar{p}}, \frac{L + \alpha_P + K}{\bar{q}}\right\} \tag{9}$$

$$\Pi > \max\{K + \alpha_P, Lq\gamma + \alpha_P\} \tag{10}$$

Essentially, (9) says that x cannot be too big or too small. If it is too big, the asset-substitution moral hazard problem becomes irrelevant and we will get the first-best solution. If it is too small, no competing bank will find it profitable to pry a g borrower away from an incumbent bank. (10) simply asserts that investing in B would allow the bank to overcome the cost of intermediation and the cost of poaching a borrower from another bank.

Proposition 1. *In the second-best case, if no competitor arrives, the incumbent bank will choose a deposit level $\bar{D}^i \in (0, L)$ and equity capital $\bar{E}^i = L - \bar{D}^i$ to finance itself (where $i \in \{g, G\}$ depending on which socially efficient loan the bank has). If a competitor arrives, the incumbent bank will choose deposits of $\widehat{D}^i \in (0, L)$ and equity capital $\widehat{E}^i = L - \widehat{D}^i$, where $\widehat{D}^i < \bar{D}^i \quad \forall i \in \{g, G\}$. Moreover, $\bar{D}^G > \bar{D}^g$ and $\widehat{D}^G > \widehat{D}^g$. **Proof in Appendix**.*

In the second best, the bank has to post some equity capital as "skin in the game" in

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order to assure depositors that it will invest in the socially efficient loan (g or G). The worse the incentive compatibility problem, the more equity capital it must post. If no competitor arrives, the bank can charge a higher loan price on either g or G, so the incentive compatibility problem is less severe and the bank can finance with more deposits. Also, since G is valued higher than g, the incentive compatibility problem with G is less severe and a higher level of deposit financing can be used. Competition, therefore, reduces the bank's profitability both due to its direct effect on the loan interest rate the bank can charge (e.g., the loan repayment) and its indirect effect because the lower loan interest rate decreases the leverage the bank can optimally finance itself with.

Note that the bank's choice of capital structure does not internalize the social cost of bank failure, Ω. So, if we were to solve for the (constrained-efficient) socially optimal capital structure that could be the regulatory capital requirement, it may call for a higher level of capital than in Proposition 1, as shown below.

Lemma 1. *Suppose the regulator is solving the bank's problem in (4) – (8) but is taking into account the social cost Ω. Then the constrained social optimum for the regulator is to invest in the socially efficient (g or G) loan that it has available and to choose a deposit level lower than or equal to $\bar{D}^i$ (with competitive entry) and lower than or equal to $\widehat{D}^i$ (without competitive entry).* **Proof in Appendix**.

Our next result is about competitive interactions among banks.

Corollary 1. *No competing bank will ever successfully take a borrower away from an incumbent bank, as long as both face the same K. The loan-repayment obligation will be lower when a competing bank arrives than when it does not.* **Proof in Appendix**.

This result is straightforward. All banks are identical, but to take a borrower away from another bank, the competing bank has to incur a "poaching cost" of α, so the incumbent can match the competing bank's best offer and still make a positive expected profit on this loan. The only exception is if the competing bank has a lower K and the difference between

the incumbent bank's K and the competing bank's K is greater than the competitor's α. It is convenient to define:

$$A_1 \equiv K[1 - p\gamma]\left(\frac{\bar{p}}{p}\right) - \gamma[pL - \Pi\bar{p}] \tag{11}$$

$$A_2 \equiv K[1 - q\gamma]\left(\frac{\bar{q}}{q}\right) - \gamma[qL - \Pi\bar{q}] \tag{12}$$

The following result can now be proved.

Proposition 2. *If the realized $\alpha_P \equiv (\alpha + b + c) \in [A_1, A_2)$, then banks with g loans lose their borrowers to P2P lenders, but banks with G loans do not experience any loan migration. If $\alpha_P \geq A_2$, then no bank loses any loans to P2P lenders. When P2P lenders arrive to compete with banks, the banking system is more likely to lose g loans than G loans. For $\alpha_P < A_2$ the probability that banks will lose g loans to P2P lenders is increasing in consumer awareness of P2P lending, and growth in P2P lending will be correlated with a decline in bank lending. As the strength of the incumbent bank's relationship, s, with the borrower increases, the probability of losing any loans to P2P lenders declines. And as borrower awareness of P2P lending, w, increases the probability that banks lose loans also increases.* **Proof in Appendix**.

The key to this result is that the G loan requires less capital for the bank to finance it. Hence, its profitability to the incumbent bank always exceeds the profitability of the g loan, and an incumbent bank competes more aggressively with P2P lenders for this loan than for the g loan. Whether banks lose G loans to the P2P lenders depends on the poaching cost, α_P, that the P2P lenders realize. If this poaching cost is very low, then all banks stand to lose loans to P2P lenders, and if it is very high, no bank loses loans. For intermediate values of α_P, banks lose their riskiest loans to P2P lenders, and P2P loan growth is at the expense of bank loan growth. Note also that when loans migrate to P2P lenders, it is because the realized poaching cost, α_P, is low enough to overcome the combination of the bank's deposit-based funding cost advantage and its intermediation cost disadvantage. Thus, risk-adjusted interest rates on P2P loans are lower than what they would be had these loans stayed on the

banks' books. Further, the P2P lender's poaching cost declines when consumer awareness of P2P lending increases, and it increases when the strength of the incumbent's relationship with the borrower is stronger. These results are intuitive.

In practice, banks face capital requirements when they put loans on their books. If we had capital requirements in our model and there was an exogenous shock that required some banks to post capital beyond what was needed for incentive compatibility, then our analysis implies that those banks would lose more loan market share to P2P lenders than banks that did not face higher capital requirements. Similarly, if a bank faces an exogenous shock that increases K, it will lose market share to P2P lenders and banks that do not experience a higher K. This is summarized below:

Corollary 2. *If a bank experiences an increase in K (or regulatory capital requirements beyond the level needed for incentive compatibility), the measure of $[A_1, A_2)$ increases, increasing the probability that the bank will lose its g loan to P2P lenders. Moreover, the incumbent bank may also lose its g loan to another bank that has not experienced an increase in K if the incumbent bank faces a sufficiently large increase in K or regulatory capital requirements.* **Proof in Appendix**.

If there are no P2P lenders, then an increase in K or capital requirements for some banks and not for others would have no perceptible effect on overall bank lending, since loans will simply shift from some banks to others.[22] But if it is P2P lenders that take some loan volume away from the affected banks, then overall bank lending will fall. Thus, if we can identify an exogenous shock to K, it may help us identify a causal link between the presence of P2P lenders and bank lending.

Which loans are likely to migrate to P2P lenders? Note that condition (2) implies that the loan has a positive NPV to the bank. If there are loans for which $\bar{q}x > L > qx - K$,

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[22]Starting with an equilibrium in which banks are making g and G loans, if some banks experience an increase in K and others do not, the banks that do not experience an increase in K will always outcompete P2P lenders in taking loan volume away from the adversely affected banks if poaching costs are equal for P2P lenders and unaffected banks (i.e. c is equal to zero). Thus, in our model, unaffected banks will let business go to P2P lenders only if they are somewhat constrained.

then these loans will be positive-NPV for P2P lenders but negative-NPV for banks. Hence, if banks face a sudden increase in regulatory costs that leads to $L > qx - K$ for some loans, then these loans will migrate to P2P lenders if their poaching costs are not too high, unless the banks unaffected by the increase in K step in and satisfy the loan demand not being met by the treated banks. But if the unaffected banks are capital-constrained, then they may not step into the vacuum created by treated banks, and P2P lending will grow at the expense of overall bank lending.

Moreover, to the extent that regulators are attempting to control bank risk, K may be higher for riskier loans, so these loans are most likely to be taken away by P2P lenders when they gain market share. This discussion leads to the following corollary.

Corollary 3. *If some banks experience an increase in K that makes g loans unprofitable for them, these loans may be picked up by unaffected banks if they are not capital-constrained. If the unaffected banks are capital-constrained and cannot expand their lending, these loans will go to P2P lenders, and overall bank lending will decline.*

Also, we have not considered a bank that has both g and G loans in its portfolio. We have conducted this analysis, but do not present it here because all of our predictions are sustained, albeit at the cost of more algebraic complexity. The following observations emerge from that analysis:

- The amount of equity capital the bank needs to keep against a two-loan portfolio consisting of g and G is lower than the sum of the equity capital levels of two separate banks, one with g and one with G.
- When faced with competition for a loan from a P2P lender, the bank will be willing to give up g before it gives up G.
- It will be more difficult (will require a lower α_P of realization) for a P2P lender to take a g loan away from a bank when a bank has both g and G loans than when it has only g.

The intuition for these results comes from the fact that when the bank already has G on its balance sheet, g is more valuable as an addition than if the bank has only g, since the diversification across g and G increases the expected value of liquidity services to depositors, reducing the bank's cost of funding and making the incentive compatibility condition easier to satisfy. Thus, in this more complicated case of the incumbent bank possessing both g and G loans, our results are strengthened. Note that if banks are making both g and G loans and they lose g loans, their average profitability in lending will improve even though overall lending by banks declines. Further, if bank deposits are insured and deposit insurance is underpriced, our results will be strengthened, and they will be unaffected with actuarially-fairly-priced insurance. It is important to stress that we have considered a general model to reflect what the literature has highlighted: i.e. the superior ability of banks to screen and monitor risk. However, this difference between banks and P2P lenders is not the main driver of our results. Even when $\bar{p} = p$, $\bar{q} = q$ and $\alpha_B = \alpha_P$, the results are qualitatively the same. Our analysis generates the following hypotheses that we confront with the data:

Hypothesis 1: There is a negative relationship between bank lending and P2P lending, and banks lose market share to P2P lenders when banks are faced with an exogenous increase in regulatory costs. The greater is borrowers' awareness of P2P lending, the bigger is the loss of bank market share. Similarly, the more capital constrained unaffected banks are, the bigger is the loss of banks' market share in the aggregate.

Hypothesis 2: P2P loans are riskier than bank loans.

Hypothesis 3: The risk-adjusted interest rate on bank loans is higher than the risk-adjusted interest rates on P2P loans.

III. Institutional Background and Data Description

A. *Institutional Background*

The German banking sector is a vast landscape of different types of banks. Large banks have a relatively small market share of the consumer credit market whereas small banks – mainly savings banks (Sparkassen) and cooperative banks (Volksbanken) – have about half of the consumer credit market. The so-called "regional principle" restricts these banks to their own municipalities and prohibits them from serving customers elsewhere. This restriction results in fragmentation and leads to the existence of a large number of Sparkassen and Volksbanken. Currently, there are a little over 1900 banks in Germany (about 540 Sparkassen and 900 Volksbanken).

At the end of 2015, Sparkassen had a 22.1% consumer credit market share, and a 37.4% household deposit market share, whereas Volksbanken had a 23.7% consumer credit market share, and a 36.5% household deposit market share.[23] By comparison, large commercial banks had 6.3% and 11.2% of the consumer credit and household deposit markets, respectively.

Sparkassen are typically owned by their municipalities or group of municipalities. Their customer base consists mainly of small and medium enterprises as well as households.

Because they are cooperative banks, the customers of Volksbanken are also their members and shareholders. Historically, some of these banks were developed as self-help organizations, and this mission still permeates many banks.

In part to avail of scale economies and offer customers a large menu of financial services, Sparkassen and Volksbanken link themselves to "umbrella" banks. Those banks provide their member Sparkassen and Volksbanken services that include clearing, insurance, syndication, underwriting among others, and they also assist with state financing. In the case of Sparkassen, the umbrella bank is called Landesbank (or state bank in English). Landes-

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[23]Savings Banks Finance Group Financial Report (2015)

banken are jointly owned by their member Sparkassen and the state government.[24] There are currently 11 Landesbanken (in 17 states), with no more than one in each state. In the case of Volksbanken, the umbrella bank is DZ Bank. It provides similar services to its members, but without a political link to regional governments.

The institutional structure described above is an integral part of the bank-based German financial system.[25] The nature of the savings and cooperative banks in Germany means that they are engaged in relationship banking. As suggested by the relationship banking literature, this creates stickiness in the bank-borrower relationship and creates customer acquisition costs for the banks competitors.[26] This includes not only other banks but also P2P lenders.

