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P2P Lenders versus Banks: Cream Skimming or Bottom Fishing?

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We derive three testable predictions from a bank-P2P lender model of competition: (a) P2P lending grows when some banks are faced with exogenously higher regulatory costs; (b) P2P loans are riskier than bank loans; and (c) the risk-adjusted interest rates on P2P loans are lower than those on bank loans. We test these predictions against data on P2P loans and the consumer bank credit market in Germany and find empirical support. Overall, our analysis indicates that P2P lenders are bottom fishing, especially when regulatory shocks create a competitive disadvantage for some banks. (*JEL* G21)

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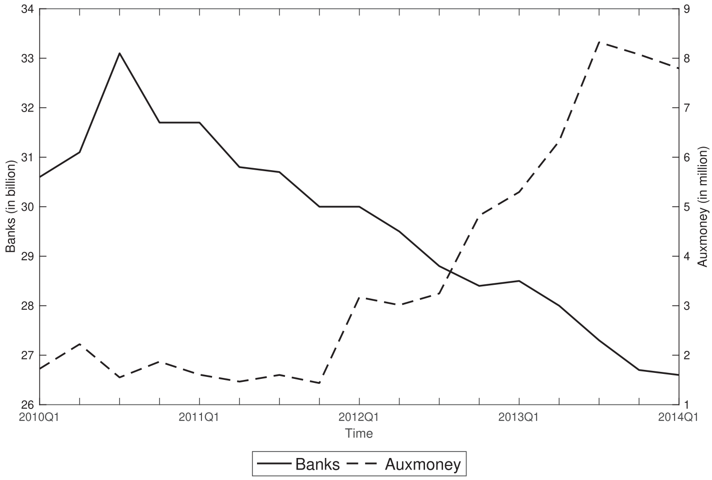

Fig. 1
New lending by P2P platforms and banks
This figure shows the volume of new consumer loans per quarter of German banks and Auxmoney, the largest P2P lending platform in Germany. Bank lending refers to nonconstruction consumer credit lines (overdraft credit, lines up to a 1-year maturity, and lines with between 1- and 5-year maturities) in 105 Sparkassen and Volksbanken in Germany, and is defined in billions of euros. Auxmoney's credit provision is defined in millions of euros. The sample period is the first quarter of 2010 until the first quarter of 2014. *Sources:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics, and Auxmoney.

Contemporary financial intermediation theories assign a pivotal role to banks as intermediaries between borrowers and savers (e.g., Boyd and Prescott 1986; Coval and Thakor 2005; Diamond 1984; Millon and Thakor 1985; Ramakrishnan and Thakor 1984),[1] with some emphasizing the value of deposit-taking and lending within the same institution.[2] Peer-to-peer (P2P) lending, which directly matches borrowers and lenders without relying on deposits and eliminates an intermediating bank, has gained traction in recent years in Europe, the United States, and China (see, e.g., Milne and Parboteeah 2016; Federal Reserve Bank of New York 2018; Braggion, Manconi, and Zhu 2020; Cornelli et al. 2020).

This increase in fintech lending is particularly interesting in light of Figure 1, which depicts the volume of new consumer loans in Germany provided by Auxmoney, the country's largest P2P platform, and by

[1] In these theories, banks either provide valuable screening to enhance investment efficiency (e.g, Coval and Thakor 2005; 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, whereby the 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.

savings and cooperative banks. As the figure makes clear, new bank loans are trending downward and new P2P loans are trending upward, although the absolute volume of bank lending far exceeds that of P2P lending.[3]

Commonly given explanations for the decline in bank lending relative to P2P lending point to advances in information technology—those that diminish the *relative* advantage of banks—and a heavier postcrisis 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; that is, are P2P platforms skimming the cream off of bank loans or bottom fishing? Are P2P platforms lending at higher or lower risk-adjusted interest rates than banks?

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] Leverage on the bank's balance sheet creates a risk-shifting distortion that must be attenuated with sufficient bank equity. Each bank also incurs a regulatory intermediation cost, which is the price of having access to profitability-enhancing deposits. In contrast, a P2P platform is a nonintermediated lender that finances its loans with money from investors. Following Philippon (2016), we view P2P loans as being all-equity financed; that is, 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.

Our summary statistics indicate that prior to the regulatory capital shock suffered by banks, about half of the P2P loans were riskier than the riskiest bank loans, suggesting that P2P lending is complementary to bank lending; the other half composed loans whose riskiness overlapped with the riskiness of bank loans, suggesting they are substitutes. We

3 Our focus is on the *interaction* between P2P lending and bank lending, that is, on the changes induced by this interaction, *not* on the *levels* of lending. Nonetheless, as we will discuss later, the volume of new lending by Auxmoney was about equal to that of a midsized bank in our sample by the end of 2018.

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.

mainly focus on the impact of an exogenous shock to bank capital requirements (which represented an increase in regulatory costs for banks) on the competitive interaction between banks and P2P lenders, not on the relative magnitudes of substitutability and complementarity. Our theoretical model predicts the following:

1. If some banks are subject to an exogenous shock in the form of an unexpected increase in regulatory costs, the unaffected competing banks increase their lending (at the expense of the affected banks) but only if they are sufficiently well-capitalized. These competing banks have an advantage over P2P platforms in taking market share from the affected banks because of their access to deposits. However, banks in the aggregate lose loan market share to P2P lenders when the unaffected banks are not sufficiently capitalized to replace the reduction in credit supply from the affected banks. This loss in market share is greater when the preshock awareness of P2P lending is higher. Thus, our theory presumes the potential substitutability between bank and P2P loans, because it deals with the migration of loans from banks—and the decline of aggregate bank lending—following a regulatory shock to some banks.
2. Loans pried away by P2P platforms are the riskiest bank loans, so that bank loan portfolios are subsequently safer. Thus, P2P platforms are bottom fishing.
3. The risk-adjusted interest rates on P2P loans are lower than those on bank loans.

Thus, our analysis focuses on the impact of higher regulatory costs as well as the presence of P2P lenders on (a) *new* lending by banks and (b) *new* loans by P2P lenders. We confront these predictions of our model with data on P2P and bank lending in Germany. The data on P2P lending are provided by Auxmoney, the largest and oldest P2P lending platform for consumer credit in Germany. Data on bank lending come from the Deutsche Bundesbank.

Because of the differences in origination between P2P and bank lending, we also compare the two data sets by examining risk and interest rate differences. Unlike those used by previous studies, our database includes detailed information on interest rates for new loans and the risk profiles of P2P and bank loans. Using German rather than U.S. data offers some advantages.[6] First, the U.S. consumer lending market is highly heterogeneous: it includes not only banks and P2P lending platforms but also

[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 the bulk of consumer lending is done by banks and lending platforms and banks face regulatory costs that exceed those of P2P lenders but have a

nonbank lenders like payday and title lenders. By contrast, consumer lending in Germany is primarily handled by banks, and the Bundesbank provides good bank-level data. Second, P2P lending platforms in the United States do not serve subprime borrowers. Lending Club and Prosper apply the minimum FICO score cutoffs of 660 and 640, respectively, to define credit-eligible borrowers; subprime borrowers typically have scores below 600.[7] Auxmoney does not apply this restriction, and subprime borrowers are also served by P2P lenders. Third, our data include interest rates on new loans, which permits a comparison of rates charged on bank loans and P2P loans. Fourth, the German financial system is bank-based, in contrast to the market-based U.S. system. These differences make the German setting ideal for our investigation, and the German data allow us to focus squarely 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]). These banks have geographical restrictions that facilitate a clean analysis at the bank-state level. Moreover, their primary mandate is to provide credit for the local economy, which makes them closer than global banks to the bank described in our model.

Our empirical results support the theoretical predictions. To provide causal evidence for our key result (Prediction 1), we employ a quasinatural experiment in which capital requirements for some banks—and hence their regulatory costs—unexpectedly increased because of a new regulation. The experiment is the European Banking Authority (EBA) capital exercise, which occurred in October 2011, a few months after the 2011 stress test and the subsequent failure of Dexia bank. The capital exercise required participant banks to attain a 9% core tier 1 capital ratio by the end of June 2012.[8] Two large Landesbanken in Germany reported large capital shortfalls: NordLB and HELABA (about €2.5 billion and €1.5 billion, respectively). Consequently, NordLB had to increase its capital as a percentage of total assets by about 1.1%, and HELABA had to increase capital as percentage of total assets by 1% (total assets of about €228 billion and €151 billion in 2011, respectively). Both represented substantial increases, and the precipitating shock was largely unexpected. Landesbanken are also known as the "central bank" of

deposit-related funding advantage over these platforms. Thus, the external validity of our results is not a concern.

[7] Nonetheless, evidence from U.S. P2P lending is also consistent with a prediction of our model, namely, that P2P platforms lend to borrowers who are riskier than those served by banks (see Chava et al. 2021; Di Maggio and Yao 2021).

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

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, while HELABA covers savings banks in Hesse and Thuringia.[9] We follow Puri, Rocholl, and Steffen (2011) and link the savings banks to their respective Landesbanken. When a Landesbank is required to raise more capital, the savings banks of these states also face higher regulatory costs due to their links with their Landesbank, since much of the additional capital is provided by these local savings banks. This has two effects on savings banks that both reduce their lending by these banks. One effect is direct: these banks are using loanable funds to purchase equity in their Landesbanken rather than lending 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 decreased their lending after the capital exercise, when compared to other savings banks and cooperative banks.[10] Moreover, we test (a) whether P2P lending rose more in those states where NordLB and HELABA operate and (b) whether this 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 preshock actions of the 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 (a) overall bank lending in affected states and (b) Auxmoney lending activity in affected states.

We find that overall bank lending decreases in states in which banks affected by the EBA exercise are present. Affected banks reduce their lending more than unaffected banks in these states. Auxmoney also increases its lending in the treated states and increases it by more if the *unaffected* banks in these states have low capital ratios.

To gain further insight into the effect of P2P lending, we examine whether the decline in bank lending in the regions with treated banks is affected by the cost to P2P lenders of luring bank borrowers away. We proxy this poaching cost with a measure of consumer awareness of P2P

9 In its 2012 Annual Report, NordLB describes its sources of capital to meet the higher requirements. They include 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 Pomerania, the State of Lower Saxony, and the State of Bremen. The capital came from a cash injection and the conversion of silent participations and other capital instruments.

10 Numerous papers have examined the impact of higher capital requirements on bank lending. See, for example, Gropp et al. (2018), who specifically examine the credit supply effect of the EBA exercise.

lenders, the idea being that greater awareness implies a lower poaching cost. Consumer awareness is measured by their Google search for "Auxmoney" in the treated states before the capital exercise. We document that Auxmoney experienced a larger increase in loan volume when consumers searched more often for the word "Auxmoney" prior to the capital exercise. We also verify that, subsequent to the capital shock, these internet searches increased more in treated states than in control states.

We then test Prediction 2 of our model, that P2P lenders pry away the riskiest borrowers from banks, thereby leaving banks with a safer borrower pool. Consistent with this prediction, we find that bank portfolios are less risky after the regulatory shock, whereas P2P lending becomes riskier.

Finally, we test Prediction 3 by examining risk-adjusted interest rates, and find that banks charge higher risk-adjusted interest rates than P2P lenders.

