Learning about Competitors: Evidence from SME Lending

Darmouni, Olivier and Sutherland, Andrew

Columbia University, MIT

2018

Learning about Competitors: Evidence from SME Lending

Olivier Darmouni and Andrew Sutherland*

November 16, 2018

Abstract

This paper provides evidence of strategic complementarities in lenders' contract terms in SME financing. To isolate this strategic effect from lenders' joint reaction to unobserved common shocks to fundamentals, we exploit the staggered entry of lenders into an information sharing platform. Upon joining, lenders adjust their terms toward what others are offering. This effect is mediated by market power and seems to be driven by incentives to match rivals in order to preserve market share as opposed to learning about fundamentals. We also find evidence that this strategic behavior increased delinquencies during the recent crisis.

Keywords: competition, strategic complementarities, information sharing, credit bureau, corporate loans, SME

*Olivier Darmouni (omd2109@columbia.edu) is at Columbia Business School, New York City, NY. Andrew Sutherland (ags1@mit.edu) is at the MIT Sloan School of Management, Cambridge, MA. We would like to thank Hassan Afrouzi, Xavier Giroud, Andrew Hertzberg, Jennifer La'O, Andres Liberman, Erik Loualiche, Jonathan Parker, Ryan Pratt, Tomasz Piskorski, Johannes Stroebel, David Thesmar, Laura Veldkamp, Edison Yu and seminar participants at Columbia Business School, the Federal Reserve Bank of Philadelphia, MIT Sloan, NYU Stern, and the University of Bonn for their comments.

Introduction

Information plays a fundamental role in markets and strategic behavior. Indeed, in many settings information is *dispersed*: market participants do not have full information about their counterparties or their competitors' actions. Strategic and information considerations are linked: agents' optimal actions depend on their information about competitors' actions. In the context of credit markets, although there is a consensus that loan terms are affected by perceived fundamentals and risk, there is a pervasive view that strategic forces among lenders also play a role.[1] Indeed, if competitors aggressively offer better terms, a lender has incentives to match them in order to preserve its market share. These incentives potentially played a role in the recent crisis: aggressive competition from banks and non-banks led to lax lending standards that partially ignored fundamentals. Even ten years after the crisis, this strategic channel seems important: aggressive competition by other lenders is the main reason cited for relaxing business lending standards, far above improvements in economic outlook or risk tolerance.[2]

This suggests that lenders are not "price takers" and that oligopolistic competition for borrowers leads to strategically adjusting loan terms. Interestingly, the industrial organization literature suggests two possibilities: lenders can mimic their rivals if there are strategic complementarities, or on the contrary they can differentiate themselves through product choice.[3] The sign and magnitude of these strategic responses are in fact important for predicting, for instance, the industry effects of lifting barriers to entry or a change in the information available about peer lenders. However, empirically estimating this strategic effect is challenging: lenders might simultaneously offer better terms not because they respond to each other, but simply because they respond to the same shock, for example, an improvement in the economic outlook (Manski, 1993).

This paper addresses this challenge by exploiting a shift in information that lenders have about rivals. Specifically, we use micro lending data around the introduction of an information sharing platform in credit markets for small and medium enterprises (SME) in the United States. The platform provides information on contract terms offered by other lenders that was previously impossible to observe at a large scale. We exploit the staggered timing of lenders joining the platform to estimate the response to competitors and find that lenders adjust their terms toward what others are offering. Consistent with a strategic channel, this effect is mediated by market concentration and only present in the most competitive

[1] See for example Dell'Ariccia et al. (2012) for evidence in the subprime mortgage market.

[2] 2017 New Business Lending Survey, Federal Reserve Bank of Kansas City.

[3] Two rivals' actions a_i and a_j are strategic complements if the optimal choice of a_i is increasing in a_j, and vice versa. For endogenous product differentiation, see Shaked and Sutton (1982).

markets.[4] On the other hand, we provide additional evidence that this result cannot be explained away by lenders' learning about fundamentals from the platform or by lenders' joining at the same time as shocks unrelated to the platform. Finally, we look at one important implication of this strategic behavior: lenders who matched their competitors suffered an increase in delinquencies during the recent crisis, possibly because these lenders neglected future risk as they aggressively competed to preserve their current market share.

We document this effect in the context of maturity dynamics for SMEs' equipment financing contracts from 2001 to 2014. This setting is relevant for multiple reasons. Because of their implications for firms' liquidity positions and investment behavior, maturity cycles became a concern during the recent crisis and recovery: maturity on loans lasting over a year fell by 30% between 2007 and 2010 before slowly recovering.[5] Moreover, with over $1 trillion of annual volume, equipment financing is a major component of corporate investment, and lending to SMEs is particularly important for policy makers.[6] In our context of financing a specific piece of equipment, it is natural to focus on maturity as it is negotiable, while contract size is largely dictated by the equipment needed, and by design, interest rates are not shared in the platform.[7] Moreover, because these contracts involve fixed monthly payments, maturity has a drastic effect on firms' debt burden: for the median contract in our sample, reducing maturity by a year implies up to 25% larger monthly payments. Finally, there is evidence consistent with oligopolistic competition in this market (Murfin and Pratt (2017b), Mian and Smith Jr (1992), or Bodnaruk et al. (2016)).

Our empirical strategy is designed to address key empirical challenges associated with estimating strategic responses driving loan terms. Specifically, two lenders can offer similar contracts not because they react to what the other is offering, but simply because they react to the same shock to fundamentals. This is a crucial issue because it is plausible that at least some of these fundamentals cannot be observed by the econometrician and therefore cannot be controlled for. To address this challenge, we rely on two features of our setting. First, we exploit lenders' joining the platform in a staggered fashion to generate variation in information sets within and across lenders over time. Second, for each borrower-lender

[4] This a key empirical prediction of Bebchuk and Goldstein (2011).

[5] Source: Survey of Terms of Business Lending. In our sample, the peak-to-trough variation is closer to 15%.

[6] Chairman Bernanke argued in a 2010 speech that "making credit accessible to sound small businesses is crucial to our economic recovery and so should be front and center among our current policy challenges." Moreover, information sharing can be particularly valuable when lending to these firms: their repayment behavior is erratic and their size and opacity make tailoring contracts costly.

[7] Like many other credit bureaus (i.e. consumer bureaus in the United States), to avoid antitrust concerns and reduce proprietary costs of sharing interest rates are not shared. Schalheim and Zhang (2017) estimate the mean interest rate for leases to be 15% in this market.

relationship, we observe contracts made before and after the lender joins the platform.[8] Our empirical test does not take an a priori stand on the direction of the response. The key idea is that, while a lender's terms may track the bureau average before, they should track it relatively *better* after joining if strategic complementarities dominate, while the opposite is true if the differentiation effect dominates. We make the argument formal by embedding our regression model into a canonical model with strategic interaction and dispersed information.

However, this strategy creates the possibility of two important confounders. First, lenders can respond to information in the platform other than rivals' terms – specifically borrower credit records. There is evidence that this reduction in asymmetric information leads lenders to start lending to new borrowers with different characteristics (Liberti et al. (2016), Liberti et al. (2017), Foley et al. (2018)). To abstract from any change in borrower composition, all of our tests are conducted within an existing relationship. We therefore study how maturity changes relative to what others are offering over a short window around the lender's joining the platform for the *same borrower-lender pair*. Second, the decision to join the platform is voluntary and can therefore depend on a number of factors that could potentially affect maturity independently of the information revealed by the platform. We leverage our micro-data to show that borrower or lender shocks coinciding with the timing of joining cannot explain away our results. Specifically, we conduct a series of additional within lender-time and within borrower-time tests (Khwaja and Mian, 2008) that are described in the robustness section below.

In our main specification, we show that the gap between the maturity offered by a lender and what others in the platform are offering shrinks by 7% after the lender joins the platform. Lenders' terms therefore track the bureau average relatively better after joining, consistent with a strategic response to partially match rivals. In economic terms, this corresponds to a 2% change in monthly payments, or a change in debt burden that is comparable to a 2 percentage point change in APR. We measure average maturity within quarter-collateral type for members, and control for year, loan size, credit history, and contract type. Consistent with strategic complementarities, the effect is symmetric: sometimes lenders match rivals by increasing maturity, sometimes by shortening it.

There is additional evidence that this finding is driven by a strategic response. In the cross-section of local markets, the incentives to match others should be mediated by lenders' market power over borrowers (Bebchuk and Goldstein, 2011). Lenders with market power have less incentive to match rivals, as their market share is less sensitive to competing

[8]The PayNet platform launched in 2001; since then they have attracted 8 of the 10 largest lenders in the market. Joining involves an invasive implementation process in which PayNet establishes access to the lenders' IT systems to ensure complete and truthful sharing. PayNet uses shared information to create credit scores and reports for members. Nonmember cannot access the system or its reports and scores.

offers. Indeed, we find that loan terms adjust toward rivals' only in the least-concentrated market segments, where markets are defined as a collateral type x census region pair, and concentration is measured using the HHI index. We confirm this finding using relationship switching rates as an alternative proxy for the degree of market power.

Moreover, additional results suggest that more conventional effects of information sharing in credit markets cannot fully account for our findings. For instance, information can trigger "run-like" behavior by creditors and financial distress for firms with multiple lenders (Hertzberg et al., 2011). However, we do not find that lenders shorten their maturity systematically upon joining or that the effect is smaller for borrowers of high credit quality or with a single relationship (for which the incentives to run are muted).[9] Another possible explanation is information aggregation: lenders react to others' terms because they reveal some of their private information about credit risk or borrower demand in the economy (Hellwig, 1980). However, specialist lenders with expertise in a specific market segment do not appear to react less than nonspecialist lenders, according to various measures of specialization. Overall, these findings strongly support the view that strategic complementarities are an important driver of loan terms in this market. Any alternative mechanism would have to explain why the effect: (i) exists within an existing relationship, (ii) is symmetric, (iii) varies by market concentration, and (iv) does not vary by borrower creditworthiness or lender expertise.

Finally, we discuss some implications of this strategic behavior. In particular, with the improvement in IT and data processing techniques, the link between information and competition is at the center of policy makers' attention. In the words of European Commissioner for Competition Margrethe Vestager, "the future of big data is not just about technology. It's about things like. . . competition".[10] At a general level, the implications for consumer welfare or production efficiency are not obvious (Vives, 2006): while mimicking the best lenders can increase "production efficiency," cut-throat competition can potentially lead to ignoring fundamentals. In order to relate these questions to our setting, we study delinquencies during the recent crisis. We find suggestive evidence that matching competitors comes with an increase in delinquencies. One interpretation is that competition can lead lenders to neglect future risk as they compete aggressively to preserve their market share today.

We then address several important remaining threats to identification. Specifically, as pointed out above, there could be shocks either to the lender or borrower that exactly coincide with the time of joining the platform and drive maturity independently of observing rivals'

[9] Although all contracts are formally collateralized, there is still significant default risk. For instance, our sample contains contracts to finance copiers and computers, whose value depreciates quickly, as well as other equipment that is movable and therefore difficult to recover in default.

[10] EDPS-BEUC Conference on Big Data and Competition, Brussels, September 29, 2016.

offers. We therefore conduct two additional tests. First, on the borrower side, our results hold when comparing contracts made to the same firm by two lenders with different information sets: one joining the platform, the other not. Specifically, we include borrower-time fixed effects (Khwaja and Mian, 2008) and find the lenders joining PayNet offers a maturity closer to the bureau average relative to the other lender in the same period.

Second, on the lender side, joining the platform might coincide with a shift in business model correlated with its propensity to offer specific contract terms. However, our result holds within lender-year across different market segments. Specifically, the information coverage in the platform depends on contracts made by other lenders and thus varies by collateral type over time in a way that is not directly driven by the decision to join.[11] Including lender x year fixed effects, we show that the maturity of collateral types with higher coverage tracks the bureau average better than collateral types with low coverage. These additional stringent tests support the interpretation that lenders adjust their contract terms in reaction to the information revealed in the platform.

Related Works

This paper is related to several strands of literature. First, it relates to empirical studies of complementarities in credit markets. Hertzberg et al. (2011) provides clean evidence of the role that public information plays in credit market coordination. They find that lenders react strongly to the public revelation of information they already possess about a borrower. This publicity effect triggers "run-like" behavior by creditors and financial distress for firms with multiple lenders. By comparison, we study the effect of observing information about other lenders and find evidence of a strategic channel independent of creditor runs. Bebchuk and Goldstein (2011) analyze a model in which lenders decisions are strategic substitutes and can lead to a self-fulfilling market freeze. Chen et al. (2010) provide evidence from mutual fund outflows that strategic complementarities among investors can generate financial fragility.