Regarding the P2P market, Auxmoney is the oldest and largest P2P lending platform in Germany and one of the top 10 in Europe. According to its website, from the day it began business in 2007 until late 2017, the total volume of credit provided was about €1 billion with an average rate of 85% per year. In 2018 Auxmoney new lending was €551 million (an increase of 75% with respect to 2017). Auxmoney, since the biginning, carries out essentially all tasks related to loan evaluation and origination. As stressed by Morse (2015) and Balyuk and Davydenko (2019), even in the case of Auxmoney, a significant fraction of the lenders are institutional investors, such as for example Aegon, a Duch insurace company.

B.   Data Description

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.

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[24]The details of ownership sharing vary from state to state. See Puri et al. (2011) for an ownership list of each Landesbank.

[25]See Allen and Gale (2001) that classify the US financial system as market-based and the German financial system as bank-based.

[26]See, for example, Boot and Thakor (2000) who show that competition induces banks to increase the value added in the relationship with their borrowers.

Auxmoney is the oldest and largest P2P lending platform in Germany and one of the top 10 in Europe. According to its website, from the day it began business in 2007 until late 2017, the total volume of credit provided was about €1 billion with an average rate of 85% per year. In 2018 Auxmoney new lending was €551 million (an increase of 75% with respect to 2017).

Auxmoney provided us with two different datasets.[27] The first includes all loans segregated by state between January 2010 and September 2014 but 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.[28] Auxmoney also provided us data on the distribution of its loan maturities. The maturity of Auxmoney loans is between one and five years. Three-year loans have the highest frequency and one-year maturity loans the lowest. However, the largest volumes are for loans with four-year and five-year maturities.[29]

The Deutsche Bundesbank statistics used in this study are provided by two different datasets. The first is the Interest Rates Statistics[30], which is a stratified sample of the German banking sector used for supervisory activities and gives the amounts and the interest rates per bank and per month applied to nonconstruction consumer credit lines (outstanding and new business) for different maturities (overdraft, up to one year, and more than one year).[31]The statistics are composed of monthly observations between January 2010 and September 2014. The second is the dataset from the Balance Sheet Statistics (BISTA, see Beier, Krueger, and Schaefer (2016) for further information on this data source), which gives

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[27]For reasons of data confidentiality, Auxmoney provides its credit intermediation by month and state only if five or more loans were made in that month in that state.

[28]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.

[29]The descriptive table provided to us by Auxmoney is reported in *Table AI* in the internet appendix.

[30]The Interest Rates Statistics (MIR) is the German part of a larger dataset that is used by the ECB for regulatory purposes. It does not cover the whole German banking sector, only a stratified sample. For this reason, our sample does not cover all Sparkassen and Volksbanken in Germany, just the ones present in this data source. See Bade and Beier (2016) for further information on this data source.

[31]Our study does not include credit card lending because credit card lending is very limited in Germany. According to Bundesbank statistics, only 6.8% of revolving loans and overdrafts in 2013 happened to be by credit card loans. Two-thirds of credit card loans are provided by large banks.

information on write-ups and write-downs, from which we derive the loan loss provisions of banks.

Our analysis is at the bank-state level. There are 105 banks in our sample which make loans of relatively small sizes, making them more comparable to their P2P competitors then large commercial banks would be.[32]

Data on the geographic distribution of consumer credit across states by banks and Auxmoney are provided in *Figure 3*. Each individual gray 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 black-colored bar represents the share of P2P credit provided in a specific state in relation to the total amount of P2P credit provided in all states. For three states (Brandenburg, Saarland, and Thuringia), there is no information on Sparkassen credit, so these are excluded from our sample.

[Figure 3]

From the Deutsche Bundesbank, we received data on three types of non-construction consumer credit lines: overdraft, maturity less than a year, and maturity larger than a year and smaller than five years. Those credit lines have maturities and loan purpose (non-construction consumer credit) similar to those for P2P loans. In order to have one comparable measure for interest rate and risk for each bank, we aggregate all three lines of credit into one variable using weighted means. This gives us a single observation for each bank and month.

Table II provides data on the total volume of P2P lending and the total volume of new loans per bank. The average total volume of new loans granted by Auxmoney per state per month is €252,089, substantially lower than the average monthly total new loan volume per bank per month, which is €90.5 million. While the mean size of Auxmoney loans is smaller than that of banks, the standard deviation of loan volume volatility for Auxmoney is higher.

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[32]These banks are also used by Puri, Rocholl, and Steffen (2017) in their examination of how relationship information affects default risk.

Moreover, Auxmoney operates in all of Germany, so the size of total new lending per month is much larger than the one reported in the table that refers to single states.[33]

[Table II]

Table II also provides data on the interest rates on new loans by banks and Auxmoney during January 2011 - August 2014. The bank interest rates are the average across three consumer credit lines: overdrafts, short-term loans (less than a year maturity), and midterm loans (from one to five years maturity). This average is 10.25%, and its value is pushed up by overdraft loans, which typically carry higher interest rates than other consumer loans. During the same period, the average interest rate on P2P loans is 12.82%, which includes the 1% fee charged by the Auxmoney platform. To compare these interest rates, we need to adjust for the risks of these loans.

To assess loan risk, we measure the default rates of Auxmoney borrowers by using the Schufa score data. The Schufa score is the German consumer credit rating, similar to FICO scores in the US. The distribution of Auxmoney loans Schufa score is provided in Figure 4.

[Figure 4]

As Figure 4 shows, Auxmoney loans have Schufa scores that are primarily in the 174-519 range, with the highest concentration being between 243 and 405. Banks also have access to the Schufa scores of their clients, but this information is confidential and not included in the Deutsche Bundesbank data available to us. However, Korczak and Wilken (2010) report the aggregate Schufa score distribution for all Sparkassen clients, which we report in Figure 4 as well. The figure shows that in about 50% of cases, households that borrow from banks have higher scores than those for Auxmoney borrowers. This indicates that, in contrast to US P2P lenders (as documented by Chava et al. (2018) and Di Maggio and Yao (2018)),

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[33]Our estimate is that it is at least 14 times. In fact, as we mentioned above, by the end of 2018 its new lending volume was similar to that of a mid-sized bank in our sample, that is, 551 million of Euro (46 million on average per month).

Auxmoney lends to some borrowers not served by banks. However, for about 50% of the loans, the Schufa scores on bank loans coincide with those for Auxmoney loans. This suggests that Auxmoney serves borrowers who tend to be riskier than bank borrowers but also many borrowers with risk similar to that of bank borrowers, indicative of significant market overlap. Korczak and Wilken (2010) report the default rates corresponding to different Schufa scores; see Table III. The data allow us to map the Schufa scores in our data into loan-default rates.

[Table III]

In our Deutsche Bundesbank data, the only proxy we have for loan risk is the loan-loss provision. Whenever a bank expects a loan to not perform (typically, when it is 90 days delinquent), it will write the loan down on its balance sheet and create a provision called a loan-loss allowance. Similarly, a loan can be written up if it was expected to default and was written down, but was paid in the end. In the BISTA dataset of the Deutsche Bundesbank, loans are written up/down in full regardless of their recovery rate[34]. We calculate distributions of the ratio of the loan write-downs to outstanding loans for each bank and we adjust the mean of the distribution to match the one provided by Schufa German Private Bureau (that is around 2%), maintaining the relative mean difference across banks. We also use the Schufa score distribution around the mean provided by Korczak and Wilken (2010) to match the dispersion around the mean that is observed in the distribution of the ratio of loan write-downs to outstanding loans. This means that our calculation of default rates across Auxmoney and bank loans employs the same methodology, using the relationship between Schufa scores and default rates provided by Korczak and Wilken (2010). This methodology, is not free of potential measurement errors, to be clear, but the bias would be mainly an overestimation of the risk of bank loans; the ratio of bank loan write-downs to outstanding loans is actually lower than the default rates we calculate with our methodology.

The results are summarized in *Table IV*, which provides the default probabilities of bank loans and P2P loans.

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[34]See, for example, Memmel, Gündüz, and Raupach (2015).

As *Table IV* shows, P2P borrowers have an average default rate of 0.0732 (or 7.32%). Dorfleitner, Priberny, Schuster, Stoiber, Weber, de Castro, and Kammler (2016) also use Auxmoney data. They find that the average realized default rate on Auxmoney loans is about 12% for the period March 2008 - September 2013. Auxmoney itself reports a default rate of about 6% on its webpage. Our estimate falls between these two numbers. In either case, the point to note is that the default rate on Auxmoney loans is substantially higher than on bank loans (2.22% in our sample). Other studies report similar default rates for German banks. ber (????), using a sample of 100,000 borrowers from a large German private bank between 2008-2010, report a 2.5% default rate. Puri, Rocholl, and Steffen (2017) use a sample of a million observations from 296 German savings banks in the pre-crisis period and report a 1.1% default rate. Schufa (2017) uses a sample of 17.4 million German consumer loans in 2016 and finds a 2.2% default rate. In their regulatory filling the two largest lenders in Germany, Deutsche Bank and Commerzbank, provide default rates of 1.5% and a 2%, respectively. These data collectively indicate that the default rate on Auxmoney loans is higher than that on bank loans.

IV. Empirical Findings

The summary statistics presented above are broadly in line with the predictions of our theoretical model. In this section, we investigate formally the three hypotheses stated in Section II.

A. *Hypothesis 1:*

There is a negative relationship between bank lending and P2P lending, and banks lose market share to P2P lenders when banks are faced with an exogenous increase in regulatory costs. The greater is borrowers' awareness of P2P, the bigger is the loss of bank market

share. Similarly, the more capital-constrained unaffected banks are, the bigger is the loss of banks' market share in the aggregate.

Figure 1 shows that the overall volumes of new bank loans and new P2P loans appear to be negatively correlated. In this section, we formalize the analysis. First, we present evidence that bank lending volume is negatively correlated with P2P lending volume. Second, we use a quasi-natural experiment to show that when banks are faced with an exogenous increase in regulatory costs, P2P lending increases.

A.1 Relationship between bank lending and P2P lending.

We investigate the relationship between bank lending and Auxmoney lending using time and state fixed effects to account for timing within a business cycle and conditions related to local geography. Also, since every bank is physically constrained to operate within one state, we use the new credit supplied by all other banks in that state as a proxy for bank competition within the state, since this competition may influence the relation between bank lending and Auxmoney lending. We estimate:

$$log(L_{t,b_j}^{bank}) = \gamma_1 log(L_{t,j}^{P2P}) + \gamma_2 log(L_{t,-b_j}^{bank}) + \Delta_j + \Delta_t + \epsilon_{t,b_s} \tag{13}$$

where L_{t,b_j}^{bank} is the new-loan volume by bank b_j (the subscript j indicates that bank b is active in state j) at time t, $L_{t,j}^{P2P}$ is the new-loan volume by Auxmoney in state j at time t, and $L_{t,-b_j}^{bank}$ is the sum of new lending by all other banks in state j at time t.

Table V presents the results. The first regression shows that if we do not include time and state fixed effects, no significant relationship emerges. However, when we include both state fixed effects and time fixed effects, the relationship between bank lending and P2P lending is statistically significantly negative, as predicted by the theory. In all equations, lending by a bank in a given state is also negatively correlated with the sum of new lending provided by all the other banks in that state. These results provide support for our first hypothesis.

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[Table V]

A.2 Bank lending and P2P lending responses to higher regulatory capital requirements: A quasi-natural experiment.

In order to examine the impact of an exogenous increase in regulatory costs for banks on the relationship between bank lending and P2P lending, we use the 2011 EBA capital exercise as a quasi-natural experiment, in which bank capital requirements were exogenously shocked.[35] We investigate whether Auxmoney significantly increases its new lending in those states where some banks were affected by the EBA capital exercise.

The 2011 EBA capital exercise: The EBA published its capital exercise results on October 26, 2011, and it required banks to reach and maintain a 9% core tier 1 capital ratio by the end of June 2012. This requirement represented an exogenous increase in bank regulatory costs. This shock is useful for our purposes for a number of reasons. First, the core tier 1 ratio of 9% required by the capital exercise is substantially higher than the 5% previously required. Second, the capital exercise was largely unexpected as the EBA had conducted the 2011 stress tests only a few months earlier (June 2011) and provided no indication of the subsequent capital exercise. Third, none of the banks in our sample (Sparkassen and Volksbanken) participated *directly* in the capital exercise. Each Sparkasse is linked to a Landesbank, and each Volksbank is linked to the DZ Bank. Since all Sparkassen of a given state are linked to the same Landesbank and all Volksbanken are linked to the DZ bank, the direct effect of the capital exercise was on some Landesbanken, and the effect on the banks in our sample was indirect. This indirect effect is consistent with the assumption that the treated banks could not anticipate whether they would be affected by the capital exercise and were unlikely to have changed their lending behavior in anticipation.