Although P2P lending in its present form is a relatively recent phenomenon that started in 2005 with the launch of Zopa, research interest has grown since Prosper (a competitor of Zopa) made the data for its entire platform available in 2007 (see, e.g., Pope and Sydnor 2011; Lin, Prabhala, and Viswanathan 2013; Morse 2015). P2P lending today is not limited to the peer-to-peer retail lending that marked its earliest days. Rather, the investors now include hedge funds and large institutions.[11]

Also relevant is the growing literature on fintech, which includes P2P lending as a component. Examples are Philippon (2015, 2016), Greenwood and Scharfstein (2013), and Buchak et al. (2018). Philippon (2016) argues that fintech can bring about efficiency-enhancing structural change in the financial services industry, but that political economy factors may impede that effect. Greenwood and Scharfstein (2013) emphasize that shadow banking activities, such as P2P lending, significantly facilitate higher household credit. Buchak et al. (2018) find that fintech firms set interest rates that are more predictive of ex post default rates than rates set by banks in the U.S. residential mortgage market.[12] A contemporaneous paper by Tang (2020) examines whether bank and P2P lending are complements or substitutes. Using a change in U.S. accounting rules that required banks to consolidate some off-balance-sheet securitization vehicles (with FAS 166/167)

[11] See Morse (2015) and Balyuk and Davydenko (2019). Buchak et al. (2018) point out that many of these institutions are recipients of government safety nets, protection, and subsidies, a scenario that raises concerns about the implications of risk spillover.

[12] In the same spirit, Vallee and Zeng (2019) focus on the investor side of P2P lending. Iyer et al. (2016) highlight the importance of soft information for borrower screening, and Butler, Cornaggia, and Gurun (2017) show that good access to local bank financing causes consumers who seek P2P 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 a screening device.

as a negative shock to bank credit supply, the paper documents that P2P lending in the U.S. is a substitute for bank lending in that it serves inframarginal bank borrowers, and is a complement for small loans. Thakor (2020) reviews this literature, and discusses various aspects of fintech, with a focus on the relationship between bank and P2P lending.

Our paper differs from this literature in various ways. First, unlike the above papers, we develop a theoretical model in which (a) intermediation costs for banks, (b) their role in providing liquidity services to depositors, (c) bank leverage, and (d) competition among banks and with P2P lenders are all elements that interact to generate predictions about the kinds of loans that will migrate from banks to P2P platforms. The theory illuminates the specific channels through which an increase in capital requirements for some banks leads to P2P lenders lending more and highlights the dependence of this market share gain by P2P lenders on the capital structure of the banks *unaffected* by the regulatory shock.

Second, this theory then permits us to use a shock to bank capital that differs from shocks considered in previous papers.[13] The fact that this shock affected banks *heterogeneously* allows us to examine its impact on subgroups of banks, aggregate bank lending, and on P2P lending, as well as the associated *reallocation* effects. This investigation leads to a nuanced view of the interaction between bank and P2P lending. Specifically, we document—consistent with the predictions of our model—that when banks face higher regulatory costs, the riskiest bank loans migrate to P2P lenders, causing declines in average risk in both bank lending and overall bank lending. This shift happens more when the *unaffected* banks in the region are capital constrained. None of these results appears in the previous literature. For example, Tang (2020) does not have any of our results on the supply of aggregate bank credit and credit reallocation effects across banks in response to a bank capital shock.[14]

Third, we also document that P2P loans have lower risk-adjusted interest rates than do banks. This finding is in sharp contrast to that of Buchak et al. (2018),[15] and is a finding not yet encountered in the prior literature.

[13] For example, our shock is both qualitatively and quantitatively different from that used by Tang (2020). We argue that our bank capital shock was unexpected and quite sudden. The absence of contemporaneous changes for P2P lenders permits a sharp delineation of the timing of the shock and facilitates our identification. We provide evidence of the lack of anticipation of the regulatory change.

[14] Tang (2020) examines whether bank and P2P loans are complements or substitutes. Although we find evidence similar to Tang's, her question is *not* our focus. However, our reallocation analysis sheds light on an important unanswered question in Tang (2020): given the heterogeneity among banks because FAS 166/167 did not affect all banks, why did nontreated banks not fill the "lending vacuum" created by the treated banks? This question is relevant in the context of earlier research that provides evidence of credit reallocation in response to systemic shocks (e.g., Berger and Bouwman 2013). We show that the ability of nontreated banks to react in this way depends on their capital ratios.

[15] The reason for this in our theory is different from the technological advantage in analyzing big data suggested in Buchak et al. (2018). They define fintech to include all types of financial-technology-assisted

Finally, we show that borrowers' pre-capital-shock awareness of P2P lending correlates with how the shock affected the migration of bank loans to P2P platforms. Greater awareness is related to higher migration.

In summary, to the best of our knowledge, our paper is the first to show that when some banks are hit with a capital shock, the effect of this on P2P lending, bank lending, and loan interest rates, depends on the capital levels of *unaffected banks* and *consumer awareness* of P2P lending, and that the bank loans that P2P platforms pry away have lower risk-adjusted interest rates than the rates on bank loans. In this respect, our paper also differs from papers that examine the *interbank* credit reallocation consequences of a capital shock suffered by *some* banks (e.g., Bord, Ivashina, and Taliaferro 2021).

1. Theory and Predictions

In this section, we develop a theoretical model that generates testable predictions about how bank lending is affected by competition between P2P lenders and banks.

1.1 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. Each borrower always has the possibility that a competing bank could bid for their business. For a competing bank, the cost of acquiring a borrower who is presently with another bank is $\tilde{\alpha}_B$, which represents the cost of prying away a borrower who has a loan from the incumbent bank. The variable $\tilde{\alpha}_B$ comprises (a) a random variable, $\tilde{\alpha} > 0$, and (b) a deterministic function, $b(s) \geq 0$, where s represents the strength of the incumbent bank's relationship with its borrower; that is, $\tilde{\alpha}_B = \tilde{\alpha} + b(s)$. 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 $\tilde{\alpha}$, which we refer to as α, becomes common knowledge at $t = 0$, before competition between lenders begins. Similarly, a P2P platform also faces a borrower acquisition cost $\tilde{\alpha}_P$ in prying away a borrower from a bank, where $\tilde{\alpha}_P \equiv \tilde{\alpha} + b(s) + c(w)$, 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 $\tilde{\alpha}_B \geq \tilde{\alpha}_P$.

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

lending, not just P2P loans, whereas we focus on P2P loans. Thus, ours is a more direct comparison of banks (which may use fintech) and P2P lenders.

structure for financing the loan. At $t = 1$, the borrower's project (financed with the loan) either pays off or does not pay off. The loan is repaid in full if the project pays off, and defaults if the project fails.

1.1.1 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 the "regulatory cost of intermediation" to the bank to be $K > 0$. We assume that the social cost of bank failure is $\Omega(D) > 0$, which is increasing and convex in D.[16] To minimize this cost, the regulator may supervise banks and impose other regulations (including capital requirements) on depositories, which can generate a regulatory cost K for banks. In the empirical analysis, we will interpret an increase in regulatory capital requirements for banks as a factor that contributes to an increase in K for banks. The base theoretical model does not have a regulatory capital requirement, so capital structure decisions are made to maximize the lender's shareholder value. We then go beyond the base model and discuss how a capital requirement will affect the analysis. Note that banks will not internalize Ω in their capital structure or lending decisions.

1.1.2 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 also x for this borrower. The payoffs on G and g are random variables. Whether the bank has g or G is exogenously specified for now.[17] In the cross-section of banks, some banks have g and some have G. Regardless of whether a bank has g or G, it has the option to unobservably invest instead in a loan, call it B, that generates a private benefit of $\Pi > 0$ for bank insiders (i.e., the manager who is also the inside shareholder) but no contractible payoff for outside financiers (i.e., depositors).[18] This moral hazard in lending is similar to that in Holmstrom and Tirole (1997). Further, banks' specialization in monitoring (e.g., Holmstrom and Tirole 1997) and screening (e.g., Ramakrishnan and Thakor 1984) may give them an advantage over P2P lenders in controlling borrower risk. To

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

[17] In Section 1.2, we will discuss what happens if the bank has both G and g.

[18] One can think about this loan in many ways. For example, the loan could be made to a family member or a friend.

reflect this possible advantage, we assume that the repayment probabilities of G and g for a P2P lender are $\bar{p}$ and $\bar{q}$, respectively, with

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

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

Both g and G are socially efficient, whereas B is not.[19] The competitive structure of the loan market is similar to that in Holmstrom and Tirole (1997) in the case in which intermediary capital is scarce. The incumbent bank can set the borrowers' repayment L^i_R 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 the one offered by the competing bank; that is, $L^i_R = \min\{x, \widehat{L}^i_R\}$, where $i \in \{g, G\}$ and $\widehat{L}^i_R$ is the loan repayment the incumbent bank must offer when there is a competing bank for loan i.

1.1.3 The bank's financing choices. The bank can finance the loan with any combination of deposits and (inside) equity. Let E denote (inside) equity[20] raised at $t = 0$ and D denotes 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 to $t = 1$, D^i_R, $i \in \{g, G\}$, after observing these terms. All corresponding values for the competing bank are designated with a tilde, $\tilde{D}^i$, $\tilde{D}^i_R$, $\tilde{L}^i_R$, $i \in \{g, G\}$.[21]

1.1.4 Liquidity value of deposits. Depositors derive a liquidity benefit of $\gamma > 0$ per dollar of deposits if the bank does not default.[22] An extensive literature tackles the microfoundations of this assumption.[23]

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19 Assuming $p\bar{p} = q\bar{q}$ means that the disadvantage faced by P2P lenders vis-à-vis banks is the same for g and G loans.

20 We do not address the agency problem between managers and shareholders in this context, and we simply assume managers and shareholders are the same.

21 See Table 1 in the Internet Appendix for a summary of the notation that we use in the model.

22 Figure 1 in the Internet Appendix summarizes the timeline describing the sequence of events.

23 For example, Merton and Thakor (2019) view bank depositors as "customers" who receive nonpecuniary service benefits from which they derive positive utility; these benefits do not accrue to the investors in the bank. Diamond and Dybvig (1983) view liquidity benefits as synonymous with consumption smoothing. Donaldson, Piacentino, and Thakor (2018) view liquidity benefits as stemming from a wealth-safeguarding advantage possessed by the bank that enables the bank to act as a depository that can create private money by writing "fake receipts," thereby enhancing aggregate investment beyond the endowment of the economy.

1.1.5 P2P platforms. A P2P lending platform is a nonintermediated form of lending that directly links investors to borrowers. As Philippon (2015) points out, P2P is nonleveraged 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.[24] Second, the platform does not have access to deposits, so all its financing comes from investors (rather than "customers"). Third, the platform does not incur the intermediation cost K that a bank incurs. As 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 consists of various fees, one of which is the 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.[25]

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

1.1.7 The role played by different elements of the model. The model has four key features: (a) deposits have a liquidity value to depositors, so they are cheap relative to equity as a source of funds, but deposits are only available to banks; (b) moral hazard in loan choice by the bank, which necessitates equity capital on the bank's balance sheet, with more capital needed to deter asset substitution from a less-profitable socially preferred loan to a socially inefficient loan; (c) a poaching cost for P2P to pry away a loan from an incumbent bank; and (d) a regulatory cost K for banks. Each element is crucial for our results.

Having deposits cheaper than equity (element (a)) and moral hazard in the bank loan choice (element (b)) are necessary for an interior optimal capital structure for the bank (Proposition 1), a result that forms the backbone of the rest of the analysis pertaining to the effect of an

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

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

exogenous shock to the bank's regulatory cost (via a higher capital requirement) that is independent of the riskiness or profitability of loans. A poaching cost for banks and P2P lenders (element (c)) is needed to ensure there is imperfect bank competition and that P2P lenders can pry away loans from banks only under *some* circumstances, which depend on the interaction between the P2P platform's poaching cost and (element (d)) the bank's regulatory cost (Proposition 2).