Murfin and Pratt (2017a) study comparable pricing in the syndicated loan market. They find that past transactions impact new transaction pricing, but a failure to account for the overlap in information across loans leads to pricing mistakes. While our data lacks the power to trace out paths of influence like they do, we nevertheless find suggestive evidence of complementarities leading to more frequent delinquencies during the recent crisis. Bustamante and Frésard (2017) argue that managers are imperfectly informed about their investment

[11] For example, after a truck captive joins there is a large increase in the platform's coverage of truck contracts, but no new contracts for copiers. Thus, lenders who had joined before this truck captive experience an information shock for reasons beyond their control (they have no say over the truck captive joining), and only to the extent they participate in the truck market. And recall that we control for collateral market conditions in our gap measure directly, which will absorb common demand shocks to the truck market.

opportunities and show investment complementarity between firms due to learning from peers.[12]

We also contribute to the literature that studies the drivers of loan terms, and specifically maturity. Hertzberg et al. (2018) provide evidence from an online consumer lending platform showing that loan maturity can be used to screen borrowers based on their private information. Milbradt and Oehmke (2015) argue that loan maturity has real effects by distorting firms' decisions toward inefficiently short-term investments. In the auto loan market, Argyle et al. (2017a) show that borrowers display a demand for maturity and target low monthly repayments, while Argyle et al. (2018) find that loan maturity impacts the pricing of cars.

Moreover, we provide novel evidence of the effect of oligopolistic competition in credit markets. There is evidence that imperfect competition and market power are relevant to the financing of durable goods. Murfin and Pratt (2017b) show that market power is important to understand the large share of captive lenders in equipment financing. A number of recent papers study the effect of competition on consumer credit markets: Gissler et al. (2018) and Argyle et al. (2017b) focus on auto loans, while Foley et al. (2018) and Nelson (2017) study credit cards, and Dell'Ariccia et al. (2012) and Palmer (2015) the mortgage market. On the other hand, we focus on loans to small and medium enterprises (Rice and Strahan, 2010).

Finally, this paper relates to the work on information sharing and credit bureaus, including Liberman et al. (2018), Sutherland (2018), Liberti et al. (2017), Doblas-Madrid and Minetti (2013), Jappelli and Pagano (2006), Giannetti et al. (2017), and Balakrishnan and Ertan (2017), and more broadly on the role of information in lending markets (Hertzberg et al. (2010), Liberti et al. (2016), Hauswald and Marquez (2003), Liberti (2017), Liberti and Mian (2009), Berger et al. (2017), and Ryan and Zhu (2018)).

1 Equipment Financing and PayNet

1.1 The PayNet Platform

Our data come from PayNet, an information sharing platform focusing on the U.S. equipment finance market and SMEs. Borrowers in this market seek loans and leases for an array of assets, including agricultural, construction, manufacturing, medical, office, and retail equipment, as well as computers, copiers, and trucks. Lenders include banks, manufacturers ("captives"), and independent finance companies.[13] Since PayNet's 2001 launch, it has

[12]For applications of strategic complementarities in macroeconomics, see the survey of Angeletos and Lian (2016) or Afrouzi (2017), Amador and Weill (2012), Schaal and Taschereau-Dumouchel (2015), Angeletos and La'O (2010), Veldkamp (2011) and Van Nieuwerburgh and Veldkamp (2006).

[13]Murfin and Pratt (2017b) provide an explanation for the presence of captives in equipment financing.

attracted 8 of the 10 largest lenders in the market, as well as several hundred others as members. Like other credit bureaus, PayNet operates on the principle of reciprocity: members must share information, and only members can purchase the credit files, credit scores, and default probability products offered. PayNet gathers its data by directly connecting into lenders' IT systems, ensuring that the information shared is comprehensive and reliable. PayNet has developed these products using 24 million contracts for over $1.6 trillion in transactions collected from members.

Prior to PayNet, lenders generally had access to very limited information about new borrowers and other lenders. Competing data providers such as Experian offered limited (and rarely timely) information about trade liabilities, which were much smaller than the typical equipment contract. Public UCC filings documented the existence of a contract but did not detail whether the borrower paid on time or the terms they received. Thus, PayNet provided equipment finance lenders with a source of timely, contract-level information about a borrower's ability to service similar liabilities and details on previous contracts it received. This development was particularly relevant for small borrowers, who typically lacked audited financial statements or public information about their creditworthiness (Berger et al., 2017). Although PayNet does not allow lenders to mine its data (e.g., by accessing all credit files for a given industry or zip code), lenders can observe how their counterparts contract. During the frequent process of accessing individual credit files, they can see the terms other lenders are providing or have provided a given firm in the past. PayNet's data collection and verification process is further detailed in Doblas-Madrid and Minetti (2013) and the Online Appendix of Sutherland (2018).

Crucially for our purpose, unlike many consumer credit bureaus, the platform includes detailed information about contracts offered by competitors. Figure 1 illustrates the detailed information available exclusively to PayNet members. The figure displays a snapshot of a (fictitious) borrower's credit file accessible on the platform in return for a fee. While the first page of the credit file contains a summary of past payments as well as the borrower's state, industry, and age (omitted), subsequent pages reveal the terms of past and current contracts offered by all lenders members of PayNet. In the example of Figure 1, the borrower had two lenders and five contracts in total. For each contract, the maturity, amount, and delinquency status are detailed. However, similar to other credit bureaus (e.g., the consumer bureaus in the United States), PayNet does not collect or distribute interest rate information and takes care that it is not easily identifiable. We therefore unfortunately cannot trace directly the pricing implications of our hypothesis.

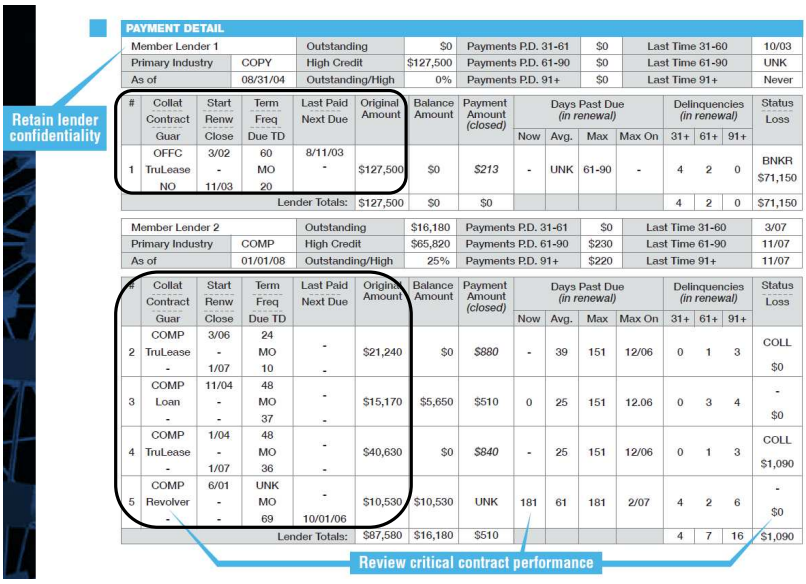


Figure 1: Past Contract Terms in PayNet Credit File

Note: This figure illustrates the type of detailed information contained in a borrower credit file in PayNet. The terms of previous contracts signed by the borrower are highlighted.

1.2 Sample

We construct our sample from the quarterly credit files of 20,000 borrowers randomly chosen from PayNet's database. The credit files contain detailed information for each of the borrower's current and past contracts with PayNet members. This information includes the contract's amount, maturity, payment frequency, collateral type, contract type, and delinquency status, as well as the borrower's state, industry, and age. The data set provides a constant identifier for borrowers and lenders, which we use to track contracting behavior over time. One limitation is that we cannot match lenders and borrowers to external data with this identifier. Importantly, also note that while we have a large amount of information about lenders' contract choices, we cannot observe the universe of contracts in the bureau. This implies that an estimate of the average of rivals' contract terms, although unbiased, is measured with error. Such measurement error can in general reduce the statistical significance of our results.

Our research question focuses on estimating the effect of observing competitors' contract terms on one's own contract terms. We therefore restrict the sample of contracts used for our main analysis to a relatively short window around the lender's joining PayNet. We include contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type. This sample selection has little effect on the

distribution of loan terms in the population.

Table 1 describes the lenders and borrowers that meet our regression sample requirements described below. We have 2,076 unique borrowers and 44 unique lenders involved in 8,194 credit relationships with 54,290 contracts. Relationships can span multiple contracts because a borrower's needs for capital grow over time, and old fleets depreciate and new ones with updated features are released. Lenders on average maintain 94 relationships; this understates their true scope given we only observe a random snapshot of their clients. Borrowers maintain multiple relationships, in part because lenders can specialize by collateral type. A given firm may, for example, require both computers and forklifts, and can access different lenders to finance each. The average lender is exposed to just over six collateral types and the average borrower to 1.7. Table A.1 illustrates the distribution of collateral types in the sample. The five most common collateral types are copiers, trucks, construction and mining equipment, computers, and agricultural equipment.

1.3 Oligopolistic Competition

As in other credit markets for big-ticket items (cars, real estate, etc.), borrowers in the equipment financing market transact at regular intervals, and search for and negotiate with lenders.[14] At the same time, relationships are prevalent and lenders are plausibly able to exercise some degree of market power. Nevertheless, market power likely varies across market segments, consistent with existing evidence in Murfin and Pratt (2017b), Mian and Smith Jr (1992) or Bodnaruk et al. (2016). Defining market segments as collateral type-census regions, the median probability that a new contract is issued with a previous lender is 70%, the 25th percentile is 55% and the 75th percentile is 92%. The median number of lenders in each segment is 12, with an interquartile range of 5 to 31.

Lenders have incentives to respond to rivals' offers, even if their market power means they do not have to necessarily fully match competing offers. Intuitively, this reflects the basic trade-off behind profit-maximization: more-generous terms increase the probability that an offer is accepted but reduce profits conditional on acceptance. Importantly, the incentives to match depend on the degree of market power over borrowers,[15] whether it comes from specialization or product differentiation, private information or any other reason behind relationship stickiness. Indeed, for lenders with sizable market power, the probability of losing a client does not change much with rivals' offers and their strategic response is muted.

[14] For this reason, these markets tend not be defined by a single market-clearing price (Argyle et al., 2018).

[15] More precisely, in terms of the industrial organization literature, they depend on the elasticity of residual demand.

1.4 Contract Terms

Table 3 describes the terms for a typical contract in our sample. The median contract size is \$20,300, with an average of \$101,000. The median maturity is 37 months from origination; the average is 44.3 months. Eighty-one percent of contracts are some form of lease (including true leases, conditional sales, and rental leases) while the remaining 19% are loans.[16] The overwhelming majority of contracts require fixed monthly payments. Seventeen percent of contracts involve some form of guarantor. The level of these contract terms are broadly similar before and after a lender joins the platform, although these levels are affected by changes in lender and borrower composition over time.

In this paper, we focus on contract maturity as our key variable for three reasons. First, maturity impacts firms' liquidity positions and investment behavior. During the recent crisis, maturity on loans lasting over a year fell by 30% between 2007 and 2010 before recovering slowly (Survey of Terms of Business Lending). Figures 3 and 4 show that contracts in our sample also display considerable time variation across the business cycle. Second, in the context of financing a specific piece of equipment, maturity is negotiable but contract size is largely dictated by the equipment needed. In addition, interest rates are not shared in the platform for fear of collusion, which is similar to many other credit bureaus (i.e. consumer loans in the United States). Finally, maturity has a drastic effect on firms' debt burden because virtually all contracts involve fixed monthly payments. For instance, for the median contract in our sample, reducing maturity by a year implies up to 25% larger monthly payments.[17] This plausibly results in a demand for maturity in the same way as is documented in other settings such auto loans (Argyle et al., 2017a) or student loans (Cox, 2017): everything else equal, the majority of borrowers is likely to prefer longer maturities.[18]

Maturity choices appear to be far from mechanical and display substantial unexplained variation in the cross-section of borrowers and lenders over our sample period. The raw standard deviation is 17 months, a little less than half of the sample mean. Table A.2 in the Appendix shows that only about a third of this variation can be explained by collateral type, year, and borrower-lender fixed effects. In the analysis below, we analyze the dispersion in contract terms by computing, for each contract, the gap between its maturity and the

[16] The borrower's choice between a lease or a loan can relate to many considerations, including cost, tax or financial reporting treatment, different services offered under each contract type, the borrower's credit risk and liquidity, and obsolescence risk. For our purposes, these contracts function similarly. In the context of captive financing, Murfin and Pratt (2017b) highlight the fundamental similarities of leases and loans.