The capital exercise forced two Landesbanken, HELABA and NordLB, to raise additional

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[35]A similar quasi-natural experiment has been performed by Gropp, Mosk, Ongena, and Wix (2018) to investigate the bank response to higher capital requirements; it showed that affected banks increase their capital ratios not by increasing capital but by reducing their risk-weighted assets for corporate and retail exposures.

capital equal to 2.67% and 2.99%, respectively, of their assets.[36] In its 2012 Annual Report, the NordLB quantifies its capital increase as €2.56 billion from outside sources including its associated Sparkassen and state governments (Lower Saxony, Mecklenburg-Western Pomerania, and Saxony-Anhalt), and €638 million from own sources. Economically, the link between Landesbank and Sparkassen comes from the ownership structure – i.e., Sparkassen partially own their respective Landesbank and vice versa. For example, Savings Banks and Giro Association of Hesse-Thuringia own 85% of HELABA. This means that Sparkassen have to contribute significantly to the recapitalization of their Landesbanken. This has two effects on the lending by these banks. One effect is *direct*: these banks have to purchase the equity of their Landesbanken rather than lending the money. The other effect is *indirect*: the equity investment increases the savings banks' risk and requires a higher capital ratio. Thus, an exogenous increase in the capital required of Landesbanken represents an exogenous decrease in the funds that can be used for lending, as well as an increase in the regulatory costs faced by the Sparkassen – since their capital ratio increases, that also reduces their lending capacity, holding their stock of capital fixed.

Empirical strategy: Our empirical strategy is to examine first whether the Sparkassen linked to HELABA and NordLB reduced their lending enough to cause the overall bank lending in those states to decline. In other words, we investigate whether *all* banks in the states where HELABA and NordLB are present (Hesse, Lower Saxony, and Mecklenburg-Western Pomerania)[37] have an overall lending reduction. Further, we test whether Auxmoney filled the vacuum by increasing its lending more in these states.

To analyze the *overall* impact of the EBA capital exercise on lending, we conduct two types of diff-in-diff analyses.[38] First, we sum up the volume of new loans over all banks in

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[36]Note: The information used in this study regarding HELABA and NordLB was not provided by the Bundesbank, but comes from public data sources, including the EBA and Gropp, Mosk, Ongena, and Wix (2018).

[37]HELABA and NordLB are also present in the states of Thuringia and Saxony-Anhalt, but the Bundesbank database on new bank loans does not provide any information about savings banks in these states, as we highlighted in Figure 3

[38]See also Cerqueiro, Ongena, and Roszbach (2016), who use a similar approach.

a given state and investigate whether, during the EBA capital exercise, the total volume of new bank lending declines more in the states where HELABA and NordLB are present than in the other states. Specifically, the first diff-in-diff model that we estimate is the following:

$$log(L_{t,s}) = \alpha_1 treated_s * EBA_t + \alpha_2 EBA_t + \alpha_3 treated_s + \Pi W_{t-1,s} + u_{t,s} \qquad (14)$$

where $log(L_{t,s})$ is the logarithm of lending volume by banks in state s in period t, $treated_s$ is a dummy variable that identifies the treatment group – i.e., it is equal to one for the states where HELABA and NordLB are present, which we call *treated states*, and zero for all the other states, which we call *control states*. EBA_t is the treatment time dummy that takes the value 1 from October 2011 onwards, and 0 prior to October 2011. $W_{t,s}$ is a vector of control variables, including the weighted average of interest rates on the new loans and risk in state s at time t, and $u_{t,s}$ is the error term.

Second, to confirm that our results are robust even in a disaggregated form and not driven by the largest banks, we perform a similar estimation in the bank dimension. Instead of summing up lending by all banks in a given state, we estimate a similar diff-in-diff model at the individual bank level. In this setup, the treatment group is *all* banks (Sparkassen and Volksbanken) in states where HELABA and NordLB are present, which we call *treated banks*.[39] The control group consists of all other banks (i.e., Sparkassen and Volksbanken) in other states. The diff-and-diff model that we estimate is the following:

$$log(L_{t,b}) = \alpha_1 treated_b * EBA_t + \alpha_2 EBA_t + \alpha_3 treated_b + \Pi W_{t-1,b} + u_{t,b} \qquad (15)$$

where $log(L_{t,b})$ is the logarithm of new-loans volume in period t by bank b, $treated_b$ is a dummy variable that identifies the treatment group – i.e., it is equal to 1 for all the banks (Sparkassen and Volksbanken) in the treated states. The control group consists of all the banks (Sparkassen and Volksbanken) located in the other states. The EBA_t variable is the

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[39]Note that unaffected banks in treated states – i.e., Volksbanken – are considered treated banks in this estimation.

same as in equation (14), $W_{t,b}$ is a vector of control variables, including interest rates and risk at the bank level, and $u_{t,b}$ is the error term.

In order to check if Auxmoney increased its lending in states where overall bank lending decreased, we perform a diff-in-diff analysis on new Auxmoney lending. Similar to equation (14), states where HELABA and NordLB are present are called *treated states*. The control group consists of all other states. The diff-and-diff model that we estimate is the following:

$$log(L_{t,s}^{P2P}) = \beta_1 treated_s * EBA_t + \beta_2 EBA_t + \beta_3 treated_s + \Pi W_{t-1,s}^{P2P} + e_{t,s} \qquad (16)$$

where $log(L_{t,s}^{P2P})$ is the logarithm of new Auxmoney loan volume in state s in period t, EBA_t and $treated_s$ variables are the same as in equation (14), $W_{t,s}^{P2P}$ is a vector of control variables, including interest rates and risk of new Auxmoney loans in state s at time t, and $e_{t,s}$ is the error term.

Data: *Table VI* in Panel A shows summary statistics for the treatment and control groups before the treatment at the state level. For simplicity, we aggregate all three types of bank loans mentioned previously into one – i.e., our lending variable is the total of nonconstruction consumer loans by all banks in a given state.[40] Summary statistics at the state level indicate that treated banks have higher loan volume and higher loan interest rates than control banks and the difference is statistically significant at the 5% level. Moreover, the treated banks' loans are riskier than those of the control banks, but the difference is not statistically significantly different from zero.

Panel B in *Table VI* reports statistics at the individual bank level for banks in treated states and control states. The panel shows that both new loan volume and risk are not statistically different across control and treated banks, but interest rates are higher for treated banks and the difference is statistically different from zero. This indicates that the difference in new loans volume is largely due to state characteristics rather than bank

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[40]We conducted the analysis separately for each loan type and all results are consistent with the ones presented.

characteristics.

On the Auxmoney side (Panel C), the difference of log volume of new loans is not statistically significantly different across treated and control states. Interest rates are higher in the treated states than in the control states: 13.84% versus 13.69%, with a difference of 0.15% that is statistically significantly different from zero at the 5% level. The risk is smaller in treated states than in the control states, with a difference of 0.67% but is statistically significantly different from zero only at the 10% level.

In summary, this table shows that treated banks charge higher loan interest rates than control banks and the volume of new loans is higher for treated banks when aggregated at the state level, but there is no difference between treated and control states when disaggregated individual bank-level data are used. For Auxmoney, treated and control states have similar loan volumes, but treated states have higher interest rates as treated banks.

[Table VI]

Parallel trends: To check the parallel-trends assumption, we present *Figure 5*, which shows lending by banks over time for the two groups (treated and control) normalized to the value of 100 for the third quarter of 2011.

The figure shows that in treated states, the volume of new bank loans is similar to that in control states before the EBA capital exercise – i.e., until October 2011. This indicates that the parallel-trends assumption is valid. After the EBA capital exercise, the new-loan volume dropped both for control and treated banks, but it dropped more and faster in treated states than in control states. We also perform an anticipation test on the percentage change in bank lending, which also indicates that the parallel-trends assumption holds. Results are reported in the internet appendix.

[Figure 5]

Similarly, we check the parallel-trends assumption with Auxmoney. *Figure 6* shows Auxmoney credit provision for the two groups normalized to the value of 100 for the third quarter

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of 2011. It shows that the volumes of new Auxmoney loans in treated and control states exhibited parallel trends prior to the EBA capital exercise. After the EBA capital exercise, Auxmoney lending increases in both treated and control states. However, the increase is larger in treated states than in control states. In this case too, we check whether there is any anticipation but we find no evidence. See the internet appendix for the placebo diff-in-diff test.

[Figure 6]

Difference-in-differences analysis: We perform the diff-in-diff analyses presented in equations (14), (15) and (16). The estimations are reported in *Table VII*.

[Table VII]

The first three columns of *Table VII* report the estimation results of equations (14); columns (I), (II), and (III) show the results for the new-loan volume of banks without any fixed effects, with bank fixed effects, and with both bank and time fixed effects, respectively. The analysis shows that lending in the treated states after the EBA capital exercise declined more than in control states for the period after the EBA capital exercise. The coefficient is negative and significant for estimations with fixed effects and equal to -0.06 using state fixed effects and equal to -0.05 using state and time fixed effects. Thus, in the post-capital-exercise period, total bank lending in treated states declined more than in control states as already highlighted by *Figure 5*.

Next, we present the diff-in-diff estimation of loans equation (15). Results are reported in columns (IV), (V), and (VI) of *Table VII*. The coefficient of the interaction term, $treated_b * EBA_t$, is negative and significant in all the estimations and equal to -0.05 in the estimation with state and time fixed effects. This means that banks in treated states (both Sparkassen and Volksbanken) reduce their lending relative to banks in the control group after the 2011 capital exercise. This result is consistent with the decline in total bank lending – i.e.,

unaffected banks in treated states were unable to make up for the reduction in lending by the affected banks, confirming our previous result.

Finally, we estimate equation (16). Results are reported in columns (VII), (VIII), and (IX) of *Table VII*. As the table shows, P2P lending increased significantly in these states during this period. The coefficient of the interaction term is positive and significant at the 1% level and equal to 0.20 if we include state fixed effects and equal to 0.22 if we include state and time fixed effects. Therefore, consistent with our theoretical model, we find that P2P lending increased, with the largest increase occurring in the states where the treated banks were located.

As a robustness check, we repeated the diff-in-diff analysis above for only the 30% of the banks in our sample having the lowest volume of new consumer lending (SMALL banks), i.e., banks with new loans more comparable in size to Auxmoney loans during the sample period. The results are even more significant. At both the state bank lending level and at the individual bank level, we have an even bigger negative coefficient for the interaction term: $treated_b * EBA_t$, and this coefficient is always significant at the 1% level. Detailed results are reported in Table AV in the internet appendix.

Disaggregated diff-in-diff analysis: So far we have shown that total bank lending declined in treated states, but we did not distinguish between the savings banks that were affected by the EBA exercise (Sparkassen) and the others (Volksbanken). So now we perform two other diff-in-diff analyses. The first focuses on new Sparkassen lending in treated states and the second focuses on new Volksbanken lending in treated states.

For the first diff-in-diff analysis, we define the treatment group as the Sparkassen in the treated states that were linked to HELABA or NordLB. In this analysis, the control group consists of the Sparkassen and Volksbanken in other states – i.e., states unaffected by capital exercise (the Volksbanken in the treated states are left out of this estimation). The results are reported in *Table VIII*. Columns (I), (II), and (III) show the results for treated banks without any fixed effect, with bank fixed effects, and with both bank and time fixed

effects, respectively. The coefficient of the interaction term, EBA_t*$treated_b$, is negative and significant at the 1% level in all the estimations. This means that treated Sparkassen reduced their lending compared to the control group after the 2011 capital exercise.

For the second diff-in-diff analysis, we investigate the effect of the EBA capital exercise on the unaffected banks in treated states. Therefore, we define the treatment group as the Volksbanken in treated states. The control group is defined as the Sparkassen and Volksbanken in other states as before. The aim is to see if the reduction of lending by banks in the treated states is due to an unobserved, coincidental common shock affecting *all* banks within the treated states or it is driven by reduced lending by the Sparkassen linked to HELABA and NordLB. Columns (IV), (V), and (VI) in *Table VIII* present the results for a diff-in-diff estimation using Volksbanken in treated states as the "treatment group" for this exercise. The coefficient of the interaction term EBA_t*$treated_b$ is positive but not significant, including only bank fixed effects; it is significant when both time and bank fixed effects are included. This suggests that the Volksbanken in treated states may have increased their lending in response to the decline in lending by the Sparkassen, but it was not enough to arrest the decline in total lending in the treated states. In summary, we find that the Sparkassen linked to HELABA and NordLB decreased their lending after the capital exercise, whereas the Volksbanken operating in the same states did not significantly change their lending in response. This result is consistent with the prediction of our model but also with the view that unaffected banks in treated states were not able to make up for the reduction in lending by the affected banks.