1.2 Analysis

First, we consider the case without P2P lenders, so there is only interbank competition. In this case we show that no bank will lose its borrowers to another bank, so the main effect of competition is to reduce loan prices. In what follows, there is no regulatory capital requirement on banks, but we discuss below 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 $V_i(D_i^*)=S_i[L_R^i-D_R^i]-E^i$ and D_i^* is the solution to $D_i^*\in_D\{V_i(D_i)-[1-S_i]\Omega(D_i)\}$, subject to $S_i[L_R^i-D_R^i]-E^i-K\geq 0$ 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:

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

subject to

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

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

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

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

The objective function in Equation (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. Equation (5) is the bank's participation constraint; Equation (6) is the incentive comparability (IC) constraint to ensure that the bank prefers G to B; Equation (7) is the depositors' pricing constraint that links the amount of deposits raised at $t=0$ to the deposit repayment obligation at $t=1$; and Equation (8) is simply the bank's balance sheet identity. If the bank has g, then we simply replace p with q and D_R^G with D_R^g.

To home in 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 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 case, the bank has to post some equity capital as "skin in the game" 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. In addition, 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 due to both 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 with which the bank can optimally finance itself.

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 Equations (4)–(8) but takes 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 less than or equal to $\bar{D}^i$ (without competitive entry) and less than or equal to $\widehat{D}^i$ (with 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 banks face the same K. The loan repayment obligation will be lower when a competing bank arrives than when it does not.

This result is straightforward. All banks are identical, but to take a borrower away from another bank, the competing bank incurs a "poaching cost" of α, so the incumbent can match the competing bank's best offer and still earn a positive expected profit on the 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 proven.

Proposition 2. If the realized $\alpha_P \equiv (\alpha + b + c) \in [A_1, A_2)$, banks with g loans lose borrowers to P2P lenders, but banks with G loans do not. If $\alpha_P \geq A_2$, no bank loses loans to P2P lenders. When P2P lenders 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 P2P lending growth is correlated with a decline in bank lending. As s, the strength of the incumbent bank's borrower relationship, increases, the probability of losing loans to P2P lenders declines. As w, the borrower awareness of P2P lending, increases, banks are more likely to lose loans. **Proof in Appendix.**

The intuition for this result arises from the fact that the G loan requires the bank to hold less capital to satisfy its incentive compatibility constraint than it would have to hold against the g loan. From this standpoint, the key difference between the G and g bank loans is not their innately different exogenous profitabilities, but rather the *endogenously higher* capital required for the g loan. Note that when a P2P competitor arrives, there is (Bertrand) competition between it and the incumbent bank, *so the bank loan is priced to yield the P2P lender zero expected profit, regardless of whether it is a g or G loan*. Nonetheless, at the loan price that yields zero expected profits to the P2P competitor, the incumbent bank's expected profit is higher on the G loan than on the g loan. This is because the G loan requires less capital than the g loan, which means that the bank's deposit funding cost advantage over P2P lenders is endogenously smaller with the g loan than with the G loan.

Whether banks lose G loans to P2P lenders depends on the poaching cost, α_P, that the P2P lenders must incur. 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 occurs 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 have been had these loans stayed on the banks' books. Because the bank optimally posts more capital against the g loan than against the G loan, the set of poaching cost values for which banks lose the g loan to P2P lenders is bigger. Further, the P2P lender's poaching cost declines when consumer awareness of P2P lending increases, and increases when the strength of the incumbent's relationship with the borrower is stronger. These results are intuitive.

To gain further insight into why this result is related to the incentive-compatibility-linked endogenous capital the bank needs to hold rather than the profitability difference *per se* between g and G, we show that our analysis holds even when the two loans have the same expected pledgeable payoff.

Suppose the G loan has a pledgeable payoff of x_G and the g loan has a pledgeable payoff of x, with $x > x_G > 0$ and $px_G = qx$ (maintaining the assumption $p > q$). *That is, both G and g loans have identical expected values*. With this, we have:

Corollary 2. Proposition 2 holds even if the G loan has a pledgeable payoff of x_G with probability $p \in (0,1)$ and 0 with probability $(1-p)$, and the g loan has a pledgeable payoff of x with probability $q \in (0,1)$ and 0 with probability $(1-q)$, with $x > x_G > 0$ $px_G = qx$. **Proof in Appendix.**

The intuition is as follows. As indicated earlier, when a P2P competitor arrives, the competitively set loan price yields the P2P lender zero expected profit on both g and G loans. Since the P2P lender's expected profit also includes its poaching cost and the bank has access to (cheap) deposit financing that the P2P lender does not, the incumbent bank still earns a positive expected profit on both g and G loans, even at prices at which the P2P competitor just breaks even. However, since g is *riskier* than G, the bank needs to keep more capital against g than against G to satisfy the IC constraint that guarantees the bank will eschew the private-benefit loan. This means less deposit financing with g than with G, making G more attractive to the incumbent bank.

Our model has no *regulatory* capital requirements. If we had capital requirements in our model and an exogenous shock required some banks to post capital beyond what was needed for incentive compatibility, then our analysis implies that those banks would lose more of their loan market share to P2P lenders than would banks that did not face higher capital requirements, independent of the profitability of the loans. Similarly, if a bank faces an exogenous shock that increases K, the bank will lose market share to P2P lenders and other banks that do not experience a higher K. This is summarized as follows:

Corollary 3. 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, and this increases the probability that the bank will lose its g loan to P2P lenders. Moreover, the incumbent bank may 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. **Proof in Appendix.**

If there are no P2P lenders, then an increase in K or capital requirements for some banks and not for others will have no perceptible effect on overall bank lending, since loans will simply shift from some banks to others.[26] But if P2P lenders take some of the loan volume away from the affected banks, then overall bank lending will fall. Thus, identifying an exogenous shock to K may help us identify a causal link between the presence of P2P lenders and bank lending.

Which loans are more 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 $\bar{q}x > L > qx - K$, then these loans will have a

[26] We can begin 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 constrained.

positive NPV for P2P lenders but a 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 4. 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. After this loan migration, the average risk-adjusted interest rate on the bank's loans increases. 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. **Proof in Appendix.**

Our model predicts that when banks are lending to borrowers who fall into two risk classes, competing P2P lenders pry away the riskier borrowers from banks (a prediction for which we provide large-sample evidence). One might view the fact that U.S. P2P lenders have FICO cutoffs below which they will not lend is an indication that they do not lend to the riskiest borrowers. We have two observations on this. First, our model best fits a credit market with two principal lenders: P2P platforms and depository institutions. This is what the German credit market that we use in our empirical analysis looks like. The U.S. credit market is a little different in that there is a richer variety of lenders, some of which, like payday and title lenders, specialize in lending to very risky borrowers. If we had a dynamic model that also had these lenders, it might well be the case that the intertemporal evolution of P2P lenders would lead them to compete with banks for loans of intermediate risk and leave the riskiest borrowers for payday and title lenders and others of their ilk; they would still make riskier loans than banks. Formally modeling these additional issues may be an interesting topic for future research but is outside the scope of our analysis. Second, the implication of our model is that P2P lenders that compete with banks for borrowers will lend to riskier borrowers on average than banks (not that P2P lenders will always seek the riskiest borrowers in the credit market). The evidence in Chava et al. (2021) and Di Maggio and Yao (2021) provides empirical support for this in the U.S. context as well. These papers document that those who borrow from marketplace lending platforms have higher default rates in the long run relative to those who receive bank loans.

We also analyze the situation in which a bank has both g and G loans in its portfolio, but we do not present the analysis here because all of our predictions are sustained, albeit with more algebraic complexity. The following observations emerge:

- 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 (it will require a lower α_P realization) for a P2P lender to pry away a g loan when a bank has both g and G loans than when it has only g loans.

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 starts with nothing and ends up with only g. The diversification across g and G increases the expected value of liquidity services to depositors, reduces the bank's cost of funding, and makes 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 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 will be unaffected if deposit insurance is actuarially fairly priced. We stress that we have considered a general model to reflect what the literature has highlighted: that is, 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 some banks are faced with an exogenous increase in regulatory costs. The greater the 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 aggregate.

Hypothesis 2. P2P loans are riskier than bank loans.

Hypothesis 3. The risk-adjusted interest rates of bank loans are higher than the risk-adjusted interest rates of P2P loans.

1.3 Link between the model and the empirical analysis

As discussed in Section 1, our model has four key features in a setting with two main lenders: bank (depositories) and P2P (or marketplace) platforms. We briefly explain here how these elements of the model and the ensuing analysis help to set up to the empirical examination that follows in the next section. The four elements—banks deposits are cheaper than equity, there is moral hazard in loan choice that requires the bank to hold equity, banks face a regulatory cost, and any lender faces a poaching cost to pry a borrower away from another lender—interact to give us the three hypotheses stated above.

An increase in regulatory costs makes lending less profitable for the bank, leading to a loss of market share. This loss in market share can be to other banks that may not suffer the same regulatory cost increase, in which case the banking system as a whole simply reallocates credit supply within the system but does not lose market share in the aggregate. However, if the banks unaffected by the regulatory-cost-increase shock are capital constrained, then they will be unable to pick up the entire slack. This allows P2P lenders to usurp market share from the banking system, as long as their poaching cost is not too high, that is, consumer awareness of P2P lending is high enough. This leads to Hypothesis 1.

Hypothesis 2 follows from the fact that moral hazard in lending necessitates that banks must hold more equity capital against riskier loans. Since capital is costly, banks optimally first shed their riskier loans when faced with P2P competition. Hypothesis 3 follows from the competitive structure of the credit market: a P2P lender can pry away a borrower from a bank only if its poaching cost is low enough to overcome the *net* effect of bank's funding-cost advantage and its regulatory cost disadvantage.

2. Institutional Background and Data Description

2.1 Institutional background

The German banking sector is a vast landscape of different types of banks. Large banks hold a relatively small market share of the consumer credit market, whereas small banks, mainly savings banks (Sparkassen) and cooperative banks (Volksbanken), hold about half 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 the existence of a large number of Sparkassen and Volksbanken. Currently, Germany has over 1,900 banks (about 540 Sparkassen and 900 Volksbanken).

At the end of 2015, Sparkassen had a 22.1% consumer credit market share, whereas Volksbanken had a 23.7% consumer credit market share. By comparison, large commercial banks had 6.3% of consumer credit. The other commercial banks and branches of foreign banks had a 41.8% share of the consumer credit market, Landesbank had 2.9% and non-bank credit institutions had 3.2%.[27]

Sparkassen are typically owned by their municipalities or a group of municipalities. Their customer base mainly consists of small and/or medium enterprises, as well as households. Volksbanken are cooperative banks, so their customers are also the bank's members and shareholders. Some of these banks historically developed as self-help organizations, a mission that still permeates many banks.

In part to avail themselves of economies of scales 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, and underwriting, and they also assist with state financing. In the case of Sparkassen, the umbrella bank is called a Landesbank (or state bank in English). Landesbanken are jointly owned by their member Sparkassen and the relevant state government.[28] In the case of Volksbanken, the umbrella bank is the DZ Bank, which provides similar services to its members, but without a political link to the regional government. This institutional structure is an integral part of the bank-based German financial system.[29]

The nature of the savings and cooperative banks in Germany means that these banks are largely engaged in relationship banking. For example, using a large sample of Sparkassens' loans, Puri, Rocholl and Steffen (2017) show that 73.6% of these loans were relationship loans. As suggested by the relationship banking literature, this creates stickiness in the bank-borrower relationship and creates customer acquisition costs for a bank's competitors.[30] This includes not only other banks but also P2P lenders.

Regarding the P2P market, Auxmoney is one of the ten leading P2P lending platforms in Europe. According to its website, from the day it

[27] Savings Banks Finance Group Financial Report (2015).

[28] The details of ownership sharing vary from state to state. See Puri, Rocholl, and Steffen (2011) for an ownership list of each Landesbank.

[29] See Allen and Gale (2001), who classify the U.S. financial system as market based and the German financial system as bank based.