[17] This back-of-the-envelope calculation relies on Schalheim and Zhang (2017)'s estimate of a mean interest rate of 15% on leases. The exact number depends on contract type, residual value estimates, and any options embedded.

[18] Hertzberg et al. (2018) documents that demand for maturity is heterogeneous in consumer credit markets, and that maturity can be used screen applicants. We abstract from screening by focusing on repeat borrowers.

bureau's average maturity (excluding the lender's own contracts) for that collateral type in the previous quarter. The median gap in our sample is 11 months, which is a substantial fraction of the underlying variation in maturity choice.[19]

1.5 Lender Participation to PayNet

When a lender joins the PayNet platform, it gains access to information about others' contracts, but must share information about its own contracts, *including past contracts*. This is enforced through PayNet's direct access into lenders' IT systems and extensive audit and testing procedures. This back-fill requirement is crucial to our empirical design: We can observe contracts made before and after the lender joins the platform. This allows us to study changes in contracting between the same firm and lender during a relatively short window around the lender's joining PayNet.

Another key feature of our setting is that lenders join in a staggered pattern over the entire sample period. This variation in time of joining brings two benefits. First, the platform information is not publicly revealed: in the same period, some lenders have access to it, while others competing in the same market do not. This within market-period, across-lender variation allows us to distinguish the effects of the new information from other events affecting lenders or borrowers in a given year. Second, the information revealed to entrants by the platform varies over time as a function of what *other lenders* are offering. Indeed, lenders often specialize by collateral type; therefore the bureau coverage across collateral types evolves in a nonsystematic pattern. Thus, members regularly experience shocks to the information coverage in their markets driven by other lenders, which is by construction outside of their control.[20] We leverage these additional sources of variation in our main specification and robustness tests.

Table 3 shows the variation in the timing of joining the platform for lenders meeting our sample criteria described in Section 3. Lenders join in all years between 2002 and 2014 except one. While large lenders tend to join earlier than small lenders, in any given year, a variety of lenders join. At the same time, joining PayNet is voluntary and the timing of joining the platform is not randomly assigned. Below, we leverage the variation in our data to ensure that results are not driven by lender or borrower shocks coinciding with the timing of joining. Note also that Liberti et al. (2017) study in detail the decision to join PayNet and show that a key driver of lenders' joining is access to new markets, but our tests are

[19]Hertzberg et al. (2018) show that lenders can use maturity to screen new applicants. To control for this aspect, we focus on existing relationships as opposed to new customers, as explained in detail below.

[20]Figure A.1 in the Online Appendix shows there is considerable time variation in the volume of contracts in the bureau across collateral types.

performed exclusively within an existing relationship. Note also that our sample of lenders is by design different from Liberti et al. (2017) in that, given our purpose, we impose a different event window and sample requirements, as described in Section 2.

2 Estimating Strategic Response to Rivals

The key empirical challenge in testing for strategic response in lending is the existence of unobserved common shocks: lenders might start offering better terms not because they respond to each other, but simply because they react to the same news about fundamentals, for instance, an improvement in the economic outlook.[21] To address this challenge, we exploit a shift in information that lenders have about rivals that comes with joining the platform. Moreover, to abstract away as much as possible from other forces, we perform our tests within an existing borrower-lender pair. Specifically, we ask whether the maturity of contracts issued after joining matches rivals' maturities better relative to contracts issued before for the same borrower. This effect would be consistent with lenders adjusting their terms toward what others are offering.

2.1 An Illustrative Model

Strategic response: The market for financing equipment is not centralized and not all lenders offer the same contract terms in equilibrium. Instead, buyers search for good deals and lenders' choice of terms is driven by attracting or retaining borrowers. We present a simple framework to understand strategic incentives to match rivals. For a given borrower, lenders set maturity m_i to maximize expected profits, which depend on beliefs about rivals' offers m_{-i} and their market power MP:

$$\mathbb{E}[\pi] = \mathbb{P}(\text{offer is accepted}|m_i, m_{-i}, MP) \times \pi(m_i)$$

Market power comes from the lack of rivals in the area, specialization, expertise or differentiation, as well as private information about borrowers or any other interpretation that can rationalize switching costs. Given some nonzero demand for maturity from borrowers, it is plausible that the probability that the offer is accepted increases in the lender's own term m_i and decreases in rivals' terms m_{-i}. This would naturally lead to strategic complementarities: the optimal maturity choice m_i^* increases with the lender's belief of its rivals' offers. On the other hand, the industrial organization literature has also raised the possibility that rivals choose to differentiate themselves through product choice (Shaked and Sutton,

[21] See the "reflection problem" of Manski (1993).

1982). Our empirical test does not take an a priori stand on the direction of the response, and will directly estimate which explanation dominates in the data. Denote the degree of complementarity or substitutability by $\alpha(MP) = \partial m_i^* / \partial m_{-i}$ and note that in both cases it depends on market power. Intuitively, for lenders in a dominant position, the probability of losing a client does not change much with rivals' offers.[22]

Dispersed information: A key ingredient absent in the simple framework above is that lenders likely do not have full information about their rivals' offers nor their borrowers. We therefore adapt a canonical version of the "beauty contest" popularized by Morris and Shin (2002).[23] We use the model to transparently describe: (1) the effect of joining the platform and (2) how we empirically account for some important confounders.

We decompose lender i's choice of maturity m to firm f, which is part of a group of similar firms g, linearly as follows:

$$m_i^f = \underbrace{m_0^g}_{\text{public information}} + \underbrace{\mathbb{E}[\phi^g | I_i]}_{\text{borrower fundamentals}} + \underbrace{\alpha \mathbb{E}[m_{-i}^g | I_i]}_{\text{competitors' terms}} + \underbrace{\eta_{if}}_{\text{idiosyncratic to relationship}}$$

When deciding what maturity to offer, lenders are influenced by their beliefs about borrower fundamentals, that is, any force that influences its ability to repay. Lenders also care about their competitors' terms, with α denoting the degree of strategic complementarity or substitutability as discussed above. The idiosyncratic term η_{if} includes borrower characteristics, news about its creditworthiness, or shocks to the lender's balance sheet that affect its propensity to lend.

Crucially, lenders are uncertain about both fundamentals and their competitors' actions. Before joining the information sharing platform, lenders have two sources of information: (1) public information about fundamentals or competitors' terms that can be gleaned from, for instance, forecasts of local and national economic conditions or industry reports and newsletters, summarized in m_0, and (2) private signals $s_i = (s_i^\phi, s_i^m)$, reflecting the lender's own effort to determine the appropriate contract maturity.

After joining the platform, lenders can also observe an additional signal: the average terms offered by competitors $\bar{m}^g$ to similar borrowers.[24] This signal is potentially informative

[22] A natural question is whether lenders can adjust other terms in order to compensate for the change in maturity. The answer is yes, but note that any adjustment comes at the risk of losing the borrowers. Argyle et al. (2018) for instance show that changes in the price of cars induced by a change in financing terms is unlikely to leave the borrower indifferent.

[23] Our main text is limited to notation and key ideas, while technical details are relegated to the Appendix. For tractability, we make some standard parametric assumptions, namely linearity and joint normality, although the setting can naturally be extended. Note also that while the setup is similar, we study a different question from Morris and Shin (2002), namely the effect of observing others as opposed to the social value of public information.

[24] Concretely, lenders can learn about others' terms by purchasing individual credit files from PayNet. This

about both fundamentals and competitors' terms. Intuitively, in equilibrium, the maturity choice depends on the information available to the lender at the time. Before joining, lenders weight their own private signals depending on how precise their prior and signals are about fundamentals and their competitors' terms. After joining, lenders place less weight on their own private signals and place some weight on the bureau average.

Importantly, note the clear identification challenge in cross-sectional data. Maturity choices are naturally correlated across agents due to public information m_0 as well as private signals $\{s_i\}$, independent of the information revealed by the bureau. This is the idea that lenders might start offering better terms at the same time not because they respond to each other, but simply because they react to the same news about fundamentals. The main contribution of our empirical strategy is to specifically account for these unobserved common components.

Effect of joining platform: We exploit the time dimension associated with the lender joining PayNet. Joining the information sharing platform leads to a shift in the lender's information set. Our main specification measures how maturity changes within a relationship over a short window around the lender joining's PayNet. An intuitive prediction of the model is that, while a lender's terms may track the bureau average before joining, they track it relatively *better* after joining if there are complementarities. Figure 2 provides a graphical illustration of this idea, and a formal proof within the context of the model is provided in the Appendix. In case of strategic substitutability, the reverse pattern should be observed. In the data, we can follow lender-borrower relationships over time, including the time before the lender joined the platform. Moreover, we can also observe rivals' offers before as well after the lender joins. This allows us to test this prediction directly within a fixed effects regression framework.

2.2 Addressing Confounders

By construction, our empirical strategy is not confounded by the existence of a number of factors: public information unobservable to econometrician m_0, other sources of information outside of the platform s_i, or idiosyncratic loan terms η_{lf}. Indeed, all of these forces exist in the model, and our tests based on comparing before and after joining are valid independent of the sequence of realization of any of these shocks.[25] This is the main contribution of our approach. However, this strategy creates the possibility of two important confounders,

collection process makes it unlikely they can learn the entire distribution of competitors' terms or that they can leak this information easily.

[25] However, a necessary assumption for identification is that their precision or dispersion is constant around the time lenders join within fixed effects groups. This cannot be taken for granted, given that lenders' decisions to join is not randomly assigned, a concern we address thoroughly below.

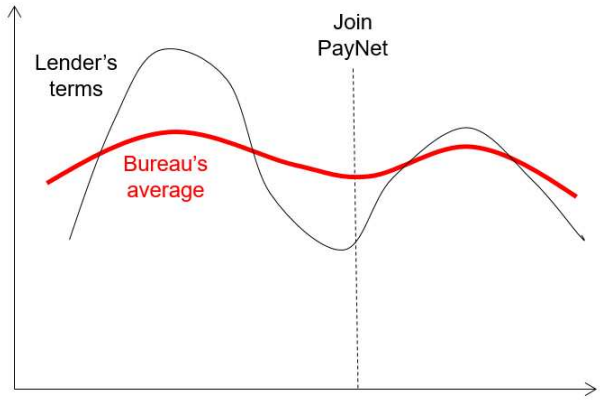


Figure 2: Hypothesis: lender's terms track bureau average better after joining

i.e forces besides strategic interactions that can lead lenders to adjust terms toward what rivals are offering. Specifically, lenders' responses might be driven by (i) information in the platform other than rivals' offers, namely borrower fundamentals, or (ii) by shocks unrelated to the platform information but whose timing coincides with the decision to join. We take both concerns seriously and design our main specification, as well as additional tests to specifically address them as best we can.

Learning about fundamentals: There are two distinct learning channels. First, lenders can learn about the borrower through its PayNet *credit file*. However, because we restrict attention to lending to previously existing borrowers, the credit file is not necessarily informative. Nevertheless, we show our main result holds for borrowers with a single relationship, for which the credit file carries no additional information. Second, lenders can learn from others through *information aggregation*: rivals' terms to other similar borrowers partly reflect their private signal s^{ϕ} about fundamentals. We carry additional tests to see if "specialist" lenders, with more expertise in their specific market, react less compared to others.

Other shocks correlated with joining PayNet: The decision to join the platform is voluntary and can therefore depend on a number of factors that could potentially affect maturity independently of the information revealed by the bureau. On this front, note first that Liberti et al. (2017) show that the key driver of lenders' joining PayNet is a desire to enter new markets. However, our main test is exclusively within existing markets. In addition, we conduct a series of additional within borrower-time (Khwaja and Mian, 2008) and within lender-time tests to show that borrower or lender shocks coinciding with the timing of joining cannot explain away our results.