[Table VIII]

The role of bank capital: Next, we want to explore further why the unaffected banks in treated states were not able to fill the lending vacuum created by the treated banks. Our hypothesis is that it was because they lacked sufficient capital to expand their lending. In our sample, there were nine unaffected banks in the treated states. For this examination, we focus on the capital ratios of the unaffected banks in the treated states. We compare banks'

lending in 2012 to lending in the same month one year earlier. We define a dummy variable called *Expansion* that takes the value one if the observation belongs to the top quartile of lending increases. We then regress this dummy on bank capital lagged, as reported in the bank balance-sheet data for the year 2011. More specifically, we estimate the following regression:

$$Expansion_{t,b} = \alpha_0 + \alpha_1 capital_{t-1,b} + \Delta_t + u_{t,b} \tag{17}$$

The dependent variable $Expansion_{b,t}$ is a dummy variable that takes the value one if the one-year increase in lending volume in 2012 puts the bank in the top quartile of lending increases, and zero otherwise. Δ_t is the time-fixed-effect variable and $u_{t,b}$ is the error term. $capital_{t-1,b}$ is the equity capital of bank b at time $t - 1$. The sample includes only banks unaffected by the capital exercise in states where HELABA and NordLB are present, and the time period is from January 2012 to December 2012. The estimation results are reported in Table IX.

[Table IX]

Table IX shows that the unaffected banks in treated states that had higher capital increased their lending by a larger amount in response to the capital shock experienced by the affected banks. The coefficient is positive and significant both with and without the inclusion of time fixed effects. That is, among the banks in treated states that were unaffected by the EBA capital exercise, banks with lower capital were less able to fill the lending vacuum created by the affected banks.

Overall, consistent with the predictions of our model, P2P lending in Germany is growing more in states in which some banks experience higher regulatory costs and in which unaffected banks lack sufficient capital to replace the reduction of credit supply by the affected banks.

Google Search analysis: Lastly, we want to understand the effect of awareness "w" on

the poaching cost, α_P, faced by P2P lenders in luring away bank borrowers. Our model predicts that a lower poaching cost would enable P2P lenders to take a larger market share away from banks. Since P2P lending is an online-only service, in order to access the P2P platform, users frequently search for the word "Auxmoney" using search engines like Google. Thus, we use Google search volumes as provided by *Google Trends* to capture consumer awareness of Auxmoney in different regions. The idea is that the larger is consumer awareness, the lower is α_P, and the greater is the competition Auxmoney offers to banks.

We also use the EBA capital exercise for this investigation. We define a dummy called *Google Search* that equals one if the state was in the top 50th percentile of Google searches between January 2010 and October 2011 (i.e., prior to the EBA capital exercise) and zero otherwise.[41]

We use this dummy variable as an explanatory variable in the diff-in-diff estimation previously described. *Table X* reports the results. The first two columns of this tables correspond to the regression reported in Columns (I), (IV),and (VII) of Table *VII*, respectively. Since the results of the diff-in-diff estimation have been already discussed, we focus on the coefficient of the dummy *Google Search*.

[Table X]

As *Table X* shows, the dummy *Google Search* is statistically significant in all estimations at the 5% level. The table shows that greater awareness of P2P lending leads to a bigger decline in new lending by banks in treated states both at the aggregated (column I) and individual bank (column II) levels, and to a bigger increase in P2P lending (column III). P2P lenders also increased lending in states in which there was more search for Auxmoney prior to the EBA stress test. This result shows that P2P lending increases more and bank lending decreases more after a capital shock in regions in which there is greater consumer awareness of Auxmoney. It is worth stressing that the other coefficients retain their previous

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[41]A detailed description of how this variable has been constructuted and the descriptive statistics of the data provided by *Google Search* are reported in the internet appendix.

statistical significance as in table *Table VII*, so "consumer awareness" of P2P lending is a complementary channel for the effect of P2P lending on bank lending.

B. *Hypothesis 2*

P2P loans are riskier than bank loans.

In this section, we investigate whether Auxmoney loans are statistically significantly riskier than bank loans as predicted by our theoretical model. In *Table* IV in Subsection 3.2 we have provided the default rates on bank loans and Auxmoney loans, indicating that Auxmoney loans appear to be riskier than bank loans.

We formally test whether the difference in the means of the default rates of Auxmoney and bank loans is statistically significant; the null hypothesis is that the default rates of bank loans and P2P loans are equal. We find that the difference in means is 2.35% and the joint standard error 0.1235%, which leads to a t-value of 19.03. Hence, we can reject the null hypothesis. We also perform a more robust analysis with a panel regression in which we consider the default rates each month of all the banks considered and also include Auxmoney new loans default rates in the different states for each month, and then regress them on a dummy variable that takes the value one if the observation refers to an Auxmoney loan, and zero otherwise:

$$\sigma_{t,b} = \beta_1 \text{auxmoney}_{t,b} + \Delta_s + \Delta_t + u_{t,b}, \tag{18}$$

where $\sigma_{t,b}$ is the rate of default of loans provided by bank b, $\text{auxmoney}_{t,b}$ is a dummy variable that takes value one when the lender is Auxmoney and zero otherwise, Δ_s and Δ_t are state and time fixed effects, respectively, and $u_{t,b}$ is the error term.

[Table XI]

Table XI presents the results. It shows that the default rate on Auxmoney loans is significantly higher than the default rate on bank loans; Auxmoney borrowers have about

a 5.2% higher rate of default. The result is robust to the inclusion of state and time fixed effects. This result provides support for Hypothesis 2.

C. Hypothesis 3

The risk-adjusted interest rates on bank loans are higher than the risk-adjusted interest rates on P2P loans.

Since P2P loans are riskier and carry higher interest rates than bank loans, we compare loan interest rates after adjusting for risk differences – i.e., we test our third hypothesis.

We calculate the risk-adjusted interest rates charged by both P2P lending and banks under the assumption of risk neutrality by using the following formula:

$$r_{t,b} = (1 - \sigma_{t,b}) \times (1 + i_{t,b}) + \sigma_{t,b} \times RR_{t,b} - 1, \tag{19}$$

where $r_{t,b}$ is the risk-adjusted interest rate charged by bank b at time t, $i_{t,b}$ is the nominal (stated) interest rate, and $\sigma_{t,b}$ is the probability of default that we have already described in Section III. $RR_{t,b}$ is the recovery rate. We repeat the same procedure for P2P lending.[42] *Table XII* reports the summary statistics of the risk-adjusted interest rates for both bank and P2P loans. An eyeballing of the data in this table indicates that, after adjusting for risk differences, Auxmoney interest rates move closer to those on bank loans. The standard deviation of the risk-adjusted interest rates on P2P loans is larger than that for banks, 3.24 versus 1.43. This result is driven by the greater default-risk heterogeneity among P2P borrowers than among bank borrowers, something not evident in the earlier data presented in *Table II*.

[Table XII]

As before, we test whether the risk-adjusted interest rates on P2P and bank loans are significantly different using a dummy variable:

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[42]We assume zero recovery rate for both P2P and bank lending because loans are fully written down from banks' balance sheets.

$$r_{t,b} = \beta_2 \text{auxmoney}_{t,b} + \Delta_j + \Delta_t + e_{t,b} \tag{20}$$

where $r_{b,t}$ is the risk-adjusted interest rate charged by bank b or Auxmoney, $\text{auxmoney}_{t,t}$ is a dummy variable that takes value one when the lender is Auxmoney and zero otherwise, Δ_s and Δ_t are state and time fixed effects, respectively, and $u_{t,b}$ is the error term.

Table XIII presents the results. Consistent with our hypothesis, after adjusting loan interest rates for risk differences, we find that Auxmoney charges lower interest rates than banks on its loans. Auxmoneys risk-adjusted interest rate is between 3.35% and 3.14% lower than that on bank loans. The difference is statistically significant at the 1% level and is robust to including state fixed effects, time fixed effects, or both. This result provides support for our Hypothesis 3.

[Table XIII]

V. Conclusion

This paper examines how P2P lenders and banks compete for borrowers. We develop a simple theoretical model of bank and P2P lending that generates three predictions, and we test these predictions. First, we document that P2P lending increases and total bank lending declines when some banks face higher regulatory costs. We examine an exogenous shock to the capital requirements of some banks and provide causal evidence, through a diff-in-diff analysis, that P2P lending increases when some banks face higher regulatory costs. This effect is more pronounced in states where the banks that are unaffected by the regulatory shock are capital-constrained nonetheless, and where borrowers are more "aware" of Auxmoney's existence – i.e., where these two forms of lending are at least partial substitutes. Second, we document that Auxmoney, the largest P2P lender in Germany, charges higher loan interest rates than banks. But we also find that P2P borrowers are riskier and less profitable than bank borrowers. This means that P2P lenders are not skimming the

cream. Rather, they are bottom fishing when they pry borrowers away from banks. Third, once we control for default risk, we find that risk-adjusted interest rates are lower for P2P loans than for bank loans.

Our findings have several implications. First, P2P lending appears to be expanding with a bottom-fishing strategy that likely has positive social welfare implications because it extends credit to borrowers who were either not served by banks or are being denied credit by banks experiencing an increase in regulatory costs. Second, the advent of P2P lending may cause the banking sector to shrink, but also to be less risky and possibly more profitable in terms of risk-adjusted returns on assets. Whether this is underway on a broader scale in the credit market is an interesting topic for future research.

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Figures

Figure 1. New Lending by P2P Platforms and Banks.
This figure shows the volume of new consumer loans per quarter of German banks and Auxmoney, the largest P2P lending platform in Germany. Bank lending refers to nonconstruction consumer credit lines (overdraft credit, lines with up to one-year maturity, and lines with between one and five years maturity) in 105 Sparkassen and Volksbanken in Germany, and is defined in billions of €. Auxmoney's credit provision is defined in millions of €. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics, and Auxmoney, sample period: first quarter 2010 until first quarter 2014.
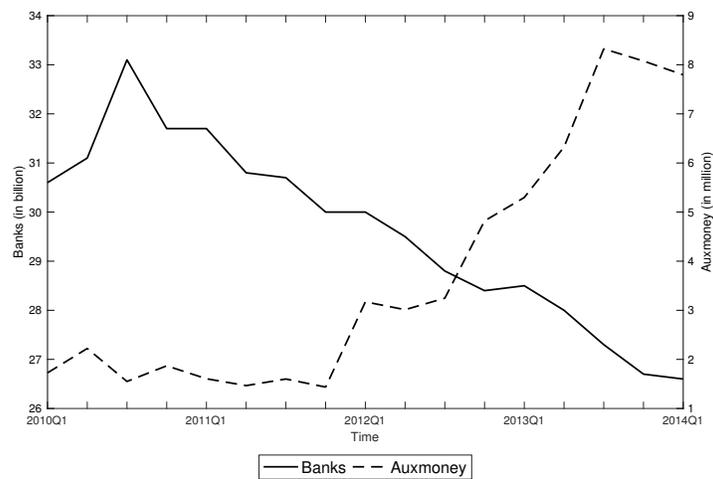
Figure 2. Sequence of events of the model. This figure summarizes the timing of the model.

Sequence of Events

t=0   t=1

- Bank's cost of acquiring a borrower, $\widetilde{\alpha}_B$ is realized.
- P2P platforms face a cost $\widetilde{\alpha}_P \geq \widetilde{\alpha}_B$.
- Borrower takes a loan of L, with repayment obligation of L_R^i, $i \in \{g, G\}$.
- Good loan can be g or G.
- Bank can also invest in B loan that generates private benefit Π.
- L is financed with a mix of debt, D^i, and equity, E^i.
- A competing bank may or may not arrive.

- g pays off L_R^g with probability (w.p.) q and 0 w.p. $1 - q$.
- G pays off L_R^G w.p. p and 0 w.p. $1 - p$.
- $p > q$.
- The repayment probabilities of G and g for a P2P lender are $\bar{p}$ and $\bar{q}$ respectively, with: $p \geq \bar{p} > q \geq \bar{q}$ and $\frac{p}{\bar{p}} = \frac{q}{\bar{q}}$
- All contracts are settled, and depositors are repaid D_R^i, $i \in \{g, G\}$, if the bank experiences loan repayment. Depositors also receive a liquid benefit γD if the bank does not default.