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

began business in 2007 until late 2017, Auxmoney had provided a total volume of credit at about €1 billion, with an average growth rate of 85% per year. In 2018, Auxmoney's new lending was €551 million (an increase of 75% over 2017). Auxmoney performs loan evaluation and origination. Consistent with Morse (2015) and Balyuk and Davydenko (2019), a significant fraction of Auxmoney's lenders are backed by institutional investors, such as Aegon, a Dutch insurance company.

2.2 Data description

We use the following data sources: (a) Auxmoney for P2P lending data; (b) the Deutsche Bundesbank (Interest Rates Statistics) for bank lending data; (c) Schufa for credit ratings data; and (d) the Deutsche Bundesbank (Balance Sheet Statistics) for loan loss provisions.

Auxmoney provided us with two different data sets.[31] The first includes all loans between January 2010 and September 2014 with information on the location of borrowers, but not their maturity. The second includes the average interest rate and the average credit rating represented by the Schufa score for each state and month.[32] Auxmoney also provided us data on the distribution of its loan maturities. The maturities of Auxmoney loans range between 1 and 5 years. Three-year loans have the highest frequency and 1-year maturity loans the lowest. However, the largest volumes are for loans with 4- and 5-year maturities.[33]

The Deutsche Bundesbank statistics used in this study come from two different data sets. The first is the Interest Rates Statistics,[34] 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 for nonconstruction consumer credit lines (outstanding and new business) for different maturities (overdraft, up to 1 year, and greater than 1 year but less than 5 years).[35] The data set includes 236 of the 1,843 banks in Germany representing 81% of the total assets of the German banking sector (values as of January 2014), and we use monthly observations from January 2010 to September 2014. The second is the data set

31 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.

32 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.

33 The descriptive table provided to us by Auxmoney is reported in Table 2 in Internet Appendix B.

34 Interest Rates Statistics (MIR) is the German part of a larger data set used by the ECB for regulatory purposes. It covers a stratified sample, not the whole German banking sector. For this reason, our sample does not cover all Sparkassen and Volksbanken in Germany, just those present in this data source. See Bade and Beier (2016) for further information about this data source.

35 Our study does not include credit card lending because it is very limited in Germany. According to Bundesbank statistics, only 6.8% of revolving loans and overdrafts in 2013 involved by credit card loans. Large banks provide two-thirds of all credit card loans.

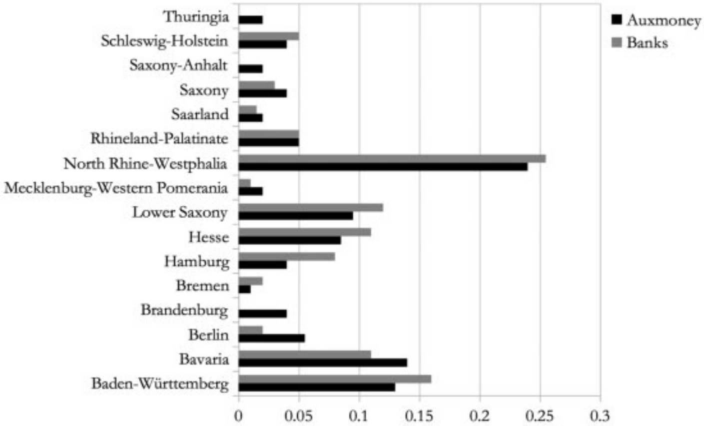

Fig. 2
Share of credit provision by Auxmoney and banks on state-by-state basis in our sample
This figure shows the geographical distribution of bank lending and P2P lending within our sample. The light-colored bar represents the share of Auxmoney lending in a given state (in %). The dark bar represents the share of bank lending in a given state (in %). The sample period is January 2010 until September 2014. *Sources:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics, and Auxmoney.

from the Balance Sheet Statistics (BISTA) (see Beier, Krueger, and Schaefer (2016) for information on this data source). It provides information on loan write-ups and write-downs from which we derive the loan loss provisions of banks.

Our analysis is at the bank-state level. Of the 236 banks in the Interest Rates Statistics sample, we consider 105 Volksbanken and Sparkassen. Restricting the sample to regional banks allows us to create a panel in the state dimension, which is comparable to our sample of P2P loans.

Figure 2 provides data on the geographic distribution of consumer credit across states by banks and Auxmoney. 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. We lack information on Sparkassen credit for three states (Brandenburg, Saarland, and Thuringia), so we exclude them from our sample.

The Deutsche Bundesbank provided data on three types of nonconstruction consumer credit lines: overdraft, maturities less than a year, and maturities greater than a year but less than 5 years. These credit lines have maturities and loan purposes (nonconstruction consumer credit) similar to those for P2P loans. To have a single comparable measure for the interest rate and risk for each bank, we aggregate all three lines

Table 1
Lending volume, L (in euros), interest rates, i, and default rate, σ, (in %) on new consumer loans by bank and month

	Banks			Auxmoney		
	L^b	i^b	σ^b	L^{P2P}	i^{P2P}	σ^{P2P}
Mean	90,512,570	10.25	2.22	252,089	12.82	7.32
SD	86,890,540	1.47	1.98	292,034	0.90	2.91
Min	–	–	–	–	9.19	0.88
25th*pcl*	44,151,000	9.37	0.60	85,503	12.21	6.25
50th*pcl*	68,470,000	10.33	1.37	160,022	12.84	6.25
75th*pcl*	106,767,000	11.29	3.60	297,367	12.12	8.77
Max	–	–	–	–	14.88	24.27
# obs.	6,512	6,512	5,800	590	590	590

The table reports 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 and their default rates, σ, on new consumer loans. Bank loans, L^b, is defined as the sum of three categories: overdraft; short-term loans, which have a maturity of less than 1 year; and midterm loans that have a maturity between 1 and 5 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 loans is smaller than the mean size of bank loans. Interest rates, i^b, are the average interest rate between the same three categories: overdraft; short-term loans; and midterm loans. All interest rates are 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. Default rates of new bank loans are the adjusted mean of three categories: overdraft; short-term loans, which have maturities less than 1 year; and midterm loans, which have maturities between 1 and 5 years. The sample period is January 2010 until September 2014. *Sources:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics, and Auxmoney.

of credit into one variable using weighted means. This gives us a single observation for each bank and month.

Table 1 presents data on the total volume of new loans provided by Auxmoney 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, which is substantially lower than the average monthly total new loan volume per bank per month: €90.5 million. While the mean size of Auxmoney loans is smaller than that of banks, the standard deviation of the loan volume volatility for Auxmoney is higher. 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 specific states.[36]

Table 1 also provides data on the interest rates on new loans by banks and Auxmoney during the January 2011–August 2014 time period. 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 1- to 5-year maturities). This average is 10.25%, and its value is pushed up by overdraft loans that typically carry higher interest rates

[36] Our estimate is at least 14 times. In fact, as we note above, by the end of 2018, Auxmoney's new lending volume was similar to that of a midsized bank in our sample, that is, €551 million (€46 million on average per month).

Fig. 3
Schufa score distribution
This figure shows the distribution of Schufa Score, the German consumer credit score. The higher the Schufa score, the lower the default rate. The figure compares the distribution of bank customers with Auxmoney customers. *Sources:* Auxmoney and Korczak and Wilken (2010)

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; that is, these are the all-in rates. To compare these interest rates, we need to adjust for the risk of these loans.

To assess loan risk, we measure the default rates of Auxmoney borrowers by using the Schufa scores. The Schufa score is the German consumer credit rating, similar to FICO scores in the United States.

Figure 3 charts the distribution of Schufa scores for Auxmoney loans. This figure shows, Auxmoney loans have Schufa scores that are primarily in the 174–519 range, with the highest concentration 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. Thus, a limitation of the data is that we do not have the actual frequencies of P2P loan defaults. Instead, we transform the Schufa scores into default probabilities. In a report for the German Ministry of Agriculture and Consumer Protection, Korczak and Wilken (2010) present a transformation table based on the Schufa score distribution for all Sparkassen clients, which we report in Internet Appendix C. That is, they report the default rates corresponding to different Schufa scores. Using this table, we convert the Schufa scores in our data into loan default probabilities. We believe this approach is reliable because Schufa scores have been shown in other studies to proxy well for default probabilities. If we compare our imputed default rates with the actual Auxmoney default rates examined by Dorfleitner et al. (2016) as well as the average default rates reported by Auxmoney on its webpage, we see that if there is any estimation bias, it is in the direction of an underestimation of the risk in our analysis.

Figure 3 shows that in about 50% of cases, households that borrow from banks have higher scores than those for Auxmoney borrowers. This indicates that Auxmoney apparently serves borrowers who are riskier than those served by banks, suggesting complementarity between P2P and bank lending. However, for about 50% of the loans, the Schufa scores on bank loans coincide with those for Auxmoney loans. This indicates a significant market overlap and suggests substitutability.

In our Deutsche Bundesbank data, the only proxy we have for loan risk is the loan loss provision. Whenever a bank considers a loan as likely to default (typically, when it is 90 days delinquent), it will write the loan down 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 data set of the Deutsche Bundesbank, loans are written up or down in full, regardless of their recovery rate.[37] We calculate distributions of the ratio of the loan write-downs to outstanding loans for each bank, and adjust the mean of the distribution to match the one provided by Schufa German Private Bureau (i.e., 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. Thus, our calculations of default rates across Auxmoney and bank loans employ the same methodology, using the relationship between Schufa scores and default rates provided by Korczak and Wilken (2010).[38]

As Table 1 shows, P2P borrowers have an average default rate of 0.0732 (or 7.32%). Matching Auxmoney data with information found on another webpage (www.wiseclerk.com), Dorfleitner et al. (2016) indicate that the average realized default rate on Auxmoney loans was about 12% for the March 2008–September 2013 period. Auxmoney itself reports a default rate of about 6% on its webpage. Our estimate falls between these two numbers. In either case, the point 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

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

[38] This methodology is not free of potential measurement error, 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.

German banks. Berg, Puri, and Rocholl (2020), using a sample of 100,000 borrowers from a large German private bank between 2008 and 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 precrisis 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. These data collectively indicate that the default rate on Auxmoney loans is higher than on bank loans.

3. Empirical Findings

The summary statistics presented above are broadly in line with the theoretical predictions. In this section, we formally investigate the three hypotheses stated in Section 1.

3.1 Hypothesis 1

There is a negative relationship between bank lending and P2P lending, and banks lose market share to P2P lenders when some banks are faced with an exogenous increase in regulatory costs. The greater the 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 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. We examine the impact of an exogenous increase in regulatory costs on banks and P2P lenders. We use the 2011 EBA capital exercise as a quasi-natural experiment in which bank capital requirements were endogenously shocked.[39] We investigate whether Auxmoney significantly increased its new lending in those states in which some banks were affected by the EBA capital exercise.

3.1.1 The 2011 EBA capital exercise. The EBA published its capital exercise results on October 26, 2011, and announced it would require 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 several reasons. First, the core tier 1 ratio of 9% required by the capital exercise is substantially higher than the 5% previously required.[40] Second, the

[39] Gropp et al. (2018) conduct a similar quasi-natural experiment to investigate bank response to higher capital requirements; their results show that affected banks increased their capital ratios by reducing their risk-weighted assets for corporate and retail exposures, not by increasing capital.

[40] Compare this to the increase of capital requirements for affected banks of about 1% because of FAS 166/167 (the shock in Tang 2020). See also Dou, Ryan, and Xie (2018).

capital exercise was largely unexpected, as the EBA had conducted the 2011 stress tests only a few months earlier (June 2011) and provided no advance 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 is on some Landesbanken, and the effect on the banks in our sample is 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 of its results.

The capital exercise forced two Landesbanken, HELABA and NordLB, to raise additional capital equal to 1% and 1.1%, respectively, of their total assets.[41] In its 2012 Annual Report, 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), along with €638 million from own sources.