2.3 Main Findings

We design our main specification to answer the following question: does the contract maturity for the same borrower match the lender's rivals' maturities better after the lender joins the bureau? For each contract, the dependent variable is a measure of the "gap" $|m_i^* - \bar{m}|$ between the maturity offered by the lender and what rivals are offering for similar transactions. The variable of interest is a "Post joining" dummy, equal to 0 for contracts issued before joining PayNet and 1 for those issued after. A negative coefficient $\delta_{post} < 0$ implies that lenders react to the bureau information by offering terms more similar to competitors. Importantly, we can account for heterogeneous deviations from average maturity by including a series of granular fixed effects.

Specifically, the main specification estimates the following fixed effect regression:

$$\log |m_{lfc,t} - \overline{m_{c,t-1}}| = \delta_{post} + \eta_{lf} + \alpha_t + \nu_{contract} + \varepsilon_{lfc,t} \tag{1}$$

The unit of observation is a contract signed between firm f and lender l to finance a specific piece of equipment. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. Because our predictions concern the intensive margin, we only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type.

The dependent variable is the log of absolute value of the gap between the contract maturity at origination and the bureau average maturity for that collateral type in the previous quarter $\overline{m_{c,t-1}}$, excluding the lender's own contracts. We show robustness to using different measures of rivals' offers below. Importantly, recall that our data set is constructed from a random sample of 20,000 borrowers' quarterly credit files. We therefore cannot observe the universe of contracts in the bureau, and this power concern somewhat restricts how finely we can measure rivals' offers.

The parameter of interest is the coefficient δ_{post}. To control for heterogeneous deviations from average maturity, we add a series of fixed effects. η_{lf} consists of a set of borrower-lender fixed effects to account for idiosyncratic time-invariant maturity at the relationship level, including industry and regional variation. Given that lenders join at different times, we can include a set of year fixed effects α_t to absorb aggregate time variation in maturity gaps across firms and lenders. Note also that the variation at the collateral type-quarter level is differenced out in the left-hand side variable. Finally, we include contract characteristic controls $\nu_{contract}$ for each of the three contract size categories, whether the contract is classified as lease or a loan, and each borrower risk category based on prior delinquencies.[26]

[26]Specifically, the three contract size categories are: small ticket (below $250k), medium ticket (between

To lend support to the empirical strategy, Table A.3 in the Appendix reports pre-trends for contract terms before joining the platform. For the entire distribution of loan size and maturity, there is virtually no difference a quarter before joining relative to a year prior to joining. The distribution of the gap relative to the bureau average also does not display any particular trend. The lack of pre-trends also assuages concerns about survivorship bias. Because our Post variable of interest captures the passage of time, it is identified only for borrowers with a contract before and after their lender joins PayNet. While in principle the passage of time (i.e. survival) can be correlated with borrower characteristics, we do not see this pattern prior to joining. In fact, the dynamic coefficient plots in Figure 5 below show that the change in maturity happens exactly on impact, the quarter after the lender joins PayNet.

Table 4 presents the main result of estimating Equation 1. The first two columns show that upon joining the bureau, the gap between a lender's maturity and the bureau average falls by 7% in absolute value. This effect reveals that observing new information about competitors leads lenders to offer maturities closer to what others are offering. Interestingly, the effect appears to be symmetric: lenders adjust terms in both directions. Indeed, the last column of Table 4 shows that maturity itself does not change on average, only the gap relative to rivals changes. This symmetry is consistent with strategic complementarities: when a lender learns that its terms are less generous than rivals, offering better terms can improve its market share. Conversely, if terms are too generous, offering worse terms will not dramatically reduce its market share.

Economically, this information effect implies a notable change in borrowers' debt burdens. To get a sense of economic magnitudes, we translate our main estimate into a change in implied monthly payments.[27] While we cannot directly observe interest rates nor any embedded options in our data, we can use Schalheim and Zhang (2017)'s estimate of the mean annualized interest rate of 15%. Given that our main estimate corresponds to a one-month change in contract maturity, this implies a 2% change in monthly payments, equivalent to a 2 percentage point change in APR.[28] Admittedly, this back-of-the-envelope calculation is an upper bound on the effect given that we cannot observe any potential impact on the rate or the price of equipment. Nevertheless, it is important to note that lenders have limited ability to undo the maturity effect by, say, increasing rates, as this would potentially turn

$250k and $5M) and big ticket (above $5M). The three delinquencies categories are: no missed payments, missed payments under 90 days late, and default or missed payments over 90 days late, all measured over the last three years.

[27] Recall that virtually all contracts in this market have fixed monthly payments.

[28] For example, the median contract is for $20,000 and 37 months, which corresponds to a $678 payment per month. Reducing maturity to 36 months increases monthly payments to $693, roughly comparable to increasing the interest rate from 15% to 17% ($698).

borrowers away.[29]

Table 5 shows that this result is robust to a number of alternative specifications, both in terms of economic magnitude and statistical significance. To account for heterogeneous shocks to collateral types across regions, column 1 calculates the bureau average by collateral type-region-quarter categories instead of collateral type-quarter and yields a similar estimate. Column 2 shows that our results are unchanged if we drop contracts originated during the crisis years of 2008-2010. Column 3 shows that our results are not driven by small collateral types with fewer than one hundred observations, for which the bureau average is likely measured with a significant amount of error. Columns 4 performs a placebo test in which we replace the bureau average for the collateral type in our dependent variable with the bureau average for all other collateral types. As expected, our results attenuate. We perform two additional placebo tests. First, in column 5 we calculate the bureau average using contracts from one year ago instead of current contracts. Second, in column 6 we calculate the bureau average using an unrelated collateral type, based on the relatedness measure introduced in Liberti et al. (2017). For both placebo tests, we find null results. Moreover, unreported results show that the effect is not tied to whether the lender joins early or late.

2.4 The Role of Market Power

One way to add support to the hypothesis that lenders' reaction is driven by strategic complementarities is to test the prediction that the effect should be mediated by market power. Indeed, lenders in a dominant position and whose market share is less sensitive to competitors' actions have less incentive to match rivals.

To test this hypothesis, we construct two proxies of market power.[30] We first calculate the degree of market concentration based on the local HHI. Table A.5 in the Appendix shows summary statistics for these measures. We define a "market" either at the collateral type-contract size level or at the collateral type-contract size-census region level. To alleviate any concern that local market concentration is directly affected by information sharing, we compute market concentration at the beginning of 2001, before PayNet was introduced. There is a considerable variation in concentration across market segments: across contracts, moving from the 25th to the 75th percentile of the distribution implies a .15-.20 increase in the HHI indices. We also use relationship switching rates as an alternative measure of market competitiveness. Some market segments see more relationship switching than others, presumably because of their unique degree of product differentiation, specialization, or other

[29] By definition, adjusting other loan terms to make borrowers indifferent would not help market shares.

[30] We rely on proxies because direct measures of market power are hard to obtain outside a fully structural model.

switching costs.

Table 6 shows that the main result is entirely driven by market segments with low concentration levels. The first two columns split the sample according the median HHI at the collateral type-contract size-census region level. In markets with low concentration levels, the gap between the lender's maturity and the bureau average falls by about 10% after joining, while it is unchanged in markets with high concentration levels. Columns 4 and 5 repeat this split with the more aggregated definition of HHI, while columns 3 and 6 use an interactive specification instead of a sample split. The last three columns show the same result for the alternative measure of market power using relationship switching rates. Table A.4 in the Appendix replicates these findings for several further alternative definitions of market concentration and switching rates.

Figure 5 shows the full dynamics of the effect across subsamples with high and low market concentrations respectively. Each panel plots the coefficients of a version of Equation 1 in which each quarter before and after joining has its own dummy variable. The omitted category is the quarter prior to joining and is labeled as time zero. The left panel shows that, in the most-concentrated markets, the gap between a lender's terms and the bureau average is unaffected by joining. The right panel paints a different picture for the most-competitive markets. After joining, there is a significant and persistent fall in the gap, implying that lenders adjust their terms toward what others are offering. The gradual reduction in the gap is intuitive: because lenders cannot mine the database, it takes time to aggregate and use the information about rivals contained in individual credit files.

These results are consistent with a strategic channel of information sharing, with the effects depending on the degree of market power over borrowers. Lenders in a dominant position and whose market share is less sensitive to competitors face little competitive pressure to respond to what others are offering.[31][32] Note also that, reassuringly, there are no significant pre-trends and the effect arises upon joining.

[31] One concern is that this concentration effect works through learning about borrowers' fundamentals instead. However, Bustamante and Frésard (2017) show in detail that this channel would lead to the opposite pattern: the effect should be stronger in more concentrated markets in which a fringe of smaller firms has stronger incentives to learn from larger product-market peers. Section 3 offers a more natural cross-sectional test of the learning channel by sorting lenders according to their expertise.

[32] Ideally, we would also use data on applications to measure directly how the take-up rate of a lender's offer depends on rivals' maturity, as in Argyle et al. (2018). Unfortunately, PayNet does not collect data on applications.

3 Robustness and Other Mechanisms

3.1 Other Mechanisms

The previous section provides robust evidence of a strategic effect of information sharing: lenders' match competitors to an extent that depends on their market power over borrowers. In this section, we put this result into perspective with more conventional channels of information sharing in credit markets. We do not claim that these channels are not at play in general; in fact, previous work using PayNet data suggests they are in our setting (Sutherland (2018), Liberti et al. (2017)). We argue only that our specific findings cannot be fully explained by a number of forces previously documented.

Revelation of Credit History: A key role of credit bureaus is to create credit files that reduce information asymmetries between lenders and borrowers. The revelation of borrowers' payment histories affects the composition of credit and contract terms. Part of this channel works through a change in the composition of borrowers: worse borrowers are screened out or offered harsher terms, while better borrowers receive better offers (Foley et al., 2018). However, by design, our tests keep the composition of borrower-lender pairs constant by including relationship fixed effects. The effect we document is therefore a change in maturity within a relationship. The revelation of credit histories can affect an existing relationship if a borrower has multiple lenders. Accessing the bureau can reveal negative information to the lender that the borrower tried to keep secret previously. If this channel were driving our result, we expect that it would be smaller or absent for borrowers with (1) a good credit history, and (2) a single relationship because for them the credit file would contain no new information.[33] However, Table 8 reveals that none of these predictions hold in this sample.

Creditor Runs: Alternatively, lenders can react to observing others' terms due to the fear of a creditor run.[34] For instance, Hertzberg et al. (2011) illustrates the effect of information sharing on lender coordination. In the context of maturity choice, Brunnermeier and Oehmke (2013) emphasize the risk of a "maturity rat race," in which new lenders offer short maturities in an effort to front-run existing creditors. In general, these incentives to run lead to strategic complementarities in maturity choice that could explain a convergence in maturities after joining the bureau. Although all loans are formally collateralized, there is still significant default risk. Nevertheless, three pieces of evidence speak against an explanation

[33] It may be news that the borrower does not have a relationship with any other lender. Nevertheless, we would expect this piece of news to be substantially less informative than a full credit history.

[34] More broadly, a number of papers have emphasized the role of information in explaining run-like behavior, such as Morris and Shin (1998), Bebchuk and Goldstein (2011), Goldstein et al. (2011), Goldstein and Pauzner (2005).

based on run-like behavior of creditors. First, it does not appear that lenders shorten their maturities systematically upon joining: lenders adjust their terms toward what others are offering, in both directions. Moreover, the aforementioned findings in Table 8 are at odds with a run interpretation; the effect is equally strong for borrowers with good credit records or with a single relationship for which the incentives to run are muted.[35]

Information Aggregation and Lender Specialization: Finally, we examine a last alternative channel based on information aggregation. In this view, lenders react to others' terms because they reveal some of their private information about credit risk or borrower demand in the economy. Note the differences with the previous channels. The strategic channel emphasizes that lenders care about others' actions per se, while the information aggregation channel argues that they care because of what they represent: maturities partially reveal competitors' private information that was used to make this choice. As opposed to learning about a specific borrower from its payment history, information aggregation postulates that lenders look at the bureau information to extrapolate to other similar borrowers (e.g., with respect to size, sector, or collateral type).[36] This insight is canon in the context of financial markets (Hellwig, 1980) and the information aggregation channel is often mentioned in antitrust debates related to the benefits of information sharing, a point we will revisit.