Figure 3. Share of credit provision by Auxmoney and banks on state-by-state basis in our sample.
This figure shows the geographical distribution of bank lending and P2P lending within our sample. The bright bar represents the share of Auxmoney lending in a giving state (in %). The dark bar represents the share of bank lending in a given state (in %). *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics, and Auxmoney, sample period January 2010 until September 2014.
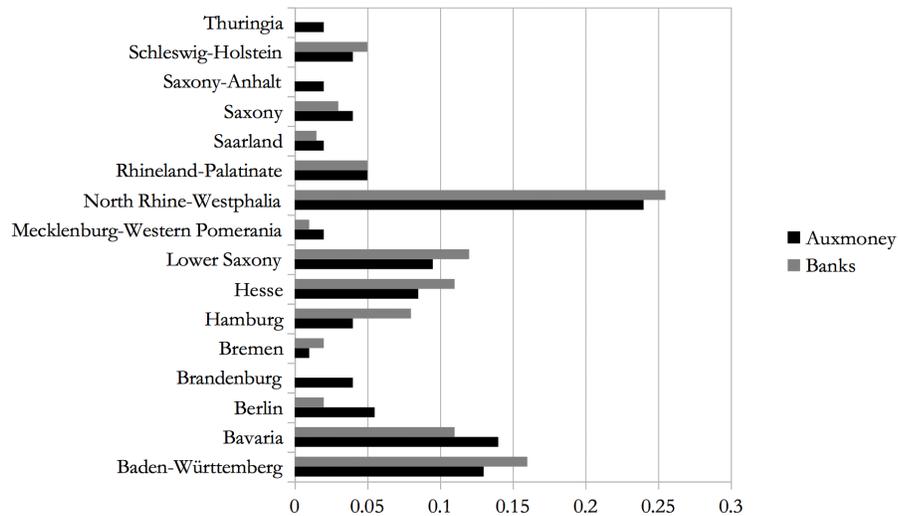
Figure 4. Schufa Score Distribution.
This figure shows the distribution of the German consumer credit score: Schufa Score. The figure compares the distribution of bank customers with Auxmoney customers. *Source:* Auxmoney and Korczak and Wilken (2010).
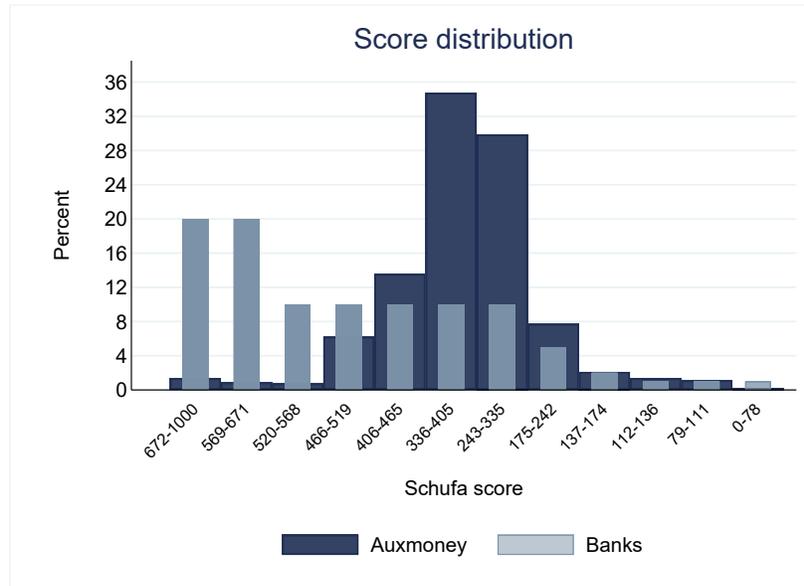
Figure 5. Lending by banks over time.
This figure shows the volume of new bank loans divided into two groups. Treated refers to states where HELABA and NordLB are present, *control* refers to all other states in the sample over the period 2010Q1-2014Q1. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics, and authors' calculation.
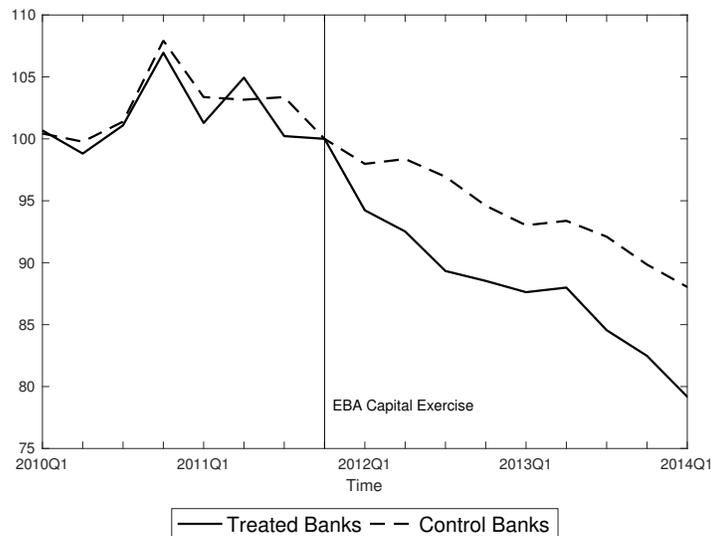
Figure 6. Lending by Auxmoney over time.
This figure shows the volume of new Auxmoney loans divided into two groups. *Treated* refers to states linked to HELABA and NordLB, *control* refers to all other states in the sample. *Source:* Auxmoney, authors' calculation.
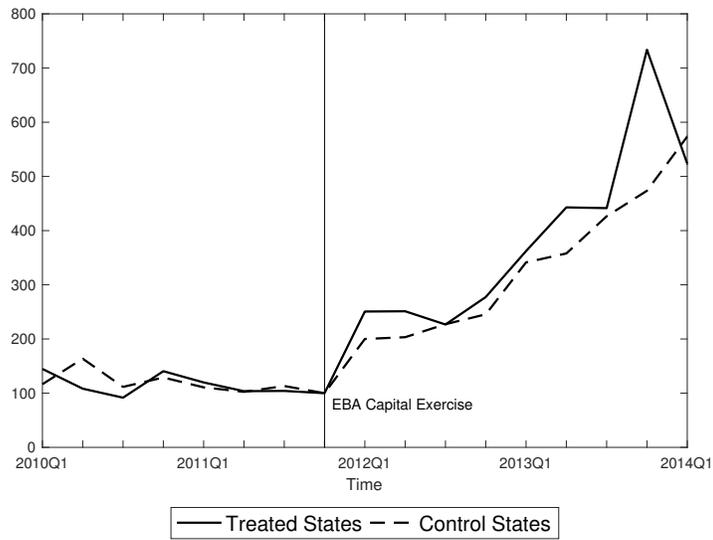
Tables

Table I Promised loan-repayment obligations to bank and the bank's promised deposit-repayment obligations.
This table summarizes the notation used in the model.

Loan Type	g		G	
Is a competing bank present?	No competing bank	Competing bank	No competing bank	Competing bank
Incumbent Bank				
Borrower's promised repayment obligation, L_R^i	x	$\widehat{L}_R^g$	x	$\widehat{L}_R^G$
Level of deposit, D^i raised at t=0	$\overline{D}^g$	$\widehat{D}^g$	$\overline{D}^G$	$\widehat{D}^G$
Repayment promised by incumbent bank and its depositors, D_R^i	$\overline{D}_R^g$	$\widehat{D}_R^g$	$\overline{D}_R^G$	$\widehat{D}_R^G$
Competing Bank				
Borrower's promised repayment obligation, $\widetilde{L}_R^i$	–	$\widetilde{L}_R^g = \widehat{L}_R^g$	–	$\widetilde{L}_R^G = \widehat{L}_R^G$
Level of deposit, $\widetilde{D}^i$ raised at t=0	–	$\widetilde{D}^g$	–	$\widetilde{D}^G$
Repayment promised by incumbent bank and its depositors, $\widetilde{D}_R^i$	–	$\widetilde{D}_R^g$	–	$\widetilde{D}_R^G$

Table II Lending volume, L, (in €) and interest rates, i, on new consumer loans by bank and month.

This table shows the descriptive statistics of the total volume of new consumer loans, L, per month by banks and for Auxmoney per German state and month and interest rates, i, charged by banks and Auxmoney on new consumer loans. Bank loans, L^b, are the mean between three categories: overdraft; short-term loans, which have a maturity from less than one year; and midterm loans which have a maturity between one and five years. New Auxmoney loan volume, L^{P2P}, is the total volume of new consumer loans provided by Auxmoney in each German state per month. This table shows that the mean size of Auxmoney is smaller than the mean size of any of the three bank loan categories. Interest rates, i^b, are the average interest rate between the same three categories: overdraft; short-term loans; and midterm loans. All charged by each single bank in each month on new consumer loans. Auxmoney interest rates, i^{P2P}, are the average interest rates charged by Auxmoney in each German state per month on new consumer loans *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics, and Auxmoney, sample period January 2010 until September 2014.

	Banks		Auxmoney	
	L^b	i^b	L^{P2P}	i^{P2P}
Mean	90,512,570	10.25	252,089	12.82
Std. Deviation	86,890,540	1.47	292,034	0.90
Min	-	-	-	9.19
25th pcl	44,151,000	9.37	85,503	12.21
50th pcl	68,470,000	10.33	160,022	12.84
75th pcl	106,767,000	11.29	297,367	12.12
Max	-	-	-	14.88
# Obs	6,512	6,512	590	590

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

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 IV Descriptive statistics of the default rate, σ, (in %).
This table shows the default rates, σ, of new bank loans and new Auxmoney, $P2P$, loans. Default rates of new bank loans are the adjusted mean of three categories: overdraft; short-term loans, which have maturities below one year; and midterm loans, which have maturities between one and five years. For data protection reasons, minimum and maximum values for banks cannot be presented. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics, and Auxmoney, sample period January 2010 until September 2014.

	Banks	Auxmoney
	σ^b	σ^{P2P}
Mean	2.22	7.32
Std Deviation	1.98	2.91
Min	-	0.88
25th pcl	0.60	6.25
50th pcl	1.37	6.25
75th pcl	3.60	8.77
Max	-	24.27
# Obs	5,800	590

Table V Relation between bank lending volume and Auxmoney lending volume.

This table shows the relation between bank and Auxmoney volumes of new consumer loans per month and per state. We estimate: $log(L_{b_jt}^{bank}) = \gamma_1 log(L_{jt}^{P2P}) + \gamma_2 log(L_{-b_jt}^{bank}) + \Delta_s + \Delta_t + \epsilon_{b_st}$, where L_{b_st} is the lending volume of bank b in state s at time t; L_{-b_st} is the lending volume by all other banks, $-b$, in state s at time t; and L_{st}^{P2P} is the lending volume from Auxmoney in state s and at time t, Δ_s is the state fixed effect, and Δ_t is the time fixed effect. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics, sample period January 2010 until September 2014.

	(I) $log(L_{b_st})$	(II) $log(L_{b_st})$	(III) $log(L_{b_st})$
$log(L_{st}^{P2P})$	0.01	-0.15***	-0.02**
	(0.03)	(0.03)	(0.01)
$log(L_{-b_s})$	-0.09	-1.30***	-1.41***
	(0.14)	(0.24)	(0.34)
State FE		Yes	Yes
Time FE			Yes
Cluster	Bank	Bank	Bank
adj. R^2	0.01	0.32	0.35
# Obs	6,026	6,026	6,026

Table VI Pre-treatment characteristics of banks and Auxmoney.
This table shows the lending volume, interest rates, and default rate for loans made by banks and Auxmoney in *treated* states and *control* states in the pre-treatment period (November 2010 until September 2011). Panel A provides average statistics for new bank loan volume aggregated by state, Panel B describes the data for individual banks' new loan volume, and Panel C describes the data for Auxmoney. We perform a test for differences in means using the Students t-test. (*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively). $\sigma_{t,s(b)}$ is risk in terms of default rate. Subscripts t represent time, s state, and b bank. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics, and Auxmoney.