Economically, the link between Landesbank and Sparkassen comes from the ownership structure; Sparkassen partially own their respective Landesbank and vice versa. For example, the Savings Banks and Giro Association of Hesse-Thuringia own 85% of HELABA. This means that Sparkassen had to contribute significantly to the recapitalization of their Landesbanken.

This ownership structure has two effects on 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, and 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.

3.1.2 Empirical strategy. Our empirical strategy is to examine first whether the Sparkassen linked to HELABA and NordLB reduced their lending enough to cause overall bank lending in those states to decline. In

[41] The information used in this study for HELABA and NordLB was not provided by the Bundesbank; rather it comes from public data sources, including the EBA and Gropp et al. (2018).

other words, we investigate whether *all* banks in the states in which HELABA and NordLB are present (Hesse, Lower Saxony, and Mecklenburg-Western Pomerania) experienced an overall lending reduction.[42] 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[43]. First, we sum the volume of new loans over all banks in a given state and investigate whether, during the EBA capital exercise, the total volume of new bank lending declined more in the states in which HELABA and NordLB are present than in the other states. Specifically, the first diff-in-diff model that we estimate is the following:

$$\begin{aligned} log(L_{t,s}) = \alpha_0 + \alpha_1 treated_s * EBA_t + \\ \alpha_2 EBA_t + \alpha_3 treated_s + \Pi W_{t-1,s} + u_{t,s}, \end{aligned} \tag{13}$$

where $log(L_{t,s})$ is the logarithm of lending volume by banks in state s in period t, and $treated_s$ is a dummy variable that identifies the treatment group; that is, it is equal to one for the states in which 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 a value of one from October 2011 onward, and zero prior to October 2011. $W_{t,s}$ is a vector of control variables including the weighted average of lagged interest rates on the new loans and lagged 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 along the bank dimension. Instead of summing 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 in which HELABA and NordLB are present, which we call *treated banks*.[44] The control group consists of all other banks (i.e., Sparkassen and Volksbanken) in other states. We estimate the following diff-and-diff model:

$$\begin{aligned} log(L_{t,b}) = \alpha_0 + \alpha_1 treated_b * EBA_t + \\ \alpha_2 EBA_t + \alpha_3 treated_b + \Pi W_{t-1,b} + u_{t,b}, \end{aligned} \tag{14}$$

42 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 highlighted in Figure 2.

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

44 Note that unaffected banks in treated states—that is, Volksbanken—are considered treated banks in this estimation.

where $log(L_{t,b})$ is the logarithm of the new loan volume in period t by bank b, and $treated_b$ is a dummy variable that identifies the treatment group; that is, it is equal to one for all the banks (Sparkassen and Volksbanken) in the treated states. The control group consists of all banks (Sparkassen and Volksbanken) located in other states. The EBA_t variable is the same as in Equation (13); $W_{t-1,b}$ is a vector of control variables, including lagged interest rates and lagged risk at the bank level; and $u_{t,b}$ is the error term.

We recognize that including loan interest rates and risk as controls involves using outcome variables as independent variables. We introduce these controls because decisions on interest rates and loan risk potentially influence subsequent loan volume, so not including these variables can potentially lead to an omitted-variables problem. To deal with the potential estimation bias introduced by these admittedly problematic controls, we lag them. However, we also recognize that lagging does not resolve the problem when variables are intertemporally sticky, as these controls are likely to be, so we have also run this regression excluding these controls and verified that our results hold. See Internet Appendix F for these results.

To check whether Auxmoney increased its lending in states in which overall bank lending decreased, we perform a diff-in-diff analysis on new Auxmoney lending. Similar to Equation (13), states in which HELABA and NordLB are present are called *treated states*. The control group consists of all other states. We estimate the following diff-in-diff model:

$$\begin{aligned} log(L^{P2P}_{t,s}) = \beta_0 + \beta_1 treated_s * EBA_t + \\ \beta_2 EBA_t + \beta_3 treated_s + \Pi W^{P2P}_{t-1,s} + e_{t,s}, \end{aligned} \tag{15}$$

where $log(L^{P2P}_{t,s})$ 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 (13); $W^{P2P}_{t,s}$ 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.

3.1.3 Difference-in-differences analysis. As a prelude to the diff-in-diff analysis, we check the validity of the parallel trends assumption. For simplicity, we aggregate into one group all three types of bank loans in our data; that is, our lending variable is the total of nonconstruction consumer loans by all banks in a given state.[45] The parallel trends analysis shows that in treated states, the volume of new bank loans is similar to that in control states before the EBA capital exercise; that is, until October 2011. This supports the parallel trends assumption. After the EBA capital exercise, the new loan volume dropped for both control and

[45] We conduct the analysis separately for each loan type, and all results are consistent with the ones presented.

Table 2
Difference-in-differences estimation to determine effect of capital exercise on aggregate bank lending in treated states

	State bank lending			Individual bank lending		
	(1)	(2)	(3)	(4)	(5)	(6)
EBA_t*$treated_{t,s(b)}$	0.01	−0.06***	−0.05**	−0.07***	−0.05***	−0.05***
	(0.07)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
EBA_t	−0.33***	−0.12***		−0.15***	−0.16***	
	(0.10)	(0.02)		(0.02)	(0.02)	
$Treated_{t,s(b)}$	1.20***			−0.01		
	(0.34)			(0.01)		
$\sigma_{t-1,s(b)}$	−0.15	0.01***	0.01	−0.01	0.01	0.00
	(0.09)	(0.00)	(0.004)	(0.00)	(0.01)	(0.01)
Int. $rate_{t-1,s(b)}$	−0.29***	−0.01	−0.04***	−0.08***	−0.11***	−0.13***
	(0.17)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)
State FE		Yes	Yes		Yes	Yes
Time FE			Yes			Yes
Cluster	State	State	State	Bank	Bank	Bank
Adj. R^2	.17	.99	.99	.04	.24	0.25
# obs	714	714	714	5,647	5,647	5,647

The table shows that overall bank lending declines in treated states. The table reports the estimated coefficients of the following three regressions: (a) state bank lending: $log(L_{t,s}) = \alpha_0 + \alpha_1 treated_s * EBA_t + \alpha_2 EBA_t + \alpha_3 treated_s + \Pi W_{t,s} + u_{t,s}$, and (b) individual bank lending: $log(L_{t,b}) = \alpha_0 + \alpha_1 treated_b * EBA_t + \alpha_2 EBA_t + \alpha_3 treated_b + \Pi W_{t,b} + u_{t,b}$. Estimation (a) is in the state dimension and estimation (b) is in the individual bank 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 onward 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 was present) and zero otherwise. In estimation (a), 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 states where HELABA or NordLB was not present. In estimation (b), 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. $W_{t,s(b)}$ is a vector of control variables that includes the default rate, σ, that is, our proxy for risk, and interest rate is the average interest rate for new loans. The notation s(b) means that the variable is in the state dimension in estimations (1)—(3) and in the individual bank dimension in estimations (4)–(6). *Sources:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics, and Monthly Balance Sheet Statistics.
*$p <.1$, **$p <.05$, and ***$p <.01$.

treated banks, but it dropped more and faster in treated states than in control states. For Auxmoney, the parallel trends analysis 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 increased in both treated and control states. However, the increase is larger in treated states than in control states. In both cases, we check for anticipation of the regulatory shock, and we find no evidence. See Internet Appendix D for a detailed analysis of the parallel trends assumption and placebo diff-in-diff tests.

Having validated the parallel trends assumption, we perform the diff-in-diff analyses presented in Equations (13), (14), and (15). Tables 2 and 3 report the estimations.

Table 3
Difference-in-differences estimation to determine effect of capital exercise on P2P lending in treated states

	P2P lending		
	(1)	(2)	(3)
EBA_t*$treated_{t,s}$	0.60***	0.20***	0.22***
	(0.10)	(0.07)	(0.06)
EBA_t	0.29***	0.60***	
	(0.10)	(0.05)	
$Treated_{t,s}$	−0.20***		
	(0.17)		
$\sigma_{t-1,s}$	−0.04***	−0.02**	−0.02**
	(0.01)	(0.01)	(0.01)
Int. $rate_{t-1,s}$	−0.10**	−0.17***	0.04
	(0.04)	(0.05)	(0.03)
State FE		Yes	Yes
Time FE			Yes
Cluster	State	State	State
Adj. R^2	.10	.62	.79
# obs.	491	491	491

The table shows that P2P lending increases in treated states. The table reports the estimated coefficient of the following regression: $log(L_{t,s}) = \beta_0 + \beta_1 treated_s * EBA_t + \beta_2 EBA_t + \beta_3 treated_s + \Pi W_{t,s} + e_{t,s}$. 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 onward and zero prior to that; and $treated_{t,s}$ is the dummy variable that identifies *treated states* and is equal to one for treated states (i.e., where HELABA or NordLB was present) and zero otherwise. $W_{t,s}$ is a vector of control variables that includes the default rate, σ, that is, our proxy for risk, and interest rate is the average interest rate for new loans. *Source:* Auxmoney.
*p <.1, **p <.05, and ***p <.01.

The first three columns of Table 2 report the estimation results of Equation (13); columns 1, 2, and 3 show the results for the new loan volume of banks without any fixed effects, with state fixed effects, and with both state 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 in 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 –0.05 using state and time fixed effects. Thus, in the period after the capital exercise, total bank lending in the treated states declined more than in the control states, consistent with Figure 2.

Next, we present the diff-in-diff estimation of loans in Equation (14). Columns 4, 5, and 6 of Table 2 report the results. The coefficient for 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) reduced their lending as a group relative to banks in the control group after the 2011 capital exercise. This result is consistent with the decline in total bank lending; that is, 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 (15). Columns 1, 2, and 3 in Table 3 report the results. The table shows P2P lending significantly increased in these states during this period. The coefficient for the interaction term is positive and significant at the 1% level and equal to 0.20 if we include state fixed effects, and it is equal to 0.22 if we include state and time fixed effects. Therefore, consistent with our theory, P2P lending increased, with the larger increase occurring in states in which the treated banks were located.

As a robustness check, we repeat the diff-in-diff analysis above for only the 30% of the banks in our sample with the lowest volume of new consumer lending (small banks); these are 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 the individual bank level, we have a bigger negative coefficient for the interaction term; $treated_b * EBA_t$, and this coefficient is always significant at the 1% level. As a further robustness check, we exclude the control variables, specifically, the lagged probability of default and the lagged interest rates, and the results are qualitatively the same. Internet Appendixes E and F report the detailed results of these robustness checks.

3.1.4 Three-way diff-in-diff analysis. So far, we have shown that total bank lending declined in treated states, but we have not yet distinguished between the savings banks that were affected by the EBA exercise (Sparkassen) and the others (Volksbanken). We now investigate whether Sparkassen in the states where HELABA and NordLB operate reduced their lending more than Volksbanken in those states and more than Sparkassen in other states, using a triple diff-in-diff analysis. The triple interaction term is characterized by three variables: $Sparkassen_b$, $Treated_b$ and EBA_t.