In the context of credit markets, this is an intriguing hypothesis. Admittedly, it is difficult to fully separate from the strategic channel, as the perfect test would rely on observing beliefs or preferences. Instead, we proxy for differences in information about fundamentals across lenders. The hypothesis is that if some lenders are more informed than others, they should react less to the information in the bureau. Indeed, a lender with more-precise prior or more private signals puts less weight on others' terms when deciding what contract to offer.[37]

Toward this end, we compare the behavior of specialist lenders relative to others upon joining the platform. We include numerous definitions of lender specialization with the intent of capturing lenders that have strong expertise in a specific market segment. Table 9 presents the results. Columns (1) and (2) define specialization as the number of quarters since the lender's first contract originated in this collateral type or collateral type-region category. Columns (3) and (4) define a lender as a specialist for a specific collateral type if that collateral type is either the most common or one of the top three originated by that lender.

[35]In general, an additional test of a maturity rat race could exploit variation in time to maturity of competitors' contracts: the effect should be more pronounced for borrowers that have another contract expiring sooner. However, in our setting, virtually all contracts have fixed equal monthly payments, making front-running other creditors difficult.

[36]Note however that it is not easy to learn about collateral values as recovery values are not reported in the platform.

[37]In the context of real estate markets, Stroebel (2016) and Kurlat and Stroebel (2015) also exploit heterogeneity in expertise.

Column (5) defines a lender as a specialist for a specific collateral type if that collateral type makes up at least 30% of its lending portfolio. The information aggregation channel would imply that specialists adjust their terms relatively less upon observing others' terms, leading to a positive interaction term $Post \times Specialist$. However, the interaction between joining and the specialist dummy is not positive in any specification. The interaction is typically small, negative, and insignificant. Given that lenders with strong expertise in a specific market segment do not appear to react less than nonspecialists, these results suggest that information aggregation plays no detectable role in our results.

Attention Allocation: Liberti et al. (2017) show that the main reason lenders seem to join PayNet is to enter new markets. In principle it could be that lenders are switching their attention to new markets at the expense of markets they were previously active in. For the old markets, they then take a more mechanical approach of simply conforming with other lenders. Directly testing this hypothesis is particularly difficult: we lack the data to measure the workload of loan officers or the information collected prior to the lender's maturity choice, assuming that would be enough. However, it is not immediately clear why this shift in attention should be correlated with market concentration and uncorrelated with lender's expertise.

Together, these findings strongly support the view that strategic complementarities are an important driver of loan terms in this market. Any alternative mechanism would have to be consistent with at least four findings. First, the effect of matching rivals exists within an existing relationship. Second, it is symmetric around zero (maturity itself is unchanged). Third, it varies by market concentration. Fourth, it does not vary by borrower creditworthiness or lender expertise.

3.2 Other Shocks Coinciding with Lender's Joining PayNet

Joining PayNet is voluntary and not randomly assigned. Therefore we cannot exclude the possibility that our results are due to factors other than the bureau information that drives both the decision to join and maturity choices. Related, note that access to new markets is the key driver of lenders' joining the PayNet platform (Liberti et al., 2017). However, our main test is exclusively within existing markets: it includes lender-borrower fixed effects and is restricted to lenders with contracts in a given collateral type before and after joining. Note also that Table A.3 and Figure 5 reveal no discernible pre-trends in our dependent variable prior to joining. Nevertheless, we leverage the granularity of our data and conduct a number of robustness tests to directly address this threat to identification.

Accounting for Borrower Shocks: On the borrower side, our results hold when

comparing contracts made to the *same* firm at the *same* time by lenders with different information sets. We exploit the fact that not all lenders join at the same time. As opposed to many other settings, this variation in joining times implies that the platform information is not publicly revealed. In the same period, some lenders have access to it while others do not. We can use this within-period, across-lender variation to distinguish the effects of the new information from other events affecting a given borrower in a given year. Specifically, we include borrower-year fixed effects for the subset of borrowers with multiple lenders:

$$\log |m_{lfc,t} - \overline{m_{c,t-1}}| = \delta_{post} + \eta_{lf} + \zeta_{ft} + \nu_{contract} + \varepsilon_{lfc,t} \tag{2}$$

Panel A of Table 7 shows the results of this extended specification. As before, the gap between a lender's maturity and the bureau average falls after joining in competitive market segments, but is unchanged in others. The estimated magnitudes are naturally lower, as the average effect on the borrower is absorbed in the borrower-time fixed effects. The coefficient reflects the reduction in the gap after joining relative to other lenders of the firm in the post period. This more stringent specification alleviates the concern that results are driven by shocks to borrower demand or creditworthiness that coincide with the lender's decision to join PayNet.

Accounting for Lender Shocks: On the lender side, joining PayNet might coincide with a shift in its business model, which is potentially correlated with its propensity to offer specific contract maturities. To address this concern, we design a within-lender-time test that exploits the behavior of *other lenders*. Specifically, the information coverage in the bureau depends on contracts originated by others and thus varies by collateral type over time in a way that is not directly driven by the decision to join. For example, after a lender joins, they have no control over how the bureau's membership or coverage evolves. Any given year could see non-systematic changes in bureau coverage across collateral types based on who else joins, and these coverage changes affect the precision of the bureau average. This variation driven by others sharing (which by construction is beyond the previously joining lender's control) allows us to check whether our result holds within lender-year across different collateral types.

We can therefore verify whether the maturity of collateral types with higher coverage tracks the bureau average better than collateral types with low coverage. Concretely, we augment Equation 1 by adding two elements:

$$\log |m_{lfc,t} - \overline{m_{c,t-1}}| = \delta_{post} * Volume_{c,t-1} + \eta_{lf} + \xi_{lt} + \nu_{contract} + \varepsilon_{lfc,t} \tag{3}$$

First, the main coefficient of interest is now the Post×Volume interaction, where Volume is

defined as the number of contracts in the bureau of the same collateral type still open as of the previous quarter.[38] Second, we include a lender-year fixed effect ξ_{lt} that absorbs any change in lender's supply that is constant across collateral types within a year.

Panel B of Table 7 shows the results for this extended specification. The estimated coefficients are consistent with our main finding. For a given lender joining in a specific quarter, the maturity of collateral types with higher coverage tracks the bureau average better than collateral types with low coverage and only so in the most-competitive market segments. The magnitudes are again lower, as the average effect on the lender is absorbed by the lender-time fixed effects. Columns 5 and 6 also include borrower-year fixed effects for robustness and arrive at the same results. These tests lend additional support to the interpretation that lenders adjust their maturities in reaction to the information revealed in the bureau, as opposed to other factors that drive the decision to join the platform.

4 Implications

In the context of credit markets, the strategic channel appears to go beyond conventional mechanisms of the effects of information sharing. This is largely because in our setting, lenders gain access to a key source of additional information: their competitors' contract terms. Importantly, how much this information matters depends on market power; lenders in dominant positions have little incentive to match their competitors' offers. This result speaks, in a novel way, to the interaction between information and market competition that has been emphasized in the literature (Vives, 2006; Jappelli et al., 2000).

Interestingly, across many markets, the debate on the effect of information sharing on market behavior has resurfaced recently due to the rise in big data and algorithm developments. European Commissioner for Competition Margrethe Vestager argued that "the future of big data is not just about technology. It's about things like. . . competition".[39] The economic forces at play are subtle. On the one hand, information from competitors could facilitate collusion. On the other hand, there are potential benefits of pooling information: it can improve production efficiency or remove barriers to competition. Similarly, having access to more information can backfire if "mistakes" are propagated as opposed to corrected when information is shared. For instance, Murfin and Pratt (2017a) document in detail how the use of comparables leads to pricing mistakes in the syndicated loan market.[40]

In order to relate these questions to our setting, we provide a final set of tests linking

[38] We omit the level effect of Volume in the regression equation for brevity.

[39] 2016 EDPS-BEUC Conference on Big Data and Competition. See also Ferretti (2014) for a discussion of the role of information sharing from the point of view of European competition law.

[40] See also Hassan and Mertens (2017) for the role of mistakes in a macroeconomic model.

our main finding to delinquencies during the recent crisis. Broadly speaking, there are two possible channels that could increase delinquencies. First, enhanced competition can lead lenders to neglect future risk as they compete aggressively to preserve their market share today. Second, reliance on hard information such as credit reports and scores exposes lenders to significant losses caused by negative shocks that are not anticipated by the hard information.[41]

To investigate this possibility, we exploit the staggered timing of lenders' joining and study how contracts originated prior to the crisis end up performing during the crisis. Specifically, for each lender joining between 2005 and 2007, we study the 2008-2009 performance of contracts originated shortly before joining, compared to contracts originated shortly after joining. Our assumption, based on our prior tests, is that lenders do more firm-specific screening before joining, and rely more on shared information after and react to what rivals are offering. In addition to lender fixed effects, our tests include indicators for the quarter of origination for each collateral type and the quarter of origination for each borrower region. These last controls ensure that our results are not driven by lending to different cohorts with differential (and potentially region-specific) default risk.

Table 10 shows that contracts originated just after the lender joined experienced more crisis-period delinquencies than the contracts originated by the same lender just before. Specifically, the post-join contracts experienced approximately 0.3 more quarters of delinquency from 2008 to 2009 than the pre-join contracts. One interpretation is that a desire to match competitors can backfire if lenders give less attention to fundamental sources of risk.

Admittedly, this is not the only possible explanation and although our data cannot reject alternatives with absolute confidence, there is additional evidence that a strategic channel plays a role. Consistent with our prior results, we also find that the effect is entirely driven by markets with low levels of market power. It is also concentrated in states that experienced the largest drops in housing prices. Moreover, there is a reduction in the average gap between the lender's contract maturity and rivals' maturity after joining PayNet, but this decline is more pronounced for contracts ending up delinquent relative to contracts that experienced no delay in payments. Finally, it does not appear that lenders target riskier borrowers after joining. On the contrary, if anything the credit record of borrowers improves, consistent with the canonical information effect of credit bureaus.

Because the set of lenders joining PayNet a few years before the crisis instead of in other periods is small and potentially selected, we take this evidence as suggestive as opposed to

[41] Rajan et al. (2015) document this phenomenon in the market for securitized subprime mortgages. More generally, this is related to the Lucas critique (Lucas, 1983). See also Farboodi et al. (2018) for a recent discussion of how the use of information by the stock market can deviate from the social optimal.

definitive. Nevertheless, it supports the idea that strategic incentives to match competitors behind contract design can have a cost if they lead to the neglect of fundamental risk.

5 Conclusion

This paper estimates the effect of learning about competitors on the behavior of market participants. We document this effect in the context of maturity dynamics for small and medium enterprises (SME) equipment financing contracts using micro-data from the introduction of an information sharing platform in this market between 2001 and 2014. The platform provides details of previous and current contracts and not simply current payment status or debt balances. We exploit the staggered timing of lenders' joining the platform to estimate the effects of learning about competitors. We find that, upon joining, lenders adjust their terms toward what others are offering. Crucially, we address two key confounders: unobserved common shocks to fundamentals and endogenous timing of joining the bureau.

Consistent with strategic complementarities, lenders' appear to match competitors in order to sustain market shares. The strength of this effect depends on the degree of market power lenders have over their borrowers. This strategic channel exists beyond more conventional channels, such as the revelation of a borrower's payment history and creditor runs. We also find that contracts originated after joining were more likely to end up repeatedly delinquent during the recent crisis relative to contracts originated before, suggesting that a desire to match competitors can backfire if lenders give less attention to fundamental sources of risk.

These results shed light on the interaction between information and market competition in credit markets, as well as many other settings. Learning about competitors is likely becoming increasingly easier given the rise of large pooled databases and improvements in data mining techniques. While we find a greater convergence between rivals in our setting, the effect could potentially go in the other direction. Indeed, a number of markets are characterized by a large degree of horizontal differentiation or populations of unsophisticated consumers facing endogenously complex products. The implications for consumer welfare, production efficiency, and policy design are important questions for future research.

References

Afrouzi, H. (2017). Strategic inattention, inflation dynamics and the non-neutrality of money. Technical report, Mimeo.

Amador, M. and Weill, P.-O. (2012). Learning from private and public observations of others actions. *Journal of Economic Theory*, 147(3):910–940.

Angeletos, G.-M. and La'O, J. (2010). Noisy business cycles. *NBER Macroeconomics Annual*, 24(1):319–378.

Angeletos, G.-M. and Lian, C. (2016). Incomplete information in macroeconomics: Accommodating frictions in coordination. In *Handbook of Macroeconomics*, volume 2, pages 1065–1240. Elsevier.

Argyle, B., Nadauld, T., and Palmer, C. (2017a). Monthly payment targeting and the demand for maturity.

Argyle, B., Nadauld, T., and Palmer, C. (2017b). Real effects of search frictions in consumer credit markets.