Panel A: State	Treated States	Control States	Δ
log(Lending Volume)	13.84	12.87	0.97**
Interest Rate (%)	10.97	10.07	0.89***
$\sigma_{t,s}$ (%)	2.66	2.29	0.37

Panel B: Banks	Treated Banks	Control Banks	Δ
log(Lending Volume)	11.06	11.18	-0.12
Interest Rate (%)	11.02	10.13	0.56**
$\sigma_{t,b}$ (%)	2.48	2.18	0.30

Panel C: Auxmoney	Treated States	Control States	Δ
log(Lending Volume)	10.57	10.77	-0.19
Interest Rate (%)	13.84	13.69	0.15**
$\sigma_{t,s}$ (%)	7.51	8.18	-0.67*

Table VII Difference-in-differences estimation to determine effect of capital exercise on aggregate bank lending and P2P lending in treated states.

This table shows that overall bank lending declines and P2P lending increases in treated states. The table reports the estimated coefficient of the following three regressions: (i) State bank lending: $log(L_{t,s}) = \alpha_1 treated_s * EBA_t + \alpha_2 EBA_t + \alpha_3 treated_s + \Pi W_{t-1,s} + u_{t,s}$, (ii) Individual bank lending: $log(L_{t,b}) = \alpha_1 treated_b * EBA_t + \alpha_2 EBA_t + \alpha_3 treated_b + \Pi W_{t-1,b} + u_{t,b}$, and (iii) P2P lending: $log(L_{t,s}) = \beta_1 treated_s * EBA_t + \beta_2 EBA_t + \beta_3 treated_s + \Pi W_{t-1,s} + e_{t,s}$. Estimation (ii) is in the individual bank dimension and estimations (i) and (iii) are in the state dimension. The dependent variable $L_{t,b}$ is the total lending volume by bank b in month t, the dependent variable $L_{t,s}$ is the total lending volume in state s in month t, EBA_t is the treatment dummy that takes the value one from October 2011 onwards and zero prior to that, and $treated_{t,s(b)}$ is the dummy variable that identifies banks in the *treated states* and is equal to one for treated states (i.e., where HELABA or NordLB were present) and zero otherwise. In estimation (i), a treated state is one where HELABA and NordLB were present and the dependent variable is the total bank lending in that state. The control is total bank lending in other states (where HELABA or NordLB were not present). In estimation (ii), all banks (i.e., both Sparkassen and Volksbanken) in treated states are considered treated banks and those in control states are control banks. The dependent variable is the lending by an individual bank in the treated state. $W_{t-1,s(b)}$ is a vector of control variables that includes the default rate, σ – i.e., our proxy for risk – and interest rate is the average interest rate for new loans. Notation s(b) means that variable is in state dimension (I-III, VII-IX), and in the individual bank dimension in estimations (IV-VI). ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics, and Auxmoney.

	State Bank Lending			Individual Bank Lending			P2P Lending		
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
	$log(L_{t,s})$	$log(L_{t,s})$	$log(L_{t,s})$	$log(L_{t,b})$	$log(L_{t,b})$	$log(L_{t,b})$	$log(L_{t,s})$	$log(L_{t,s})$	$log(L_{t,s})$
EBA_t*treated$_{t,s(b)}$	0.01	-0.06***	-0.05**	-0.07***	-0.05***	-0.05***	0.60***	0.20***	0.22***
	(0.07)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.10)	(0.07)	(0.06)
EBA_t	-0.33***	-0.12***		-0.15***	-0.16***		0.29***	0.60***	
	(0.10)	(0.02)		(0.02)	(0.02)		(0.10)	(0.05)	
Treated$_{t,s(b)}$	1.20***			-0.01			-0.20***		
	(0.34)			(0.01)			(0.17)		
$\sigma_{t-1,s(b)}$	-0.15	0.01***	0.01	-0.01	0.01	0.00	-0.04***	-0.02**	-0.02**
	(0.09)	(0.00)	(0.004)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Int. Rate$_{t-1,s(b)}$	-0.29***	-0.01	-0.04***	-0.08***	-0.11***	-0.13***	-0.10**	-0.17***	0.04
	(0.17)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)	(0.04)	(0.05)	(0.03)
State FE		Yes	Yes		Yes	Yes		Yes	Yes
Time FE			Yes			Yes			Yes
Cluster	State	State	State	Bank	Bank	Bank	State	State	State
adj. R^2	0.17	0.99	0.99	0.04	0.24	0.25	0.10	0.62	0.79
# Obs	741	741	741	5,755	5,755	5,755	590	590	590

Table VIII Difference-in-differences estimation to examine the effect of the capital exercise on lending by treated and control banks in treated states.

The table reports the estimated coefficient of the following regression: $L_{bt} = \alpha_1 treated_b * EBA_t + \alpha_2 EBA_t + \alpha_3 treated_b + \Pi W_{bt} + u_{bt}$, where the dependent variable L_{bt} is the lending volume by banks, EBA_t is the treatment time dummy that takes the value one from October 2011 onwards, and $treated_b$ is the dummy variable that identifies the *treated banks* and is equal to one for *treated banks* and zero otherwise. In columns (I) to (III), the treatment group is the set of Sparkassen linked to treated Landesbank (HELABA or NordLB) and called *affected banks*. In columns (IV) to (VI), the treatment group is the set of Volksbanken in the states where HELABA or NordLB are present, called *unaffected banks in treated states*. For all the regressions, the control group consists of all individual banks (Sparkassen and Volksbanken) located in the states where HELABA or NordLB were not active – i.e., states that were not treated. W_{bt} is a vector of control variables that includes the default rate – i.e., our proxy for risk, and the variable Int. Rate is the average nominal interest rate of new loans by bank b at time t. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics, and Auxmoney.

	Affected Banks (Sparkassen)			Unaffected Banks (Volksbanken)		
	(I)	(II)	(III)	(IV)	(V)	(VI)
	$log(L^b)$	$log(L^b)$	$log(L^b)$	$log(L^b)$	$log(L^b)$	$log(L^b)$
EBA_t*Treated$_b$	-0.07**	-0.13***	-0.13*	-0.07	0.13	0.12
	(0.03)	(0.03)	(0.03)	(0.04)	(0.17)	(0.18)
EBA_t	-0.14***	-0.15***		-0.22***	-0.29*	
	(0.03)	(0.02)		(0.04)	(0.15)	
Treated$_b$	-0.06			0.06		
	(0.18)			(0.04)		
$\sigma_{t-1,b}$	-0.00	0.01	0.00	-0.00	0.00	0.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Int. Rate$_{t-1,b}$	-0.08*	-0.11***	-0.13***	-0.08***	-0.11***	-0.13***
	(0.04)	(0.00)	(0.00)	(0.00)	(0.04)	(0.04)
Bank FE		Yes	Yes		Yes	Yes
Time FE			Yes			Yes
Cluster	Bank	Bank	Bank	Bank	Bank	Bank
adj. R^2	0.06	0.24	0.25	0.04	0.24	0.25
# Obs	5,755	5,755	5,755	5,755	5,755	5,755

Table IX Test of lending responses to the shock by unaffected banks in treated states.
The table reports the test of whether, among banks unaffected by the EBA capital exercise, the banks with more capital increased their lending more. The test involves the following regression: $Expansion_{t,b} = \alpha_0 + \alpha_1 capital_{t-1,b} + \Delta_t + u_{t,b}$. The dependent variable $Expansion_{bt}$ is a dummy variable that takes the value one if the one-year increase in lending volume in 2012 puts the bank in the top quartile of lending increases, and zero otherwise. The explanatory variable is the bank equity capital of bank b at time t. Δ_t is the time fixed effect variable. The sample includes only banks unaffected by the capital exercise in states where HELABA and NordLB are present, and the time frame is from January 2012 to December 2012. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, Monthly Balance Sheet Statistics, and Auxmoney.

	(I) Expansion	(II) Expansion
$\text{Capital}_{t-1,b}$	15.22**	15.37***
	(6.11)	(3.07)
Time FE		Yes
Cluster	Bank	Bank
R^2	0.132	0.145
#Obs	108	108

Table X Difference-in-differences estimation and Google search for Auxmoney.
This table shows that the relationship between bank lending and P2P lending grows with consumer awareness about Auxmoney prior to the capital exercise. In column (I), the treatment group comprises the states affected by the EBA capital exercise; in column (II), the treatment group comprises the banks in treated states; and in column (III), the treatment group is Auxmoney lending in treated states. EBA_t is the treatment dummy that takes the value one from October 2011 onwards and zero prior to that; and $treated_{t,s(b)}$ is the dummy variable that identifies banks in the *treated states* and is equal to one for treated states – i.e., where HELABA or NordLB were present – and equals zero otherwise, in estimation (II). Control group is defined as lending volume in states where HELABA or NordLB were not active. σ is our proxy for risk, and interest rate is the average interest rate for new loans. Notation s(b) means that variable is in the bank dimension in estimations (I) and (III), and in the state dimension in estimations (II). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics, Auxmoney.

	Aggregate Bank Lending	Overall Bank Lending	P2P Lending
	(I)	(II)	(III)
	$log(L_{t,s})$	$log(L_{t,b})$	$log(L_{t,s})$
EBA_t*Treated$_b$	0.00	-0.06*	0.35***
	(0.10)	(0.03)	(0.10)
EBA_t	-0.27**	-0.16***	0.46***
	(0.11)	(0.04)	(0.07)
Treated$_b$	1.11***	-0.18	0.62***
	(0.09)	(0.17)	(0.15)
$\sigma_{t-1,s(b)}$	-1.16**	-0.00	-0.01**
	(0.54)	(0.08)	(0.00)
Int. Rate$_{t-1,s}$	-0.29***	-0.11**	-0.17***
	(0.08)	(0.04)	(0.04)
Google Search	-0.25***	-0.35**	1.15***
	(0.08)	(0.14)	(0.25)
Cluster	State	Bank	State
adj. R^2	0.155	0.094	0.431
# Obs	741	5,754	590

Table XI Difference in the default rate of bank loans and Auxmoney loans.
This table reports the estimation of the following regression: $\sigma_{t,b} = \beta_1 \text{auxmoney}_{t,b} + \Delta_s + \Delta_t + u_{t,b}$, where $\sigma_{t,b}$ is the default rate of bank b or Auxmoney, auxmoney_{bt} is a dummy variable equal to one when the lender is Auxmoney, and $\Delta_s + \Delta_t$ are respectively state and time fixed effects. The default rate of Auxmoney clients is derived from Schufa scores and those of banks' clients are from loan write-downs. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics, and Auxmoney, sample period January 2010 until September 2014.

	(I)	(II)	(III)
	$\sigma_{t,b}$	$\sigma_{t,b}$	$\sigma_{t,b}$
Auxmoney Dummy	5.21***	5.11***	5.09***
	(0.00)	(0.00)	(0.00)
State FE		Yes	Yes
Time FE			Yes
Cluster	Bank	Bank	Bank
adj. R^2	0.34	0.38	0.41
# Obs	6,390	6,390	6,390

Table XII Summary statistics: Risk-adjusted interest rates for bank loans and P2P (Auxmoney) loans.
This table shows that after adjusting for risk difference, Auxmoney interest rates are in line with those of banks. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics, and Auxmoney, sample period January 2010 until September 2014.

	Banks	Auxmoney
	r^b	r^{P2P}
Mean	7.79	4.45
Std Deviation	2.40	3.39
25th pcl	6.17	2.91
50th pcl	8.21	5.07
75th pcl	9.63	6.59
# Obs	5,800	590

Table XIII Test of difference in risk-adjusted interest rates on bank loans and Auxmoney loans.
This table reports the estimation of the following regression: $r_{t,b} = \beta_1 \text{auxmoney}_{t,b} + \Delta_s + \Delta_t + u_{t,b}$, where $r_{t,b}$ is the risk-adjusted interest rate of bank b or Auxmoney, $\text{auxmoney}_{t,b}$ is a dummy variable equal to 1 when the lender is Auxmoney, and $\Delta_s + \Delta_t$ are state and time fixed effects, respectively. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics, and Auxmoney, sample period January 2010 until September 2014.