The variable $Sparkassen_b$ is a dummy variable equal to one for Sparkassen and equal to zero for Volksbanken. The other two interactions term variables are the $Treated_b$ and EBA_t already defined in Equation (14). The three-way interaction term, $Treated_b*Sparkassen_b*EBA_t$, shows whether and how the new lending by the Sparkassen operating in the treated states changed after the shock. We estimate:

Table 4
Three-way difference-in-differences estimation to examine the effect of the capital exercise on lending by treated and control banks in treated states

	(1)	(2)	(3)
EBA_t*$Treated_b$*$Sparkassen_b$	−0.02	−0.05**	−0.05**
	(0.09)	(0.02)	(0.02)
EBA_t*$Treated_b$	−0.00	0.03	0.03
	(0.08)	(0.02)	(0.02)
EBA_t*$Sparkassen_b$	−0.20***	−0.13***	−0.14***
	(0.04)	(0.01)	(0.01)
$Treated_b$*$Sparkassen_b$	−0.63***		
	(0.08)		
EBA_t	−0.01	−0.01	
	(0.04)	(0.01)	
$Treated_b$	0.33***		
	(0.07)		
$Sparkassen_b$	0.87***		
	(0.04)		
Controls	Yes	Yes	Yes
Bank FE		Yes	Yes
Time FE			Yes
Cluster	Bank	Bank	Bank
Adj. R^2	.23	.96	.97
# obs.	5,647	5,647	5,647

The table reports the estimated coefficient for the following regression: $log(L_{bt}) = \alpha_0 + \alpha_1 Treated_b * Sparkassen_b * EBA_t + \alpha_2 Treated_b * Sparkassen_b + \alpha_3 Treated_b * EBA_t + \alpha_4 Sparkassen_b * EBA_t + \alpha_5 EBA_t + \alpha_6 Treated_b + \alpha_7 Sparkassen_b + \Pi W_{bt} + u_{bt}$, where the dependent variable L_{bt} is the lending volume by banks; EBA_t is the treatment time dummy that takes the value of one from October 2011 onward; $Treated_b$ is a dummy variable that identifies the banks in *treated states* and is equal to one for banks in *treated states* and zero otherwise; and $Sparkassen_b$ is a dummy variable that identifies the Sparkassen banks and is equal to one for Sparkassen and equal to zero for Volksbanken. W_{bt} is a vector of control variables that includes the default rate, that is, our proxy for risk, and the variable Int. Rate is the average nominal interest rate of new loans by bank b at time t. *Sources:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics, and Monthly Balance Sheet Statistics.
*p <.1, **p <.05, and ***p <.01.

$$\begin{aligned} log(L_{bt}) &= \alpha_0 + \alpha_1 Treated_b * Sparkassen_b * EBA_t + \\ &\alpha_2 Treated_b * Sparkassen_b + \\ &\alpha_3 Treated_b * EBA_t + \alpha_4 Sparkassen_b * EBA_t + \\ &\alpha_5 EBA_t + \alpha_6 Treated_b + \alpha_7 Sparkassen_b + \Pi W_{bt} + u_{bt}. \end{aligned} \tag{16}$$

Table 4 presents the estimation results for Equation (16). Columns 1, 2, and 3 show the results for treated banks without any fixed effects, with bank fixed effects, and with both bank and time fixed effects, respectively.

Three points are worth noting. First, the coefficient for the interaction term, $Treated_b * Sparkassen_b * EBA_t$, is negative and statistically different from zero. This coefficient is the estimated effect of the treatment for banks with Sparkassen=1. Thus, the negative coefficient for this term means that the loan volume of Sparkassen banks in treated states falls relative to that of Volksbanken and also relative to that of banks in control states following the treatment. Second, the coefficient for the interaction term, EBA_t*$Treated_b$, is positive, but not significant, in any of the estimations. This means that Volksbanken do not change their lending significantly in treated states after the 2011 capital exercise. Third, for banks in treated states, the estimated treatment effect is equal to the coefficient of EBA_t*$Treated_b$ plus the coefficient of EBA_t*$Treated_b$*$Sparkassen_b$. Adding these two coefficients in column 3 in Table 4, we get -0.05, which indicates that changes in Volksbanken lending did not offset reduced lending by the Sparkassen in the treated states. So total lending dropped more in treated states than in control states after the treatment. In other words, the vacuum created by reduced lending by the Sparkassen was not entirely filled by banks unaffected by the capital shock (Volksbanken), which is in line with the results reported in Table 2.[46]

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 change their lending sufficiently to cover the gap.

3.1.5 The role of bank capital. Next, we want to explore further why the unaffected banks in treated states were unable to fill the lending vacuum created by the treated banks. We hypothesize that it was because they lacked sufficient capital to expand their lending. 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 1 year earlier. We define a dummy variable called *Expansion* that is one if the observation belongs to the top quartile of lending increases. We then regress this dummy on bank capital lagged, using bank balance sheet data for the year 2011. 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 equal to one if the 1-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

[46] We conduct a similar analysis using two different diff-in-diff analyses instead of a three-way diff-in-diff. 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. For the second diff-in-diff analysis, we investigate the effect of the EBA capital exercise on the unaffected banks (Volksbanken) in treated states. We find that the coefficient for the interaction term for Sparkassen is negative and significant in all the estimations. This means that treated Sparkassen reduced their lending compared to the control group after the 2011 capital exercise. By contrast, the coefficient for the interaction term for Volksbanken in the second diff-in-diff analysis is not significant. This suggests that the Volksbanken in treated states did not increase their lending sufficiently in response to the decline in lending by the Sparkassen. The results are consistent with the three-way diff-in-diff analysis and are reported in Internet Appendix G.

Table 5
Test of lending responses to the shock by unaffected banks in treated states

	(1)	(2)
$\text{Capital}_{t-1,b}$	15.22**	15.37***
	(6.11)	(3.07)
Time FE		Yes
Cluster	Bank	Bank
R^2	.132	.145
#obs.	108	108

The table reports the test of whether, among banks unaffected by the EBA capital exercise, 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 of one if the 1-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 in which HELABA and NordLB are present, and the time frame is from January 2012 to December 2012. *Sources:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, Monthly Balance Sheet Statistics, and Auxmoney.
*p <.1, **p <.05, and ***p <.01.

variable, $u'_{t,b}$ is the error term, and $capital_{t-1,b}$ is the equity capital of bank b at time $t-1$. The sample includes only banks unaffected by the capital exercise in states in which HELABA and NordLB are present, and the time period is January to December 2012. Given that the focus of the analysis is to investigate cross-sectional differences in terms of capital buffers among unaffected banks, we do not use fixed effects along the cross-sectional dimension. Table 5 reports the results.

Table 5 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 displayed a lower ability to fill the lending vacuum created by the affected banks.

Overall, and consistent with our model, P2P lending increases more in states in which some banks experience higher regulatory costs and in which unaffected banks lack sufficient capital to replace the reduction in credit supply from the affected banks.

3.1.6 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 borrowers away from banks. Our model predicts that a lower poaching cost enables P2P lenders to take a larger market share away from banks. Since P2P lending is an online-only service, users who wish to access the P2P platform 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.

We conduct two analyses related to consumer awareness of P2P lending. We use the EBA capital exercise in both. First, we examine if P2P lending increased more in treated states with greater preshock awareness, which we proxy with greater preshock Google search for "Auxmoney." Second, we examine whether consumers increased their search for P2P loans in treated states in response to the shock.

For the first investigation, we define a dummy called the *Google Search dummy* that equals one if the state was in the 50th percentile of Google searches between January 2010 and October 2011 (i.e., prior to the EBA capital exercise) and zero otherwise.[47]

We use this dummy variable as an explanatory variable in the diff-in-diff estimation previously described and the results are reported in Table 6. The analysis shows that the *Google Search dummy* has a coefficient that is negative for banks and positive for P2P lending. This means that states with greater awareness of P2P lending prior to the EBA capital exercise witnessed a larger decline in new lending by banks at both the aggregate and individual bank levels. These states also saw a greater increase in P2P lending after the EBA capital exercise. Consistent with our model, consumer awareness of P2P lending affects the market share gained by P2P lenders.

For the second test, we investigate whether states affected by the EBA capital exercise experienced an increase in Google searches for the word "Auxmoney" that exceeded the increase in other states. We use the contemporaneous raw Google search variable: $GoogleSearch_{t,s}$. The test involves the following regression:

$$\begin{aligned} GoogleSearch_{t,s} = \alpha_0 + \alpha_1 treated_s * EBA_t + \\ \alpha_2 EBA_t + \alpha_3 treated_s + u_{st}. \end{aligned} \tag{18}$$

Table 7 shows that, after the capital exercise, Google searches increased more in states in which treated banks were present. The result is significant at the 5% level and is robust to the inclusion of state fixed effects (column 2) and state and month fixed effects (column 3). This means that lending volume gains by Auxmoney are related to both consumer per-shock awareness of P2P lending and the elevated post-shock consumer search for P2P lending.

[47] A detailed description of how this variable has been constructed and the descriptive statistics of the data provided by *Google Search* are reported in Internet Appendix H.

Table 6
Difference-in-differences estimation and Google Search for the word "Auxmoney"

	Aggregate bank lending (1)	Overall bank lending (2)	P2P lending (3)
Google Search dummy	−0.25***	−0.35**	1.15***
	(0.08)	(0.14)	(0.25)
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)
EBA_t*$Treated_b$	0.00	−0.06*	0.35***
	(0.10)	(0.03)	(0.10)
Cluster	State	Bank	State
Adj. R^2	.155	.094	.431
# obs.	714	5,647	491

The table shows that the relationship between bank lending and P2P lending grows with consumer awareness about Auxmoney prior to the capital exercise captured with the *Google Search dummy* variable 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. In column 1, the treatment group comprises those states affected by the EBA capital exercise; in column 2, the treatment group comprises the banks in treated states; and in column 3, the treatment group is Auxmoney lending in treated states. EBA_t is a treatment dummy that takes the value of one from October 2011 onward and zero prior to that, and $treated_{t,s(b)}$ is a dummy variable that identifies banks in the *treated states* and is equal to one for treated states—that is, where HELABA or NordLB was present–and equals zero otherwise, in estimation (b). The control group is defined as lending volume in states where HELABA or NordLB was not active. σ is our proxy for risk, and the interest rate is the average interest rate for new loans. The notation s(b) means that variable is in the bank dimension in estimations (1) and (3) and in the state dimension in estimation (2). *Sources:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics, Auxmoney, and Google.
*p <.1, **p <.05, and ***p <.01.

3.2 Hypothesis 2

3.2.1 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. Table 1 in Subsection 2.2 provides 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 is 0.1235%, which leads to a t-value of 19.03. Hence, we can reject the null hypothesis. An alternative test using time and state fixed effects is presented in Internet Appendix I, and the results confirm the ones presented in the main text.

Next, we conduct a diff-in-diff estimation similar to that described in the risk dimension to test whether the capital exercise affected banks' and Auxmoney's risk-taking. Our model predicts that a reduction of bank

Table 7
Difference-in-differences estimation of Google Search for the word "Auxmoney"

	(1)	(2)	(3)
EBA_t*Treated_s	72.67**	72.67**	72.67**
	(35.91)	(35.70)	(34.65)
EBA_t	1.54	1.54	
	(9.27)	(9.21)	
Treated_s	−12.92		
	(25.74)		
State FE		Yes	Yes
Time FE			Yes
Cluster	State	State	State
Adj. R^2	.060	.060	.059
# obs.	90	90	90

The table reports on the test of whether states affected by the EBA capital exercise experienced an increased in Google searches for the word "Auxmoney." The test involves the following regression: $GoogleSearch_{t,s} = \alpha_1 treated_b * EBA_t + \alpha_2 EBA_t + \alpha_3 treated_b + u_{bt}$. The table shows that after the capital exercise Google Search increased in states in which treated banks were present. In column 1, the estimation has no fixed effects; in column 2, the estimation has treated state fixed effects; and in column 3, the estimation has state and month fixed effects. EBA_t is a treatment dummy that takes the value of one from October 2011 onward and zero prior to that, and $treated_{t,s}$ is a dummy variable that is equal to one for treated states—that is, where HELABA or NordLB was present—and equals zero otherwise. *Source:* Google.
*p <.1, **p <.05, and ***p <.01.

lending will be accompanied by lower risk in bank loans. Our model does not predict any impact on the average risk of P2P lenders. We test the impact of the capital exercise by estimating

$$\begin{aligned}\sigma_{t,b} = \theta_0 + \theta_1 treated_b * EBA_t + \\ \theta_2 EBA_t + \theta_3 treated_b + \theta_4 \log(L_{t-1,b}) + \epsilon_{t,b}\end{aligned} \tag{19}$$

and

$$\begin{aligned}\sigma^{P2P}_{t,s} = \rho_0 + \rho_1 treated_s * EBA_t + \\ \rho_2 EBA_t + \rho_3 treated_s + \rho_4 \log(L^{P2P}_{t-1,s}) + \epsilon'_{t,s},\end{aligned} \tag{20}$$

where $\sigma_{t,b}$ is default rate in period t by bank b, and $log(L_{t,b})$ is the logarithm of the loans volume. The other variables are defined above.