Argyle, B., Nadauld, T., Palmer, C., and Pratt, R. (2018). The capitalization of consumer financing into durable goods prices.

Balakrishnan, K. and Ertan, A. (2017). Credit information sharing, loan loss recognition timeliness, and financial stability.

Bebchuk, L. A. and Goldstein, I. (2011). Self-fulfilling credit market freezes. *The Review of Financial Studies*, 24(11):3519–3555.

Berger, P. G., Minnis, M., and Sutherland, A. (2017). Commercial lending concentration and bank expertise: Evidence from borrower financial statements. *Journal of Accounting and Economics*, 64(2-3):253–277.

Bodnaruk, A., O'Brien, W., and Simonov, A. (2016). Captive finance and firm's competitiveness. *Journal of Corporate Finance*, 37:210–228.

Brunnermeier, M. K. and Oehmke, M. (2013). The maturity rat race. *The Journal of Finance*, 68(2):483–521.

Bustamante, M. C. and Frésard, L. (2017). Does firm investment respond to peers' investment? Technical report, Working paper.

Chen, Q., Goldstein, I., and Jiang, W. (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics*, 97(2):239–262.

Cox, N. (2017). The impact of interest rates and liquidity constraints on fixed-variable rate decisions. Technical report, Working Paper.

Dell'Ariccia, G., Igan, D., and Laeven, L. U. (2012). Credit booms and lending standards: Evidence from the subprime mortgage market. *Journal of Money, Credit and Banking*, 44(2-3):367–384.

Doblas-Madrid, A. and Minetti, R. (2013). Sharing information in the credit market: Contract-level evidence from us firms. *Journal of financial Economics*, 109(1):198–223.

Farboodi, M., Matray, A., and Veldkamp, L. (2018). Where has all the big data gone?

Ferretti, F. (2014). Information exchanges among competitors in eu retail financial markets. In *EU Competition Law, the Consumer Interest and Data Protection*, pages 7–31. Springer.

Foley, F., Hurtado, A., Liberman, A., and Sepulveda, A. (2018). The effects of information on credit market competition: Evidence from credit cards.

Giannetti, M., Liberti, J. M., and Sturgess, J. (2017). Information sharing and rating manipulation. *The Review of Financial Studies*, 30(9):3269–3304.

Gissler, S., Ramcharan, R., and Yu, E. (2018). The effects of competition in consumer credit markets.

Goldstein, I., Ozdenoren, E., and Yuan, K. (2011). Learning and complementarities in speculative attacks. *The Review of Economic Studies*, 78(1):263–292.

Goldstein, I. and Pauzner, A. (2005). Demand–deposit contracts and the probability of bank runs. *the Journal of Finance*, 60(3):1293–1327.

Hassan, T. A. and Mertens, T. M. (2017). The social cost of near-rational investment. *American Economic Review*, 107(4):1059–1103.

Hauswald, R. and Marquez, R. (2003). Information technology and financial services competition. *The Review of Financial Studies*, 16(3):921–948.

Hellwig, M. F. (1980). On the aggregation of information in competitive markets. *Journal of economic theory*, 22(3):477–498.

Hertzberg, A., Liberman, A., Paravisini, D., et al. (2018). Screening on loan terms: evidence from maturity choice in consumer credit. *The Review of Financial Studies*.

Hertzberg, A., Liberti, J., and Paravisini, D. (2010). Information and incentives inside the firm: Evidence from loan officer rotation. *The Journal of Finance*, 65(3):795–828.

Hertzberg, A., Liberti, J., and Paravisini, D. (2011). Public information and coordination: evidence from a credit registry expansion. *The Journal of Finance*, 66(2):379–412.

Jappelli, T. and Pagano, M. (2006). The role and effects of credit information sharing. *The economics of consumer credit*, page 347.

Jappelli, T., Pagano, M., et al. (2000). Information sharing in credit markets: a survey. Technical report, CSEF working paper.

Khwaja, A. I. and Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4):1413–42.

Kurlat, P. and Stroebel, J. (2015). Testing for information asymmetries in real estate markets. *The Review of Financial Studies*, 28(8):2429–2461.

Liberman, A., Neilson, C., Opazo, L., and Zimmerman, S. (2018). The equilibrium effects of asymmetric information: Evidence from consumer credit markets.

Liberti, J., Sturgess, J., and Sutherland, A. (2017). Economics of voluntary information sharing.

Liberti, J. M. (2017). Initiative, incentives, and soft information. *Management Science*.

Liberti, J. M. and Mian, A. R. (2009). Estimating the effect of hierarchies on information use. *The Review of Financial Studies*, 22(10):4057–4090.

Liberti, J. M., Seru, A., and Vig, V. (2016). Information, credit, and organization.

Lucas, R. E. (1983). Econometric policy evaluation: A critique.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The review of economic studies*, 60(3):531–542.

Mian, S. L. and Smith Jr, C. W. (1992). Accounts receivable management policy: theory and evidence. *The Journal of Finance*, 47(1):169–200.

Milbradt, K. and Oehmke, M. (2015). Maturity rationing and collective short-termism. *Journal of Financial Economics*, 118(3):553–570.

Morris, S. and Shin, H. S. (1998). Unique equilibrium in a model of self-fulfilling currency attacks. *American Economic Review*, pages 587–597.

Morris, S. and Shin, H. S. (2002). Social value of public information. *american economic review*, 92(5):1521–1534.

Murfin, J. and Pratt, R. (2017a). Comparables pricing. *The Review of Financial Studies*.

Murfin, J. and Pratt, R. (2017b). Who finances durable goods and why it matters: Captive finance and the coase conjecture. *The Journal of Finance, forthcoming*.

Nelson, S. T. (2017). *Private information and price regulation In the US credit card market*. PhD thesis, Massachusetts Institute of Technology.

Palmer, C. (2015). Why did so many subprime borrowers default during the crisis: Loose credit or plummeting prices?

Rajan, U., Seru, A., and Vig, V. (2015). The failure of models that predict failure: Distance, incentives, and defaults. *Journal of Financial Economics*, 115(2):237–260.

Rice, T. and Strahan, P. E. (2010). Does credit competition affect small-firm finance? *The Journal of Finance*, 65(3):861–889.

Ryan, S. G. and Zhu, C. (2018). Fintech isn't so different from traditional banking: Trading off aggregation of soft information for transaction processing efficiency.

Schaal, E. and Taschereau-Dumouchel, M. (2015). Coordinating business cycles.

Schalheim, J. and Zhang, X. (2017). An examination of yields on small business equipment leases.

Shaked, A. and Sutton, J. (1982). Relaxing price competition through product differentiation. *The review of economic studies*, pages 3–13.

Stroebel, J. (2016). Asymmetric information about collateral values. *The Journal of Finance*, 71(3):1071–1112.

Sutherland, A. (2018). Does credit reporting lead to a decline in relationship lending? evidence from information sharing technology. *Journal of Accounting and Economics*.

Van Nieuwerburgh, S. and Veldkamp, L. (2006). Learning asymmetries in real business cycles. *Journal of monetary Economics*, 53(4):753–772.

Veldkamp, L. L. (2011). *Information choice in macroeconomics and finance*. Princeton University Press.

Vives, X. (2006). Information sharing: economics and antitrust. *The Pros and Cons of Information Sharing*, 83.

Tables and Figures

Table 1: Sample Description

N. of borrowers	2,076
N. of lenders	44
N. of relationships	8,194
N. of contracts	54,290
N. of collateral types	23
N. of relationships per lender	94.0
N. of relationships per borrower	2.0
N. of collateral types per lender	6.1
N. of collateral types per borrower	1.7

Note: This table presents summary statistics for the borrowers and lenders in our regression sample. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type.

Table 2: Contract Characteristics

	All Contracts				Inside Bureau				Outside Bureau			
Contract Characteristics	N.	Mean	Median	SD	N.	Mean	Median	SD	N.	Mean	Median	SD
Loan size (thousands $)	54,290	101	20.3	593	37,333	104	20.7	589	16,957	93	19.7	605
Maturity (months)	54,290	44.3	37	17	37,333	44.5	39	17	16,957	43.8	37	16
Lease (indicator)	54,290	0.81	1	0.39	37,333	0.81	1	0.39	16,957	0.82	1	0.39
Monthly repayment (indicator)	51,568	0.91	1	0.28	35,410	0.90	1	0.29	16,158	0.92	1	0.26
Guarantor (indicator)	45,269	0.16	0	0.37	32,227	0.16	0	0.37	13,042	0.16	0	0.37
Personal guarantor (indicator)	45,269	0.01	0	0.10	32,227	0.01	0	0.09	13,042	0.01	0	0.11
|Maturity gap| (months)	54,290	13.9	11.3	12.8	37,333	14.0	11.4	13.5	16,957	13.5	11.1	11.4

Note: This table presents summary statistics of the terms for the contracts in our regression sample. The unit of observation is contract. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type.

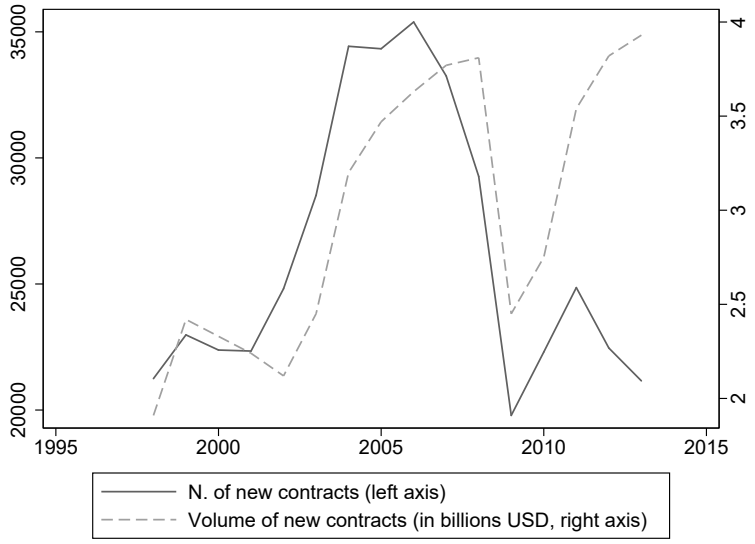


Figure 3: Origination of Contracts in PayNet

Note: This figure displays the distribution of contract originations by lenders in our setting according to origination year. The sample is not limited to our regression sample and includes all contracts in the data.

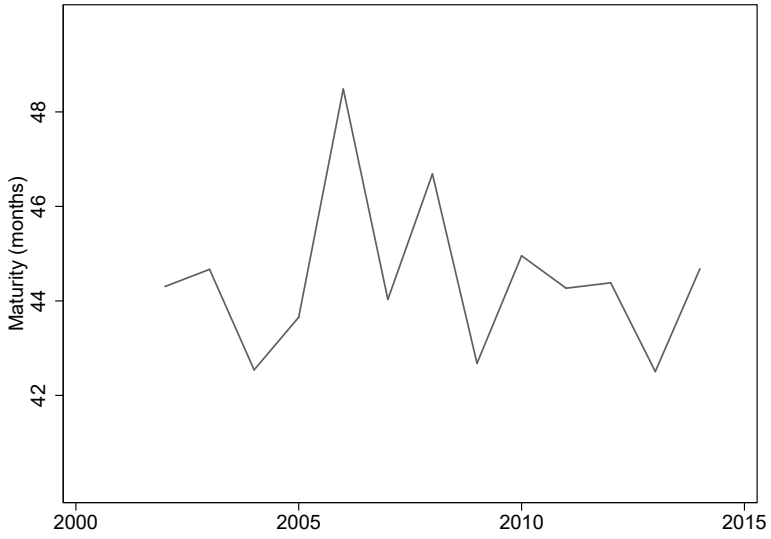


Figure 4: Contract Maturity

Note: This figure displays the average maturity of the contracts in our regression sample according to origination year. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type.

Table 3: Timing of Lenders Joining PayNet

	All lenders	Lenders size quartile			
Year		Q1	Q2	Q3	Q4
2002	2				2
2003	1			1	
2004	9	1	1	2	5
2005	2	1			1
2006	2	1			1
2007	4	1		3	
2008	4	1	3		
2009	3		2		1
2010	0				
2011	4		3		1
2012	7	1	2	4	
2013	6	5		1	
Total	44	11	11	11	11

Note: This table displays the year of joining PayNet for lenders in our regression sample according to the size of the lender. Lender size is measured according to total credit upon joining the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type.