	(I)	(II)	(III)
	r	r	r
Auxmoney Dummy	-3.35***	-3.14***	-3.06***
	(0.00)	(0.00)	(0.00)
State FE		Yes	Yes
Time FE			Yes
Cluster	Bank	Bank	Bank
adj. R^2	0.13	0.18	0.21
# Obs	6,390	6,390	6,390

Appendix

Proof of Proposition 1: Consider first the case in which no competitor arrives and the incumbent bank has the G loan. Then $L_R^G = x$. It is easy to show that the IC constraint (6) must hold tightly in equilibrium. Solving this yields:

$$\bar{D}_R^G = [px - \Pi]p^{-1} \tag{A1}$$

From the deposit pricing constraint (7), we have:

$$\bar{D}^G = \frac{p\bar{D}_R^G}{1 - p\gamma} \tag{A2}$$

Substituting (A1) in (A2) yields:

$$\bar{D}^G = [px - \Pi][1 - p\gamma]^{-1} \tag{A3}$$

Since (9) holds, we can verify that $\overline{D}^G \in (0, L)$. Thus, $\bar{E}^G = L - \bar{D}^G > 0$. Similarly, we can derive:

$$\bar{D}^g = [qx - \Pi][1 - q\gamma]^{-1} \tag{A4}$$

Since $p > q$, a comparison of (A3) and (A4) shows that

$$\bar{D}^G > \bar{D}^g \tag{A5}$$

Now suppose a competitor bank arrives. Let $\widetilde{L}_R^G$ be the loan repayment set by the competitor bank. From the IC constraint (6), we have:

$$\widetilde{D}_R^G = [p\widetilde{L}_R^G - \Pi]p^{-1} \tag{A6}$$

Substituting (A6) in the deposit pricing constraint (7) as before gives us:

$$\widetilde{D}^G = [p\widetilde{L}_R^G - \Pi][1 - p\gamma]^{-1} \tag{A7}$$

Now recognizing that $\widetilde{E}^G = L - \widetilde{D}^G$ and using (A7), the competing bank's NPV is:

$$p[\widetilde{L}_R^G - \widetilde{D}_R^G] - \widetilde{E}^G - \alpha - K \tag{A8}$$

$$= p[\widetilde{L}_R^G - \widetilde{D}_R^G] - L + [p\widetilde{L}_R^G - \Pi][1 - p\gamma]^{-1} - \alpha_B - K$$

$$= \Pi - L + [p\widetilde{L}_R^G - \Pi][1 - p\gamma]^{-1} - \alpha_B - K$$

The $\widetilde{L}_R^G$ at which this NPV becomes zero is:

$$\widetilde{L}_R^G = [p]^{-1}\{[1 - p\gamma][L - \Pi + \alpha_B + K] + \Pi\} \tag{A9}$$

Now, given (9), it follows that $\widetilde{L}_R^G = \widehat{L}_R^G < x$, where $\widehat{L}_R^G$ is the repayment obligation set by the incumbent bank to match the competing bank. From this, it follows that $\widehat{D}_R^G < \bar{D}_R^G$. Using similar analysis, it can also be shown that $\widehat{D}_R^g < \bar{D}_R^g$. The proof of $\widehat{D}_R^g < \widehat{D}_R^G$ and $\bar{D}_R^g < \bar{D}_R^G$ follows from $p > q$. Similarly, the proof for the case in which the competitor is a P2P lender follows the same lines as the proof above ∎

Proof Lemma 1: The regulator solves

$$\max_{D^G} p\left[L_R^G - D_R^G\right] - E^G - \Omega(D^G) \tag{A10}$$

subject to (5) - (8). Denote the regulator's choice of D^G that maximizes (A10) as D_O^G. Substituting for D_R^G from (7) and for E^G from (8), the first-order condition that yields D_O^G is

$$p\gamma - \Omega'(D_O^G) = 0 \tag{A11}$$

and the convexity of Ω guarantees satisfaction of the second-order condition. Now, it follows that $D_*^G = \min\{\bar{D}^G, D_O^G\}$ is the optimal solution to the regulator's problem. Thus, it follows that the regulator's choice of deposit level is less than or equal to the bank's choice.∎

Proof of Corollary 1: Solving for the incumbent bank's expected profit at $\widetilde{L}_R^G$ (from the Proof of Proposition 1):

$$= \Pi + [p\widetilde{L}_R^G - \Pi][1 - p\gamma]^{-1} - L - K$$

$$= \alpha_B \quad \text{(upon substituting for } \widetilde{L}_R^G \text{ from (A9))}$$

$$> 0 \qquad\qquad\qquad ∎$$

Proof of Proposition 2: To break even, the loan repayment set by a P2P lender on a

g loan, $\widetilde{L}_R^g$, must satisfy:

$$\bar{q}\widetilde{L}_R^g - L - \alpha_P = 0$$

which yields

$$\widetilde{L}_R^g = [L + \alpha_P]\bar{q}^{-1} \tag{A12}$$

By (9), we know that $\widetilde{L}_R^g < x$.

If a P2P lender arrives, an incumbent bank will have to offer the borrower $\widetilde{L}_R^g$. From the IC constraint (6) for the incumbent bank, we have:

$$\widehat{D}_R^g = [q\widetilde{L}_R^g - \Pi]q^{-1}, \tag{A13}$$

and using the pricing constraint (7), we have the deposit level

$$\widehat{D}^g = [q\widetilde{L}_R^g - \Pi][1 - q\gamma]^{-1}. \tag{A14}$$

Given (10), we know (after substituting for $\widetilde{L}_R^g$ from (A12)) that $\widehat{D}_g < L$.

Now, at $\widetilde{L}_R^g$, the NPV of the incumbent bank is

$$= q[\widetilde{L}_R^g - \widehat{D}_R^g] - \widehat{E}_g - K$$
$$= q[\widetilde{L}_R^g - \widehat{D}_R^g] - [L - \widehat{D}^g] - K$$
$$= \Pi + [q\widetilde{L}_R^g - \Pi][1 - \gamma q]^{-1} - L - K$$

(substituting for $\widehat{D}_R^g$ from (A13))

$$= \Pi + [\left(\frac{q}{\bar{q}}\right)(L + \alpha_P) - \Pi][1 - \gamma q]^{-1} - L - K$$

(substituting for $\widetilde{L}_R^g$ from (A12))

$$= \gamma q[L - \Pi + \left(\frac{q - \bar{q}}{\bar{q}}\right)L][1 - \gamma q]^{-1} - K + \left(\frac{q}{\bar{q}}\right)[\alpha_P][1 - \gamma q]^{-1} \tag{A15}$$

If the NPV in (A15) is non-negative, then the P2P lender will be unable to pry the borrower away from the incumbent bank. From (A15), we see that:

$$\gamma q[L - \Pi + \left(\frac{q - \bar{q}}{\bar{q}}\right)L][1 - \gamma q]^{-1} - K + \left(\frac{q}{\bar{q}}\right)[\alpha_P][1 - \gamma q]^{-1} > 0 \tag{A16}$$

if $\alpha_P \equiv \alpha + b + c \geq A_2$. In this case, no bank loses any loan to P2P lenders. In $\alpha_P < A_2$, then the bank loses g loans to P2P lenders because the incumbent bank's NPV from lending is negative at the best rate the P2P platform can offer.

Using similar steps, we can show that the bank with the G loan will have a non-negative NPV from lending when faced with P2P platform competition if:

$$\gamma p[L - \Pi + \left(\frac{p - \bar{p}}{\bar{p}}\right)L][1 - \gamma p]^{-1} - K + \left(\frac{p}{\bar{p}}\right)[\alpha_P][1 - \gamma p]^{-1} > 0 \tag{A17}$$

We can show that (A17) holds if $\alpha_P \geq A_1$. This means that if $\alpha_P \in [A_1, A_2)$, then banks with g loans lose them to P2P lenders, but banks with G loans do not. For $\alpha_P < A_z$ it is

clear that $Pr(\alpha_P > A_1)$ is increasing in c, so the probability of the bank losing the g loan to a P2P lender is increasing in consumer awareness of P2P lending. Finally, as s increases, F shifts to the right in the sense of first-order stochastic dominance, so $Pr(\alpha_P > A_1)$ decreases as s increases. ∎

Proof of Corollary 2: Let μ be the Lebesgue measure of $[A_1, A_2)$ in Proposition 2. Then

$$\mu = A_2 - A_1$$
$$= K\{[1 - q\gamma][\bar{q}/q] - [1 - p\gamma][\bar{p}/p]\} + \gamma\{L[p - q] - \pi[\bar{p} - \bar{q}]\} \tag{A18}$$

Thus,

$$\frac{\partial \mu}{\partial K} = \{[1 - q\gamma][\bar{q}/q] - [1 - p\gamma][\bar{p}/p]\}$$
$$> 0 \tag{A19}$$

To see the effect of higher capital requirements, note that we know from Lemma 1 that a bank's expected profit is strictly increasing in its leverage (deposit level), subject to the IC constraint being satisfied. Thus, if its regulatory capital requirement is raised above that needed to satisfy its IC constraint, the loan interest rate at which its profit becomes zero can become higher than the rate at which a competing bank's rate becomes zero, for some α realizations. ∎

Proof of Corollary 3: Follows immediatialy from the discussion in the text. ∎

Internet Appendix

Table AI Distribution of Auxmoney loans by maturity.
This table shows the distribution of Auxmoney loans by maturities in terms of number of loans (# Loans) and total volume (Volume). Auxmoney loan maturities range from one to five years and are divided into five buckets. *Source:* Auxmoney, sample period October 2008 until September 2014. Note: This statistic was provided separately by Auxmoney.

	Auxmoney	
Maturity	# Loans	Volume
12	1,310	3,688,350
24	2,533	9,221,550
36	3,292	15,813,900
48	2,084	16,356,700
60	1,405	16,140,600

Diff-in-diff placebo test. The placebo estimation uses fictive dates for the EBA capital exercise nine and three months before, and nine and three months after the actual exercise. Using placebo dates before the EBA capital exercise, we analyse whether the treatment was anticipated and the parallel-trend assumption violated. This is the case when the diff-in-diff interaction term is significant. The placebo estimations after the actual treatment show that the effect on bank and P2P lending is persistent but reduces with time.

We estimate the four placebo tests for equations (15), (16), and (17), which are presented in *Tables AII , AIII* , and *AIV* . For the estimation using placebo treatments before the actual treatment, we restrict our sample until October 2011, in order to avoid the possibility that the significance of the post-EBA period could influence the test results. The coefficient of our interest is the interaction EBA_t*$Treated_b$. The pattern of the results is the same in all three tables. The diff-in-diff interaction term is not significant in placebo tests before the EBA capital exercise. This result suggests that the treatment was not anticipated and we find no evidence that the parallel-trend assumption was violated. For placebo estimations, after the EBA capital exercise, we find that the diff-in-diff interaction term is significant. Moreover, we find that the effect of the treatment reduces over time. On the bank side, the intensity of the lending reduction due to the capital exercise diminishes with time. On the P2P lending side, the extra lending on treated states also reduces.

Overall, our results are consistent with the view that the EBA stress test was not anticipated and its effect reduces over time.

Table AII Placebo difference-in-differences estimation bank lending by state.
This table shows that using placebo dates for the treatment, no effect on bank lending can be found, and using placebo dates after the treatment, the effect is still significant but reduces its magnitude over time. (I) presents a placebo estimation nine months before actual treatment, and (II) three months. In both estimations, the sample is restricted to the treatment date. We estimate: $log(L_{t,s}) = \alpha_1 treated_s * EBA_t + \alpha_2 EBA_t + \alpha_3 treated_s + \Pi W_{t-1,s} + u_{t,s}$. The estimation is in the state dimension. The variable $L_{t,s}$ is the total lending volume in state s in month t, EBA_t is the placebo treatment dummy, and $treated_{t,s}$ is the dummy variable that identifies banks in the *treated states* and is equal to one for treated states (i.e., where HELABA or NordLB were present) and zero otherwise. A treated state is one where HELABA and NordLB were present and the dependent variable is the total bank lending in that state. The control is total bank lending in other states (where HELABA or NordLB were not present). $W_{t-1,s}$ is a vector of control variables that includes the default rate, σ– i.e., our proxy for risk – and interest rate is the average interest rate for new loans. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics.