Table 8 presents the results of the estimation of Equations (19) and (20). We focus on individual banks because, unlike volume, the probability of default is a variable that cannot be aggregated without biasing the results. As Table 8 shows, in all specifications, the results point in the same direction: after the capital exercise, the default rates of loans declined at treated banks. The results are statistically significant at the 5% level in all three specifications: without any fixed effects, with state fixed effects, and with both state and time fixed effects. The magnitude of the effect is also economically significant. After the capital exercise, treated banks experienced a reduction in their average default rate of about 0.38

Table 8
Difference-in-differences estimation to determine the effect of the capital exercise on default rates of bank lending and P2P lending in treated banks/states

	Individual bank lending			P2P lending		
	(1)	(2)	(3)	(4)	(5)	(6)
EBA_t*$Treated_{t,s(b)}$	−0.41***	−0.38**	−0.38**	2.13***	2.02***	2.33***
	(0.12)	(0.12)	(0.12)	(0.35)	(0.33)	(0.50)
EBA_t	−0.13	−0.14		−0.89**	−0.82*	
	(0.14)	(0.15)		(0.41)	(0.44)	
$Treated_{t,s(b)}$	0.56*			−1.47***		
	(0.26)			(0.34)		
$log(L_{t-1,s(b)})$	−0.14	−0.04	−0.06	−0.4*	−0.36	−0.66**
	(0.18)	(0.19)	(0.2)	(0.2)	(0.25)	(0.29)
State FE		Yes	Yes		Yes	Yes
Time FE			Yes			Yes
Cluster	Bank	Bank	Bank	State	State	State
Adj. R^2	.01	.07	.12	.02	.06	.10
# obs.	5,691	5,691	5,691	491	491	491

The table shows that overall bank default rates decline and the default rate in P2P lending increases in treated states. The table reports the estimated coefficient for the following two regressions: (a) bank's default rate $\sigma_{t,b} = \theta_0 + \theta_1 treated_b * EBA_t + \theta_2 EBA_t + \theta_3 treated_b + \theta_4 \log(L_{t-1,b}) + \epsilon_{t,b}$ and (b) P2P default rate $\sigma^{P2P}_{t,s} = \rho_0 + \rho_1 treated_s * EBA_t + \rho_2 EBA_t + \rho_3 treated_s + \rho_4 \log(L^{P2P}_{t-1,s}) + \epsilon'_{t,s}$. Estimation (a) is in the individual bank dimension, and estimation (b) is in the state dimension. The dependent variable $\sigma_{t,b}$ is the default rate by bank b in month t; the dependent variable $\sigma_{t,s}$ is the default rate in state s in month t; EBA_t is a treatment dummy that takes the value of one from October 2011 onward and zero prior to that; and $treated_{t,s(b)}$ is a dummy variable that identifies *treated banks* and *treated states* is equal to one for banks in treated states (i.e., where HELABA or NordLB was present) and zero otherwise. In estimation (a), treated banks (i.e., Sparkassen) in treated states are considered treated banks, and all others are considered control banks. $L_{t-1,s(b)}$ is total lagged lending volume by banks in estimations 1–3 and by P2P lending in estimations 4–6. *Sources:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics, and Auxmoney.
*p <.1, **p <.05, and ***p <.01.

percentage points. These results are consistent with the predictions of our model.

For completeness, we also perform the same analysis for Auxmoney and find that it experiences an increase in its average default rate in treated states; this default rate increases from about 2.02 to 2.33 percentage points.

As discussed in Section 2.2, a limitation of our data is that we have only Schufa scores for P2P borrowers, not data on actual defaults. This has required us to use a transformation of these scores into default probabilities. To check robustness, we repeat the estimation of Equation (20) using the Schufa score instead of the imputed default variable. Internet Appendix J reports on this analysis. The results hold.

Table 9
Summary statistics: Risk-adjusted interest rates for bank loans and P2P (Auxmoney) loans

	Banks (1)	P2P Lending (2)
Mean	7.79	4.45
SD	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

The table shows that, after adjusting for risk difference, Auxmoney interest rates are in line with those of banks. The sample period is January 2010 until September 2014. *Sources:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics, and Auxmoney.

3.3 Hypothesis 3

3.3.1 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 now adjust for risk differences; that is, we test our third hypothesis. We calculate the risk-adjusted interest rates charged on both P2P and bank loans under the assumption of risk neutrality by using the following formula:

$$r_{t,b} = (1 - \sigma_{t,b}) \times (1 + i_{t,b}) + \sigma_{t,b} \times RR_{t,b} - 1, \tag{21}$$

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 2. $RR_{t,b}$ is the recovery rate. We repeat the same procedure for P2P lending.[48]

Even though other potential ways may be employed in determining the risk-adjusted interest rate, none of them is perfect. Given the data limitation described in Section 2.2, we believe that our approach is the simplest and most direct. It permits a comparison of the interest rates charged by banks and Auxmoney and accounts for risk. While our results may be affected by the assumptions embedded in our transformation process, they are likely to be biased against the model because we are potentially underestimating the risk for Auxmoney loans. Moreover, the difference between the risk-adjusted interest rates on loans made by banks and Auxmoney is so large that concerns about our approach are further mitigated.

Table 9 reports the summary statistics of the risk-adjusted interest rates for both bank and P2P loans. An eyeballing of the data in the table indicates that, after adjusting for risk, Auxmoney interest rates move closer to those of 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

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

Table 10
Test of the difference in risk-adjusted interest rates on bank loans and P2P loans

	(1)	(2)	(3)
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	.13	.18	.21
# obs.	6,390	6,390	6,390

This table reports the estimation of the following regression: $r_{t,b} = \beta_0 + \beta_1 \text{auxmoney}_{t,b} + \Delta_s + \Delta_t + u_{t,b}$, 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 one when the lender is Auxmoney, and $\Delta_s + \Delta_t$ are state and time fixed effects, respectively. The sample period is January 2010 until September 2014. *Sources:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics, and Auxmoney.
*p <.1, **p <.05, and ***p <.01.

among P2P borrowers than among bank borrowers, something not evident in the data presented in Table 1.

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

$$r_{t,b} = \tau_1 \text{auxmoney}_{t,b} + \Delta_j + \Delta_t + e'_{t,b}, \tag{22}$$

where $r_{b,t}$ is the risk-adjusted interest rate charged by bank b or Auxmoney, $\text{auxmoney}_{t,b}$ is a dummy variable that takes the value of one when the lender is Auxmoney and zero otherwise, Δ_s and Δ_t are state and time fixed effects, and $e'_{t,b}$ is the error term.

Table 10 presents the results. Consistent with our hypotheses, after adjusting for risk differences, we find that Auxmoney charges lower loan interest rates than banks. Auxmoney's 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, and both. This result provides support for Hypothesis 3.

As before, we investigate how risk-adjusted interest rates react to the capital exercise with a diff-in-diff approach, as

$$\begin{aligned} r_{t,b} = \delta_0 + \delta_1 treated_b * EBA_t + \\ \delta_2 EBA_t + \delta_3 treated_b + \delta_4 \log(L_{t-1,b}) + u_{t,b} \end{aligned} \tag{23}$$

and

$$\begin{aligned} r^{P2P}_{t,s} = \psi_0 + \psi_1 treated_s * EBA_t + \\ \psi_2 EBA_t + \psi_3 treated_s + \psi_4 \log(L^{P2P}_{t-1,s}) + e'_{t,s} \end{aligned} \tag{24}$$

Table 11
Difference-in-differences estimation to determine the effect of the capital exercise on risk-adjusted interest rates of bank lending and P2P lending in treated banks and states

	Individual bank lending			P2P lending		
	(1)	(2)	(3)	(4)	(5)	(6)
EBA$_t$*Treated$_{t,s(b)}$	0.74***	0.69***	0.69***	−2.35***	−2.26***	−2.79***
	(0.18)	(0.18)	(0.18)	(0.39)	(0.37)	(0.55)
EBA$_t$	−0.49**	−0.49**		−0.09	0.22	
	(0.19)	(0.20)		(0.46)	(0.52)	
Treated$_{t,s(b)}$	0.03			1.68***		
	(0.36)			(0.41)		
$log(L_{t-1,s(b)})$	−0.14	−0.39	−0.40	0.31	−0.03	0.72**
	(0.27)	(0.29)	(0.30)	(0.21)	(0.29)	(0.33)
State FE		Yes	Yes		Yes	Yes
Time FE			Yes			Yes
Cluster	Bank	Bank	Bank	State	State	State
Adj. R^2	.01	.08	.12	.01	.05	.10
# obs.	5,646	5,646	5,646	491	491	491

The table shows that banks' risk-adjusted interest rates increase and P2P lending decreases in treated states. The table reports the estimated coefficient for the following three regressions: (a) Bank's risk-adjusted interest rate $r_{t,b} = \delta_1 treated_b * EBA_t + \delta_2 EBA_t + \delta_3 treated_b + \delta_4 \log(L_{t-1,b}) + \nu_{t,b}$, (b) P2P risk-adjusted interest rate $r_{t,s}^{P2P} = \psi_1 treated_s * EBA_t + \psi_2 EBA_t + \psi_3 treated_s + \psi_4 \log(L_{t-1,s}^{P2P}) + \nu'_{t,s}$. Estimation (a) is in the individual bank dimension and estimation (b) is in the state dimension. The dependent variable $r_{t,b}$ is the risk-adjusted interest rate by bank b in month t; the dependent variable $r_{t,s}$ is the risk-adjusted interest rate in state s in month t; EBA_t is a treatment dummy that takes the value of one from October 2011 onward and zero prior to that; and $treated_{t,s(b)}$ is a dummy variable that identifies *treated banks* and *treated states* is equal to one for banks in treated states (i.e., where HELABA or NordLB was present) and zero otherwise. In estimation (a), treated banks (i.e., Sparkassen) in treated states are considered treated banks, and all others are considered control banks. $L_{t,s(b)}$ is total lending volume by banks in estimations (1)–3 and by P2P lending in estimations (4)–(6). *Source:* Research Data and Service Center (RDSC) of the Deutsche Bundesbank, MFI Interest Rates Statistics and Monthly Balance Sheet Statistics, and Auxmoney.
*p <.1, **p <.05, and ***p <.01.

Consistent with our model (Corollary 3), banks increase their risk-adjusted loan interest rates.

Table 11 presents the results of the estimation of Equations (23) and (24). They are consistent with the prediction of our model. Treated banks increase their risk-adjusted interest rates, on average, by 0.70%, which is about one-tenth of the average risk-adjusted interest rate in the sample. This result is statistically significant for all three specifications we use. Auxmoney reduces its risk-adjusted interest rate by about 1.5%, which is about one-third of the average risk-adjusted interest rate in the sample. This is consistent with the implication of the model that P2P lenders compete aggressively to pry away banks' borrowers and end up prying away the more risky and less profitable borrowers from banks.