Table 4: Joining PayNet and Contract Maturity: Main Specification

	Log |gap|		Log maturity
	(1)	(2)	(3)
Post joining platform	-0.069**	-0.069**	0.024
	[-2.30]	[-2.34]	[1.16]
Year FE	Yes	Yes	Yes
Lender-Borrower FE	Yes	Yes	Yes
Contract characteristics FE	No	Yes	Yes
N	54290	54290	54290
Adj. R-squared	0.521	0.522	0.666

*Note: This table displays the regression results from estimating Equation 1. The unit of observation is contract. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type. In columns (1) and (2), the dependent variable is the log absolute value of the gap between the contract maturity and the bureau average maturity for that collateral type in the previous quarter (excluding the lender's own contracts). In column (3), the dependent variable is the log of contract maturity. Contract characteristic controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are in parentheses and are clustered by lender. *** p<0.01, ** p<0.05, * p<0.10.*

Table 5: Robustness

	Bureau average by collateral type-quarter-region	Drop crisis period	Drop small collateral types	Exc. own collateral type	Bureau average for previous year	Bureau average for unrelated collateral type
	(1)	(2)	(3)	(4)	(5)	(6)
Post joining	–0.047*	-0.078**	-0.071**	-0.044**	-0.043	0.011
	[-1.82]	[-2.52]	[-2.38]	[-2.07]	[-1.07]	[0.07]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender-Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Contract characteristics FE	Yes	Yes	Yes	Yes	Yes	Yes
N	53231	51011	54136	54845	41800	22324
Adj. R-squared	0.510	0.515	0.522	0.531	0.531	0.570

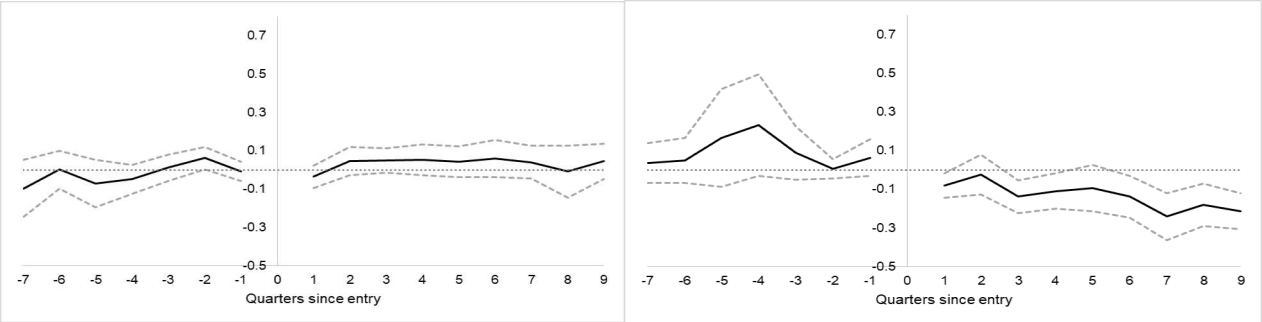
*Note: This table displays the regression results from estimating variations of Equation 1. Column (1) calculates the bureau average by collateral type-quarter-region categories, instead of collateral type-quarter. Column (2) drops observations during the crisis period, defined as 2008 to 2010. Column (3) drops the smallest collateral types, specifically those with less than 100 observations. Column (4) calculates the bureau average by including all collateral types except the one of the contract. Column (5) uses the bureau average of the previous year. Column (6) uses the bureau average for an unrelated collateral type, chosen as the median of the relatedness measure defined in Liberti et al. (2017). The unit of observation is contract. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type. Contract characteristic controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are in parentheses and are clustered by lender. *** p<0.01, ** p<0.05, * p<0.10.*

Table 6: Joining PayNet and Contract Maturity: Split by Market Power

	Log |gap|								
	Collateral type-Region-Loan Size HHI			Collateral type-Loan Size HHI			Relationship Switching Rate		
	(1) High	(2) Low	(3) All	(4) High	(5) Low	(6) All	(7) High	(8) Low	(9) All
Post joining bureau	-0.017	-0.095***		-0.012	-0.111***		-0.118***	0.003	
	[-0.56]	[-2.58]		[-0.34]	[-3.22]		[-2.67]	[0.08]	
Post × High HHI			-0.030			-0.036			
			[-0.93]			[-1.01]			
Post × Low HHI			-0.116***			-0.104***			
			[-2.91]			[-3.93]			
Post × High Switching									-0.115***
									[-4.28]
Post × Low Switching									-0.022
									[-0.58]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract characteristics FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	26142	27163	53305	25789	28312	54101	25888	28402	54290
Adj. R-squared	0.548	0.567	0.523	0.562	0.572	0.522	0.572	0.578	0.523

*Note: This table displays the regression results from estimating Equation 1 by proxies of market power. In columns 1 and 2 (4 and 5), the sample is split according to the median HHI of the collateral type-region-contract size category (collateral type-contract size category). Columns 7 and 8 use the relationship switching rate, defined as the fraction of relationships in the market last quarter that no longer exist this quarter. Columns 3, 6 and 9 provide interactive specifications instead of a sample split. The unit of observation is contract. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type. The dependent variable is the log absolute value of the gap between the contract maturity and the bureau average maturity for that collateral type in the previous quarter (excluding the lender's own contracts). Contract characteristic controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are in parentheses and are clustered by lender. *** p<0.01, ** p<0.05, * p<0.10.*

Figure 5: Joining PayNet and Contract Maturity by Market Concentration: Dynamic Coefficients Plot



(a) High HHI (b) Low HHI

Note: This figure plots the coefficients from estimating a piecewise version of Equation (1) using event quarter indicators. The dashed lines plot 90% level confidence intervals. The sample is split according to the median HHI of the collateral type-region-contract size category measured at the contract level. The unit of observation is contract. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type. The dependent variable is the log absolute value of the gap between the contract maturity and the bureau average maturity for that collateral type in the previous quarter (excluding the lender's own contracts). Contract characteristic controls include indicators for contract size categories, leases, and the borrower's risk category.

Table 7: Accounting for Other Shocks

Panel A: Borrower Shocks

	Log |gap|	
	(1)	(2)
	High HHI	Low HHI
Post joining bureau	0.048	-0.044*
	[0.89]	[-1.79]
Borrower-Year FE	Yes	Yes
Lender-Borrower FE	Yes	Yes
Contract characteristics FE	Yes	Yes
N	17615	18175
Adj. R-squared	0.523	0.561

Panel B: Lender Shocks

	Log |gap|			
	(1)	(2)	(3)	(4)
	HHI		HHI	
	High	Low	High	Low
Post*Volume	-0.002	-0.011*	0.002	-0.008**
	[-0.59]	[-1.67]	[0.38]	[-2.09]
Lender-Year FE	Yes	Yes	Yes	Yes
Lender-Borrower FE	Yes	Yes	Yes	Yes
Borrower-Year FE	No	No	Yes	Yes
Contract characteristics FE	Yes	Yes	Yes	Yes
N	26142	27163	17607	18163
Adj. R-squared	0.553	0.574	0.525	0.560

*Note: Panel A displays the regression results from estimating Equation 2. Panel B displays the regression results from estimating Equation 3, and volume is defined as the number of contracts in the bureau of the same collateral type still open as of the previous quarter. The sample is split according to the median HHI of the collateral type-region-contract size category measured at the contract level. The unit of observation is contract. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type. In Panel A and columns (3) and (4) of Panel B, in addition to our main sample restrictions, these tests are also limited to borrowers with at least two outstanding relationships. The dependent variable is the log absolute value of the gap between the contract maturity and the bureau average maturity for that collateral type in the previous quarter (excluding the lender's own contracts). Contract characteristic controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are in parentheses and are clustered by lender. *** p<0.01, ** p<0.05, * p<0.10.*

Table 8: Joining PayNet and Contract Maturity: Borrower Heterogeneity

	Log |gap|			
	(1) No past delinquency	(2) Worst delinquency <90 days	(3) Single relationship	(4) Multiple relationships
Post joining bureau	-0.146*	-0.080**	-0.275***	-0.053*
	[-1.76]	[-2.40]	[-3.40]	[-1.76]
Year FE	Yes	Yes	Yes	Yes
Lender-Borrower FE	Yes	Yes	Yes	Yes
Contract characteristics FE	Yes	Yes	Yes	Yes
N	4709	24224	7354	46936
Adj. R-squared	0.660	0.562	0.605	0.508

*Note: This table displays the regression results from estimating Equation 1 by borrower type. The sub-samples in columns (1) and (2) are created according to the worst delinquency the borrower has experienced in the previous three years. In columns (3) and (4), the sample is split according to the number of the borrower's credit relationships at the time of contract origination. The unit of observation is contract. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type. The dependent variable is the log absolute value of the gap between the contract maturity and the bureau average maturity for that collateral type in the previous quarter (excluding the lender's own contracts). Contract characteristic controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are in parentheses and are clustered by lender. *** p<0.01, ** p<0.05, * p<0.10.*

Table 9: Joining PayNet and Contract Maturity: Lender Specialization

	Log |gap|				
	(1)	(2)	(3)	(4)	(5)
Specialist definition	Quarters since 1st contract in collateral type	Quarters since 1st contract in collateral type-region	Lender's most common collateral type	In lender's top 3 collateral type	Collateral type >30% of lender's portfolio
Post x Specialist	-0.002	-0.000	-0.045	-0.019	-0.038
	[-0.90]	[-0.14]	[-1.08]	[-0.49]	[-0.79]
Post	-0.050	-0.086	-0.037	-0.062**	-0.040
	[-0.75]	[-1.33]	[-0.78]	[-2.01]	[-0.75]
Specialist	0.017	0.015	0.056	-0.250***	0.076
	[1.19]	[1.56]	[0.51]	[-2.83]	[0.52]
N	54290	54290	54290	54290	54290
adj. R-sq	0.523	0.524	0.523	0.525	0.523

*Note: This table displays the regression results from augmenting equation 1 with different specialist lender variables and their interaction with Post. All specifications include year, lender-borrower and contract characteristics fixed effects. Columns (1) and (2) define specialization as the number of quarters since the first contract originated in this collateral type or collateral type-region category. Columns (3) and (4) define a lender as a specialist for a specific collateral type if that collateral type is either the most common or one of the top three originated by this lender. Columns (5) defines a lender as a specialist for a specific collateral type if that collateral type makes up at least 30% of its lending portfolio. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type. The dependent variable is the log absolute value of the gap between the contract maturity and the bureau average maturity for that collateral type in the previous quarter (excluding the lender's own contracts). Contract characteristic controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are in parentheses and are clustered by lender. *** p<0.01, ** p<0.05, * p<0.10.*

Table 10: Joining PayNet and Delinquencies during 2008-2009 Crisis

	Number of quarters delinquent in 2008-2009				
	(1)	(2)	(3)	(4)	(5)
	All contracts	High HHI market	Low HHI market	Housing crisis states	Other states
Post joining	0.299**	-0.430	0.501**	0.594***	0.113
	[2.54]	[-1.60]	[2.73]	[3.41]	[0.73]
Lender FE	Yes	Yes	Yes	Yes	Yes
Collateral type-quarter FE	Yes	Yes	Yes	Yes	Yes
Region-quarter FE	Yes	Yes	Yes	Yes	Yes
Contract characteristics FE	Yes	Yes	Yes	Yes	Yes
N	3236	1676	1485	1324	1912
adj. R-sq	0.211	0.230	0.246	0.247	0.232

*Note: This table shows the effect of joining PayNet on delinquencies during the crisis. The sample is restricted to (1) lenders joining between 2005 and 2007, and (2) contracts originated no later than 2006 and still open in 2008-2009. The unit of observation is contract. HHI is the credit-weighted Herfindahl-Hirschman Index for the market, measured in 2001, before the bureau's inception. Housing crisis states are defined as those states with a greater than 30% housing price decline from peak, according to the FHFA index (14 states). Standard errors are in parentheses and are clustered by lender. *** p<0.01, ** p<0.05, * p<0.10.*

Online Appendix

Omitted Proofs

Assume the following information structure:

$$\begin{pmatrix} s_i^\phi \\ s_i^m \end{pmatrix} = \begin{pmatrix} \phi \\ m_{-i} \end{pmatrix} + \begin{pmatrix} \epsilon_i^\phi \\ \epsilon_i^m \end{pmatrix}$$

and $\begin{pmatrix} \phi \\ m_{-i} \end{pmatrix} \sim N(0, \Sigma)$ and $\begin{pmatrix} \epsilon_i^\phi \\ \epsilon_i^m \end{pmatrix} \sim N(0, \Sigma_e)$, with Σ and Σ_e diagonal for simplicity.