	State Bank Lending			
	(I) $log(L_{t,s})$ $t-9$	(II) $log(L_{t,s})$ $t-3$	(III) $log(L_{t,s})$ $t+3$	(IV) $log(L_{t,s})$ $t+9$
EBA_t*Treated$_s$	-0.01	-0.01	-0.05***	-0.03**
	(0.01)	(0.01)	(0.01)	(0.01)
$\sigma_{t-1,s}$	0.00	0.00	0.01*	0.01
	(0.00)	(0.00)	(0.00)	(0.00)
Int. Rate$_{t-1,s}$	-0.02	-0.02	-0.04*	-0.04*
	(0.02)	(0.02)	(0.02)	(0.02)
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster	State	State	State	State
adj. R^2	0.99	0.99	0.99	0.99
# Obs	273	273	741	741

Table AIII Placebo difference-in-differences estimation bank lending by bank.
This table shows that using placebo dates for the treatment, no effect on bank lending can be found, and using placebo dates after the treatment, the effect is still significant but reduces its magnitude over time. (I) presents a placebo estimation nine months before actual treatment, and (II) three months. In both estimations, the sample is restricted to the treatment date. We estimate: $log(L_{t,b}) = \alpha_1 treated_b * EBA_t + \alpha_2 EBA_t + \alpha_3 treated_b + \Pi W_{t-1,b} + u_{t,b}$. The estimation is in the bank dimension. The variable $L_{t,b}$ is the total lending volume in bank b in month t, EBA_t is the placebo treatment dummy, and $treated_{t,b}$ is the dummy variable that identifies banks in the *treated states* and is equal to one for treated states (i.e., where HELABA or NordLB were present) and zero otherwise. A treated state is one where HELABA and NordLB were present and the dependent variable is the total bank lending in that state. The control is total bank lending in other states (where HELABA or NordLB were not present). $W_{t,b}$ is a vector of control variables that includes the default rate, σ – i.e., our proxy for risk – and interest rate is the average interest rate for new loans. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics.

	Individual Bank Lending			
	(I)	(II)	(III)	(IV)
	$log(L_{t,b})$	$log(L_{t,b})$	$log(L_{t,b})$	$log(L_{t,b})$
	$t-9$	$t-3$	$t+3$	$t+9$
EBA_t*Treated$_b$	-0.00	-0.02	-0.05***	-0.03***
	(0.02)	(0.02)	(0.01)	(0.04)
$\sigma_{t-1,b}$	0.01	0.01	0.00	0.00
	(0.03)	(0.03)	(0.01)	(0.00)
Int. Rate$_{t-1,b}$	-0.10*	-0.10*	-0.13***	-0.13***
	(0.05)	(0.05)	(0.01)	(0.01)
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank
adj. R^2	0.19	0.19	0.25	0.25
# Obs	1,963	1,963	5,755	5,755

Table AIV Placebo difference-in-differences estimation P2P lending.
This table shows that using placebo dates for the treatment, no effect on bank lending can be found, and using placebo dates after the treatment, the effect is still significant but reduces its magnitude over time. (I) presents a placebo estimation nine months before actual treatment, and (II) three months. In both estimations, the sample is restricted to the treatment date. We estimate: $log(L_{t,s}) = \alpha_1 treated_s * EBA_t + \alpha_2 EBA_t + \alpha_3 treated_s + \Pi W_{t-1,s} + u_{t,s}$. The estimation is in the state dimension. The variable $L_{t,s}$ is the total lending volume in state s in month t, EBA_t is the placebo treatment dummy, and $treated_{t,s}$ is the dummy variable that identifies banks in the *treated states* and is equal to one for treated states (i.e., where HELABA or NordLB were present) and zero otherwise. A treated state is one where HELABA and NordLB were present and the dependent variable is the total P2P lending in that state. The control is total P2P lending in other states (where HELABA or NordLB were not present). $W_{t-1,s}$ is a vector of control variables that includes the default rate, σ– i.e., our proxy for risk– and interest rate is the average interest rate for new loans. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively. *Source:* Auxmoney.

	P2P Lending			
	(I) $log(L_{t,s})$ $t-9$	(II) $log(L_{t,s})$ $t-3$	(III) $log(L_{t,s})$ $t+3$	(IV) $log(L_{t,s})$ $t+9$
EBA_t*Treated$_s$	0.04	0.19	0.20***	0.17***
	(0.09)	(0.17)	(0.06)	(0.06)
$\sigma_{t-1,s}$	-0.02	-0.02	-0.02**	-0.02**
	(0.02)	(0.02)	(0.00)	(0.00)
Int. Rate$_{t-1,s}$	0.19***	0.18***	0.03	0.03
	(0.05)	(0.05)	(0.02)	(0.02)
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster	State	State	State	State
adj. R^2	0.53	0.53	0.79	0.79
# Obs	151	151	590	590

Diff-in-diff with small banks. To further crystalize our results we investigate whether our results hold when using a sample of smaller banks. Those are the banks better comparable to the Auxmoney platform. For this analysis, we select the lower 33 percentile of banks in the sample based on their total assets as of 2012. We repeat the same analysis and estimate Equations 15 and 16 using the restricted banks sample. Table AV presents the results. All coeficients remain significant and retain the same sign. Hence, we conclude that our results are robust even when compared only with a sample of better comperable banks.

Table AV Difference-in-differences estimation to determine effect of capital exercise on aggregate SMALL bank lending and P2P lending in treated states.

This table shows that overall small bank lending declines and P2P lending increases in treated states. The table reports the estimated coefficient of the following three regressions: (i) State bank lending: $log(L_{t,s}) = \alpha_1 treated_s * EBA_t + \alpha_2 EBA_t + \alpha_3 treated_s + \Pi W_{t-1,s} + u_{t,s}$, (ii) Individual bank lending: $log(L_{t,b}) = \alpha_1 treated_b * EBA_t + \alpha_2 EBA_t + \alpha_3 treated_b + \Pi W_{t-1,b} + u_{t,b}$, and (iii) P2P lending: $log(L_{t,s}) = \beta_1 treated_s * EBA_t + \beta_2 EBA_t + \beta_3 treated_s + \Pi W_{t-1,s} + e_{t,s}$. Estimation (ii) is in the individual bank dimension and estimations (i) and (iii) are in the state dimension. The dependent variable $L_{t,b}$ is the total lending volume by bank b in month t, the dependent variable $L_{t,s}$ is the total lending volume in state s in month t, EBA_t is the treatment dummy that takes the value one from October 2011 onwards and zero prior to that, and $treated_{t,s(b)}$ is the dummy variable that identifies banks in the *treated states* and is equal to one for treated states (i.e., where HELABA or NordLB were present) and zero otherwise. In estimation (i), a treated state is one where HELABA and NordLB were present and the dependent variable is the total bank lending in that state. The control is total bank lending in other states (where HELABA or NordLB were not present). In estimation (ii), all banks (i.e., both Sparkassen and Volksbanken) in treated states are considered treated banks and those in control states are control banks. The dependent variable is the lending by an individual bank in the treated state. $W_{t-1,s(b)}$ is a vector of control variables that includes the default rate, σ – i.e., our proxy for risk – and interest rate is the average interest rate for new loans. Notation s(b) means that variable is in state dimension (I-III, VII-IX), and in the individual bank dimension in estimations (IV-VI). ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively. *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics, and Auxmoney.

	State Bank Lending			Individual Bank Lending		
	(I)	(II)	(III)	(IV)	(V)	(VI)
	$log(L_{t,s})$	$log(L_{t,s})$	$log(L_{t,s})$	$log(L_{t,b})$	$log(L_{t,b})$	$log(L_{t,b})$
EBA_t*treated$_{t,s(b)}$	-0.22***	-0.11***	-0.10***	-0.13***	-0.12***	-0.11***
	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
EBA_t	0.03	-0.06***		-0.05***	-0.07***	
	(0.04)	(0.02)		(0.01)	(0.02)	
Treated$_{t,s(b)}$	1.05***			0.27***		
	(0.03)			(0.01)		
$\sigma_{t-1,s(b)}$	-0.16***	0.01**	0.00	0.01***	-0.02***	0.02***
	(0.03)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)
Int. Rate$_{t-1,s(b)}$	0.01	0.01***	-0.00	-0.02***	-0.04***	-0.03***
	(0.03)	(0.00)	(0.02)	(0.00)	(0.01)	(0.01)
State FE		Yes	Yes		Yes	Yes
Time FE			Yes			Yes
Cluster	State	State	State	Bank	Bank	Bank
adj. R^2	0.24	0.96	0.97	0.07	0.13	0.14
# Obs	513	513	513	1,806	1,806	1,806

Description of the *Google Search* dummy variable construction. We downloaded the time series of the search-data index of the word *Auxmoney* for each German state from January 2007 until November 2017. The search-data index in *Google Trends* are normalized to 100 for the month of highest search for each state. Also, *Google Trends* provides the relative amount of search between the states. Thus, in order to compare across states and through time within states, we renormalize the time series of the different states according to the ranking of the relative search across states. In particular, we use the ranking value as of November 2017 as the conversion factor of the time series of the state. For example, the highest search in November 2017 is in the state of Thuringia, and *Google Trends* assigns a value of 100 to this state. We, therefore, assign a conversion factor of 1 to this state. The second state is Mecklenburg-Western Pomerania with 94, and we use a conversion factor equal to 0.94 for the time series of Mecklenburg-Western Pomerania, etc.

Figure 7 presents the average Google search for the word "Auxmoney" in Germany from January 2010 until September 2014 (the sample period considered for our analysis). This value has a clear positive trend, which is consistent with the positive lending growth of P2P lending previously described.

Figure 7. Google Search for "Auxmoney".
The figure shows that the interest for Auxmoney, measured by the number of searches for the word "Auxmoney", increases over time. Google search is the average search for the word Auxmoney, and values are normalized to 100 at the largest observation. *Source:* Google Trends.
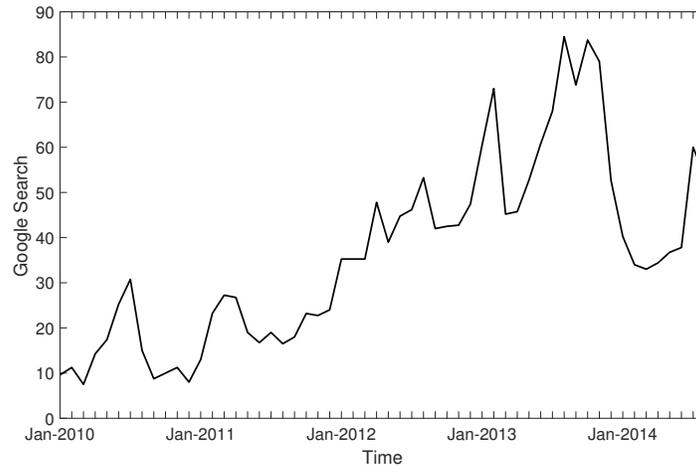
Descriptive statistics of Google search for the word "Auxmoney" in the different states and for Germany overall are reported in *Table AVI* .

Table AVI Descriptive statistics for Google searches of the word "Auxmoney."
This table shows that descriptive statistics of Google searches of the word "Auxmoney" across states and time. We renormalize the time series of the different states provided by Google Trends according to the ranking of the relative search across states. In particular, we use the ranking value as the conversion factor of the time series of the state. Source: *Google Trends*.

	Mean	SD	25 pcl	50 pcl	75 pcl	#Obs
Google Search "Auxmoney"						
All States	47.4	34.9	21.3	44.2	65.6	977
Baden-Württemberg	52.8	31.9	28.7	51.6	69.6	64
Bavaria	49.5	33.4	28.7	40.9	64.7	64
Berlin	54.4	37.3	22.9	50.8	71.3	64
Brandenburg	52.1	41.5	19.6	47.54	75.4	64
Bremen	36.7	31.1	14.7	31.1	55.7	46
Hamburg	42.3	33.3	19.7	31.1	55.7	62
Hesse	48.3	33.1	18.8	46.7	63.1	64
Lower Saxony	52.0	32.4	27.8	50.8	67.2	64
Mecklenburg-Western Pomerania	37.9	39.5	0	27.8	67.2	59
North Rhine-Westphalia	47.9	28.3	23.7	45.1	61.5	64
Rhineland-Palatinate	45.6	32.6	26.2	36.8	61.5	64
Saarland	32.7	30.0	0	24.6	55.7	58
Saxony	56.3	37.3	27.8	55.7	72.1	63
Saxony-Anhalt	37.3	30.4	14.7	36.1	55.7	58
Schleswig-Holstein	54.7	35.3	32.8	50.8	75.4	63
Thuringia	53.4	40.4	22.9	52.4	77.0	58

Table AVI shows that there is considerable heterogeneity across the different states in searches for the word "Auxmoney." The state with the lowest mean is Saarland (32.7) and one with the highest mean is Saxony (56.3). There is also a large variability in search through time within the different states. The state with the largest standard deviation is Brandenburg (41.5) and the one with the lowest is North Rhine-Westphalia (28.3). Because of this variability, the ranking changes intertemporally. This heterogeneity across states and within states through time enables us to use this variable to investigate whether different levels of "consumer awareness" matter for differences in the impact of Auxmoney lending on

bank lending cross-sectionally and through time.