4. 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, which we test. First, we document that P2P lending increases and total bank lending declines when some banks face higher regulatory costs in the form of higher capital requirements. 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 banks that are unaffected by the regulatory shock are nevertheless capital constrained and where borrowers are more aware of Auxmoney's existence; that is, 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 compete with 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. P2P lending extends credit to borrowers either who are not served by banks or who have been denied credit by banks facing an increase in regulatory costs. Second, the advent of P2P lending may cause the banking sector to not only shrink but also be less risky and possibly more profitable in terms of risk-adjusted returns on assets. Nonetheless, we cannot speak to the welfare implications of this shrinkage since the shift in credit supply from banks to nonbank lenders may generate welfare effects through its impact on the operations of these borrowers (e.g., Cerqueiro, Ongena, and Roszbach 2020) Currently, these effects are relatively small, but whether they will occur on a broader scale in the credit market is a promising topic for future research.

Appendix

Proof of Proposition 1. Consider first the case in which no competitor arrives and the incumbent bank has the G loan. Then $L_R^G = x$. One can easily 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 $\bar{D}^G \in (0, L)$. 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 $\tilde{L}_R^G$ be the loan repayment set by the competitor bank. From the IC constraint (6), we have

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

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

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

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

$$\begin{aligned} & p[\tilde{L}_R^G - \tilde{D}_R^G] - \tilde{E}^G - \alpha_B - K \\ &= p[\tilde{L}_R^G - \tilde{D}_R^G] - L + [p\tilde{L}_R^G - \Pi][1 - p\gamma]^{-1} - \alpha_B - K \\ &= \Pi - L + [p\tilde{L}_R^G - \Pi][1 - p\gamma]^{-1} - \alpha_B - K. \end{aligned} \tag{A8}$$

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

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

Now, given (9), it follows that $\tilde{L}_R^G = \widehat{L}_R^G < x$, 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 a similar analysis, one can also show that $\widehat{D}_R^g < \bar{D}_R^g$. The proofs of $\widehat{D}_R^g < \widehat{D}_R^G$ and $\bar{D}_R^g < \bar{D}_R^G$ follow 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

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

subject to Equations (5)–(8). D_O^G denotes the regulator's choice of D^G, which maximizes (A10). 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 $\tilde{L}_R^G$ (from the Proof of Proposition 1), we obtain

$$\begin{aligned}
&= \Pi + [p\tilde{L}_R^G - \Pi][1 - p\gamma]^{-1} - L - K \\
&= \alpha_B \quad \text{(upon substituting for } \tilde{L}_R^G \text{ from (A9))} \\
&> 0. \qquad \blacksquare
\end{aligned}$$

Proof of Proposition 2. To break even, the loan repayment set by a P2P lender on a g loan, $\tilde{L}_R^g$, must satisfy

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

which yields

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

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

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

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

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

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

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

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

$$\begin{aligned}
&= q[\tilde{L}_R^g - \widehat{D}_R^g] - \widehat{E}^g - K \\
&= q[\tilde{L}_R^g - \widehat{D}_R^g] - [L - \widehat{D}^g] - K \\
&= \Pi + [q\tilde{L}_R^g - \Pi][1-\gamma q]^{-1} - L - K \\
&\text{(substituting for } \widehat{D}_R^g \text{ from (A13))} \\
&= \Pi + [(q\bar{q})(L+\alpha_P) - \Pi][1-\gamma q]^{-1} - L - K \\
&\qquad\qquad \text{(substituting for } \tilde{L}_R^g \text{ from (A12))} \\
&= \gamma q[L - \Pi + \left(\frac{q-\bar{q}}{\bar{q}}\right)L][1-\gamma q]^{-1} - K + \left(\frac{q}{\bar{q}}\right)[\alpha_P][1-\gamma q]^{-1}.
\end{aligned} \tag{A15}$$

If the NPV in (A15) is nonnegative, 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, banks do not lose loans 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 nonnegative NPV from lending when faced with a 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 $\alpha_P < A_2$, 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, the distribution of α_P shifts to the right in the sense of first-order stochastic dominance, so $Pr(\alpha_P > A_1)$ increases as s increases. ■

Proof of Corollary 2. From (A-14) in the proof of Proposition 2, we see that $\frac{\partial Dg}{\partial q} > 0$, which means that the amount of deposit financing that the incumbent bank can use for G is higher than it can use for g; that is, more capital is needed to support g than to support G. Moreover, from (A-15), we see that the NPV is higher with G than with g. That none of these results depends on the fact that $x > x_G$ means all of our results go through. ■

Proof of Corollary 3. Let μ be the Lebesgue measure of $[A_1, A_2)$ in Proposition 2. Then

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

Thus,

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

To see the effect of higher capital requirements, consider the following. 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 4. This proof follows immediately from the discussion in the text.

The reason is that the risk-adjusted interest rate on G is higher when the bank does not face a competitor, so the expected value across the competition and no-competition cases is also higher. ■

References

Allen, F., and D. Gale. 2001. Comparative Financial Systems: A survey. Working Paper, Wharton School, University of Pennsylvania.

Bade, M., and R. Beier. 2016. Microdatabase: MFI interest rate statistics. Report, Deutsche Bundesbank, Frankfurt, Germany.

Balyuk, T., and S. Davydenko. 2019. *Reintermediation in FinTech: Evidence from online lending*. *Working Paper*, Emory University.

Beier, R., M. Krueger, and M. Schaefer. 2016. *Microdatabase: Monthly balance sheet statistics*. Report, Deutsche Bundesbank, Frankfurt, Germany.

Berg, T., M. Puri, and J. Rocholl. 2020. Loan officer incentives, internal rating models and default rates. *Review of Finance* 24:529–78.

Berger, A. N., and C. H. S. Bouwman. 2013. How does capital affect bank performanceduring financial crises? *Journal of Financial Economics* 109: 146—176

Berger, A., N. Miller, M. Petersen, R. Rajan, and J. Stein. 2005. Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics* 76:237–69.

Boot, A., and A. Thakor. 2000. Can relationship banking survive competition? *Journal of Finance* 55:679–713.

Bord, V., V. Ivashina, and R. Taliaferro. 2021. Large banks and small firm lending. *Journal of Financial Intermediation* 48:100924.

Boyd, J., and E. Prescott. 1986. Financial intermediary-coalitions. *Journal of Economic Theory* 38:211–32.

Braggion, F., A. Manconi, and H. Zhu. 2020. Can technology undermine macroprudential regulation? Evidence from peer-to-peer credit in China. *Journal of Financial Economics* 138:295–315.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru. 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics* 130:453–83.

Butler, A., J., Cornaggia, and U. Gurun. 2017. Do local capital market conditions affect consumers' borrowing decisions? *Management Science* 63:4175–87.

Cerqueiro, G., S. Ongena, and K. Roszbach. 2016. Collateralization, bank loan rates, and monitoring. *Journal of Finance* 71:1295–322.

———. 2020. Collateral damaged? Priority structure, credit supply, and firm performance. *Journal of Financial Intermediation* 44:100824.

Chava, S., R. Ganduri, N. Paradkar, and Y. Zhang. 2021. Impact of marketplace lending on consumers' future borrowing capacities and borrowing outcomes. *Journal of Financial Economics*. Advance Access published June 10, 2021, 10.1016/j.jfineco.2021.06.005.

Cornelli, G., J. Frost, L. Gambacorta, R. Rau, R. Wardrop, and T. Ziegler. 2020. Fintech and big tech credit: a new database. Working Paper, BIS.

Coval, J., and A. Thakor. 2005. Financial intermediation as a beliefs-bridge between optimists and pessimists. *Journal of Financial Economics* 75:535–69.

Di Maggio, M., and V. Yao. 2021. Fintech borrowers: Lax-screening or cream-skimming? *Review of Financial Studies* 34:4565–618.

Diamond, D. 1984. Financial Intermediation and delegated monitoring. *Review of Economic Studies* 51:393–414.

Diamond, D., and P. Dybvig. 1983. Bank runs, deposit insurance, and liquidity. *Journal of Political Economy* 91:401–19.

Donaldson, J., G. Piacentino, and A. Thakor. 2018. Warehouse banking. *Journal of Financial Economics* 129:250–67.

Dorfleitner, G., C. Priberny, S. Schuster, J. Stoiber, M. Weber, I. de Castro, and J. Kammler. 2016. Description-text related soft information in peer-to-peer lending–Evidence from two leading European platforms. *Journal of Banking & Finance* 64:169–87.

Dou, Y., S. Ryan, and B. Xie. 2018. The real effects of FAS 166/167 on banks' mortgage approval and sale decisions. *Journal of Accounting Research* 56:843–82.

Federal Reserve Bank of New York. 2018. Quarterly Report on Household Debt and Credit. Center for Microeconomics Data.

Greenwood, R. and D. Scharfstein. 2013. The growth of finances. *Journal of Economic Perspectives* 27:3–28.

Gropp, R., T. Mosk, S. Ongena, and C. Wix. 2018. Banks response to higher capital requirements: Evidence from a quasi-natural experiment. *Review of Financial Studies* 32:266–99.

Hertzberg, A., A., Liberman and D. Paravisini. 2018. Screening on loan terms: Evidence from maturity choice in consumer credit. *Review of Financial Studies* 31:3532–67.

Holmstrom, B., and J. Tirole. 1997. Financial intermediation, loanable funds, and the real sector. *The Quarterly Journal of Economics* 112:663—91.

Iyer, R., A. Khwaja, E. Luttmer, and K. Shue. 2016. Screening peers softly: Inferring the quality of small borrowers. *Management Science* 62:1554–77.

Korczak, D., and M. Wilken. 2010. Verbraucherinformation scoring. Report for Federal Ministry for Agriculture and Consumer Protection.

Lin, M., N. Prabhala, and S. Viswanathan. 2013. Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science* 59:17–35.

Memmel, C., Y. Gündüz, and P. Raupach. 2015. The common drivers of default risk. *Journal of Financial Stability* 16:232–47.

Merton, R., and R. Thakor. 2019. Customers and investors: A framework for understanding the evolution of financial institutions. *Journal of Financial Intermediation* 39:4–18.

Millon, M., and A. Thakor. 1985. Moral hazard and information sharing: A model of financial information gathering agencies. *Journal of Finance* 40:1403–22.

Milne, A., and P. Parboteeah. 2016. *The business models and economics of peer-to-peer lending*. Report, ECRI Research, Brussels.

Morse, A. 2015. Peer-to-peer crowdfunding: Information and the potential for disruption in consumer lending. *Annual Review of Financial Economics* 7:463–82.

Philippon, T. 2015. Has the US finance industry become less efficient? On the theory and measurement of financial intermediation. *American Economic Review* 105:1408–38.

———. 2016. The FinTech opportunity. Working Paper, New York University.

Pope, D., and J. Sydnor. 2011. What's in a picture? Evidence of discrimination from Prosper.com. *Journal of Human Resources* 46:53–92.

Puri, M., J. Rocholl, and S. Steffen. 2011. Global retail lending in the aftermath of the US financial crisis: Distinguishing between supply and demand effects. *Journal of Financial Economics* 100:556–78.

———. 2017. What do a million observations have to say about loan defaults? Opening the black box of relationships. *Journal of Financial Intermediation* 31:1–15.

Ramakrishnan, R., and A. Thakor. 2009. Information reliability and a theory of financial intermediation. *Review of Economic Studies* 51:415–32.

Schufa. 2017. Empirische Untersuchung der privaten Kreditaufnahme in Deutschland. *Kredit Kompass*.

Tang, H. 2020. Peer-to-peer lenders versus banks: Substitutes or complements? *Review of Financial Studies* 32:1900–1938.

Thakor, A. 2020. Fintech and banking: What do we know? *Journal of Financial Intermediation* 41:100833.

Vallee, B., and Y. Zeng. 2019. Marketplace lending: A new banking paradigm? *Review of Financial Studies* 32:1939–82.