We solve for a linear equilibrium, in which the signal from the bureau average is linear in ϕ and m_{-i}: $\bar{m} = a_0 + a_\phi \phi + a_m m_{-i} + \bar{\epsilon}$. It is an elementary exercise in this literature to show that, both before and after joining, there exists an equilibrium linear in the lender's signals. Before joining the bureau, lender i offers maturity:

$$m_{i,pre}^* = m_0 + \beta_{pre}^\phi s_i^\phi + \alpha \beta_{pre}^\phi s_i^m + \eta_{if}$$

After joining the bureau, lender i offers maturity:

$$m_{i,post}^* = m_0 + (\rho^\phi + \alpha \rho^m)(\bar{m} - a_0) + \beta_{post}^\phi s_i^\phi + \alpha \beta_{post}^m s_i^m + \eta_{if}$$

The weight on the bureau's signal $\rho^\phi + \alpha\rho^m$ is broken down in two terms to explicitly reflect that it is informative about both ϕ and m_{-i}. The vectors of parameters ρ, a and β are jointly determined and depend on relative signals' precision. For brevity, we do not include all the equations that implicitly determine these variable, as solving for a in terms of ρ and β is sufficient for our argument. The following proposition formalizes the argument behind the empirical strategy:

Proposition: *The variance of the gap between lender's maturity choice m_i^* and the bureau average $\bar{m}$ decreases after joining the bureau if and only if the information in the bureau is new and relevant ($\rho^\phi + \alpha\rho^m \neq 0$).*

To show this, we first solve for a_ϕ and a_m in $\bar{m}$ by aggregating $m_{i,post}^*$ across lenders and identifying the coefficient on ϕ and m_{-i}:

$$\begin{aligned} a_\phi &= \beta_{post}^\phi + (\rho^\phi + \alpha\rho^m) a_\phi \\ a_m &= \alpha \beta_{post}^m + (\rho^\phi + \alpha\rho^m) a_m \end{aligned} \iff \begin{aligned} a_\phi &= \tfrac{\beta_{post}^\phi}{1-(\rho^\phi+\alpha\rho^m)} \\ a_m &= \tfrac{\alpha\beta_{post}^m}{1-(\rho^\phi+\alpha\rho^m)} \end{aligned}$$

hence $\bar{m} = m_0 + \frac{\beta^{\phi}_{post}}{1-(\rho^{\phi}+\alpha\rho^{m})}\phi + \frac{\alpha\beta^{m}_{post}}{1-(\rho^{\phi}+\alpha\rho^{m})}m_{-i} + \bar{\epsilon}$. Substituting in $m^{*}_{i,post}$:

$$m^{*}_{i,post} = m_0 + \frac{\beta^{\phi}_{post}}{1-(\rho^{\phi}+\alpha\rho^{m})}\phi + \frac{\alpha\beta^{m}_{post}}{1-(\rho^{\phi}+\alpha\rho^{m})}m_{-i} + \beta^{\phi}_{post}\epsilon^{\phi}_{i} + \alpha\beta^{m}_{post}\epsilon^{m}_{i} + (\rho^{\phi}+\alpha\rho^{m})\bar{\epsilon} + \eta_{if}$$

The tracking error between $m^{*}_{i,post}$ and $\bar{m}$ after joining the bureau is thus:

$$d_{post} = \beta^{\phi}_{post}\epsilon^{\phi}_{i} + \alpha\beta^{m}_{post}\epsilon^{m}_{i} - (1-\rho^{\phi}-\alpha\rho^{m})\bar{\epsilon} + \eta_{if}$$

On the other hand, before joining the bureau the tracking error between $m^{*}_{i,pre}$ and $\bar{m}$ is:

$$d_{pre} = \beta^{\phi}_{pre}\epsilon^{\phi}_{i} + \alpha\beta^{m}_{pre}\epsilon^{m}_{i} - \bar{\epsilon} + \left(\beta^{\phi}_{pre} - \frac{\beta^{\phi}_{post}}{1-(\rho^{\phi}+\alpha\rho^{m})}\right)\phi + \left(\alpha\beta^{m}_{pre} - \frac{\alpha\beta^{m}_{post}}{1-(\rho^{\phi}+\alpha\rho^{m})}\right)m_{-i} + \eta_{if}$$

From the last two expressions, it is clear that, as long as the bureau information is informative, the variance of tracking error d is smaller after joining the bureau. Assuming the correlation between ϵ_i and $\bar{\epsilon}$ is negligible:

$$\begin{aligned}
V[d_{post}] &= {\beta^{\phi}_{post}}^{2}V[\epsilon^{\phi}_{i}] + \alpha^{2}{\beta^{m}_{post}}^{2}V[\epsilon^{m}_{i}] + (1-\rho^{\phi}-\alpha\rho^{m})^{2}V[\bar{\epsilon}] + Var[\eta] \\
V[d_{pre}] &= {\beta^{\phi}_{pre}}^{2}V[\epsilon^{\phi}_{i}] + \alpha^{2}{\beta^{m}_{pre}}^{2}V[\epsilon^{m}_{i}] + V[\bar{\epsilon}] + V[\eta] \\
&\quad + \left(\beta^{\phi}_{pre} - \frac{\beta^{\phi}_{post}}{1-(\rho^{\phi}+\alpha\rho^{m})}\right)^{2}V[\phi] + \left(\alpha\beta^{m}_{pre} - \frac{\alpha\beta^{m}_{post}}{1-(\rho^{\phi}+\alpha\rho^{m})}\right)^{2}V[m_{-i}]
\end{aligned}$$

Inspecting term by term reveals that the variance drops after joining the bureau (note that $\beta_{post} \leq \beta_{pre}$). Only in the limit case in which the bureau information is not informative is $V[d_{post}] = V[d_{pre}]$, as $\rho^{\phi} + \alpha\rho^{m} = 0$ and $\beta_{post} = \beta_{pre}$.

Additional Results

Table A.1: Distribution of collateral types

Collateral type	Freq.	Percent
Agricultural	3,410	6.28
Airplane	22	0.04
Automobile	595	1.10
Boat	3	0.01
Bus	128	0.24
Construction and Mining	6,049	11.14
Computer	4,538	8.36
Copier	18,737	34.51
Energy	6	0.01
Forklift	1,520	2.80
Logging	90	0.17
Medium Truck	2,547	4.69
Medical	601	1.11
Manufacturing	1,134	2.09
Office	1,217	2.24
Printing	196	0.36
Railroad	33	0.06
Real Estate	152	0.28
Retail	2,437	4.49
Telephone	2,194	4.04
Truck	8,333	15.35
Vending	237	0.44
Waste	111	0.20
Total	54,290	100.00

Note: This table presents the distribution of collateral types for the contracts in our regression sample. The unit of observation is contract. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type.

Table A.2: Unexplained Variation in Maturity Choice

Regressors included	Root MSE of maturity residual	R-squared
collateral type FE	17.27	0.04
collateral type + Year FE	17.25	0.05
collateral type + Year + Lender FE	16.17	0.17
collateral type + Year + Lender +Borrower FE	13.40	0.52
collateral type + Year + Lender-Borrower FE	10.32	0.76
collateral type + Year + Lender-Borrower + Contract characteristics FE	10.18	0.76

Note: This table displays the root mean squared error of a regression of contract maturity (in months) on a combination of fixed effects. The sample includes contracts originated between the four quarters before to the four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type.

Table A.3: Pre-Trends

	One quarter before joining	One year before joining
Loan size		
25th percentile	6,289	5,959
Median	20,241	20,000
75th percentile	67,621	68,852
Maturity		
25th percentile	36	36
Median	37	37
75th percentile	60	60
Log square gap		
25th percentile	2.19	2.22
Median	2.50	2.45
75th percentile	2.77	2.75

Note: This table displays contract terms prior to joining the bureau according to when they were originated. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type.

Table A.4: Additional Splits by Market Power

	Log |gap|							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High Switching Rate within Collateral	Low Switching Rate within Collateral	High Renewal Rate	Low Renewal Rate	High Top 3 Share	Low Top 3 Share	High Top 5 Share	Lo Top 5 Share
Post joining	-0.112***	-0.043	-0.048	-0.129***	-0.018	-0.105***	-0.034	-0.125***
	[-2.90]	[-1.02]	[-1.26]	[-2.97]	[-0.50]	[-3.39]	[-0.81]	[-3.66]
N	21772	32518	29870	24420	29656	24634	26224	28066
Adj R-squared	0.546	0.567	0.563	0.565	0.558	0.584	0.565	0.567

*Note: This table displays the regression results from estimating Equation 1 splitting the sample by additional measures of market power. In columns 1 and 2, the sample is split according to the within-collateral type relationship switching rate, i.e. the fraction of relationships that are ended to start a new relationship with a new lender for the same collateral type. Columns 3 and 4 uses the relationship renewal rate, i.e. the share of contracts issued with a lender that issued a contract in the past. Columns 5 and 6 use the Top 3 share, i.e. the market share of the three largest lender and Columns 7 and 8 use the Top 5 share. The unit of observation is contract. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type. The dependent variable is the log absolute value of the gap between the contract maturity and the bureau average maturity for that collateral type in the previous quarter (excluding the lender's own contracts). Contract characteristic controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are in parentheses and are clustered by lender. *** p<0.01, ** p<0.05, * p<0.10.*

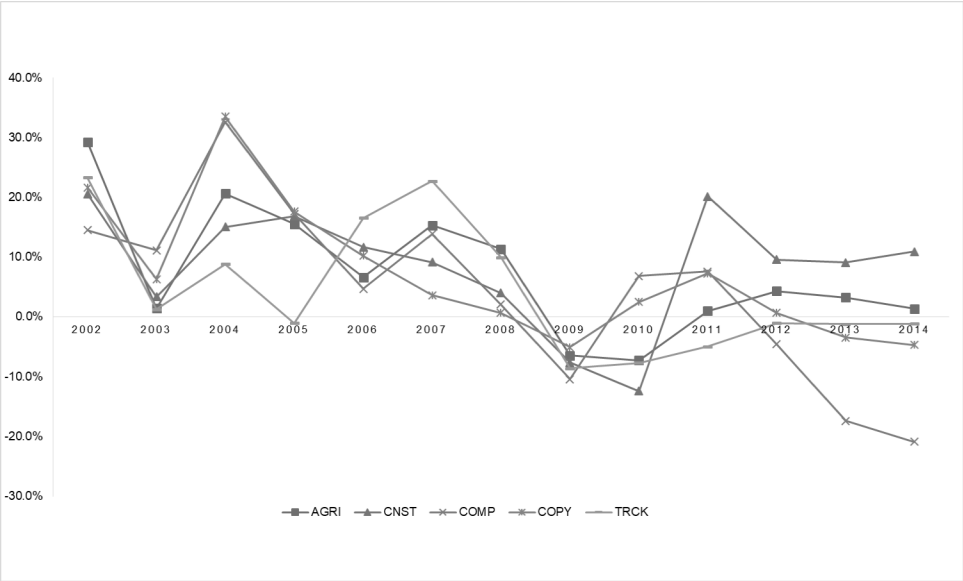


Figure A.1: Annual Growth in Contracts in Platform by Collateral Type

Note: This figure displays the annual growth rate of the number of contracts in the bureau for the five main collateral types: agricultural equipment, construction and mining equipment, computers, copiers, and trucks. The sample is not limited to our regression sample and includes all contracts in the data.

Table A.5: Market Power Proxies: Summary Statistics

Market Power Proxy	N.	Mean	S.D.	p25	Median	p75
HHI for collateral type-contract size-region	53305	0.34	0.20	0.20	0.24	0.42
HHI for collateral type-contract size	54101	0.24	0.11	0.15	0.27	0.27
Relationship switching rate	53857	0.007	0.012	0.000	0.003	0.009

Note: This table summarizes competitive features for observations in our regression sample. The unit of observation is contract. HHI is the credit-weighted Herfindahl-Hirschman Index for the market, measured in 2001, before the bureau's inception. Markets are defined as a collateral type-census region-contract size category or collateral type-contract size category combination. Ther relationship switching rate is defined as the fraction of relationships that are ended to start a relationship with a new lender.