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Learning about Competitors: Evidence from SME Lending

Olivier Darmouni and Andrew Sutherland*

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Abstract

We study how small and medium enterprise (SME) lenders react to information about their competitors' contracting decisions. To isolate this learning from lenders' common reactions to unobserved shocks to fundamentals, we exploit the staggered entry of lenders into an information sharing platform. Upon entering, lenders adjust their contract terms toward what others offer. This reaction is mediated by the distribution of market shares: lenders with higher shares or that operate in concentrated markets react less. Thus, contract terms are shaped not only by borrower or lender fundamentals but also by the interaction between information availability and competition.

Keywords: learning, information sharing, competition, corporate loans, SME lending, decentralized markets, loan maturity, financial crisis

*Olivier Darmouni (omd2109@columbia.edu) is at Columbia Business School, New York, NY. Andrew Sutherland (ags1@mit.edu) is at the MIT Sloan School of Management, Cambridge, MA. For helpful comments, we thank Hassan Afrouzi, Marieke Bos, Mariassunta Gianetti, Xavier Giroud, Andrew Hertzberg, Jennifer La'O, Andres Liberman, Erik Loualiche, Andrew MacKinlay (discussant), Jonathan Parker, Tomasz Piskorski, Ryan Pratt (discussant), Johannes Stroebel, David Thesmar, Laura Veldkamp, Rodrigo Verdi, Dong Yan, Edison Yu, and seminar participants at Columbia Business School, the Federal Reserve Bank of Philadelphia, the Federal Reserve Bank of New York, MIT Sloan, NYU Stern, the Stockholm School of Economics, the University of Bonn, Yale SOM, the 2019 Midwest Finance Association conference, and the 2019 Western Finance Association conference.

Introduction

Credit markets are characterized by dispersed information. Lenders do not have full information about their counterparties or their competitors' actions. Strategic and information considerations are thus linked: lenders' contracts depend on their information about competitors' actions. Recent advances in information technology have attracted considerable attention from academics and policymakers concerned with its effects on competition.[1] In credit markets, information technology has been studied primarily through the lens of learning about *borrowers* through the revelation of their credit records or the collection of soft information. However, there is also increased scope for learning about *competitors*, which introduces new issues related to competition, opacity, and the distribution of loan terms.

Conceptually, the implications of lenders learning about their competitors are largely unresolved (Vives, 2006). Existing theoretical models imply a wealth of empirical predictions that have considerable disagreement over channels, magnitudes, and even the sign of the effects. With imperfect competition, lenders can either mimic rivals if there are strategic complementarities, or differentiate themselves through product choice (Shaked and Sutton, 1982). There is also a role for information aggregation, in which rivals' actions partially reveal their private information. Moreover, recent work has shown that the link between information and market outcomes is more complex than previously thought (Murfin and Pratt, 2018; Liberman et al., 2018; Goldstein and Yang, 2019).

Questions related to information and imperfect competition are notoriously difficult to study empirically. Indeed, the challenge in estimating the effect of learning about competitors is how to isolate variation in agents' information sets. Specifically, lenders might offer similar terms not because they respond to each other but simply because they respond to the same economic shock.

Our paper addresses this challenge by exploiting a unique setting that permits us to observe a direct shift in information that lenders have about rivals. Specifically, we use microlending data around the introduction of a commercial credit information sharing platform, PayNet, which covers small and medium enterprises (SMEs) in the United States. PayNet launched in 2001; since then it has attracted eight of the ten largest lenders in the market, a group that includes Bank of America, Wells Fargo, PNC, John Deere, IBM, Volvo, and Caterpillar. The platform provides information on contract terms offered by other lenders that was previously not widely available. We exploit the staggered entry of lenders into the platform to estimate the response to competitors and find that lenders adjust their terms

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

toward what others are offering. Imperfect competition is a key driver of this finding: lenders in the most concentrated markets respond least to others' offers. Thus, our evidence is most consistent with lenders learning about what it takes to compete as opposed to learning about fundamentals. Finally, we investigate an important consequence of our findings: matching competitors tends to increase delinquencies during the recent crisis, possibly because of the neglect of future risk.

We document this evidence in the context of maturity dynamics for SMEs' equipment financing contracts from 2001 to 2014. With over \$1 trillion of annual volume, equipment financing is a major component of corporate investment, particularly for SMEs. Maturity cycles and rollover risk became a concern during the recent crisis and recovery because of their implications for firms' liquidity and investments. The Survey of Terms of Business Lending shows that maturity on loans lasting over a year fell by 30% between 2007 and 2010, and Kalemli-Ozcan et al. (2018) document the dramatic effect of rollover risk on firm investment. Moreover, in our context of financing a specific piece of equipment, it is natural to focus on maturity as it is negotiable, while there is little variation in payment frequency or contract type to study. And by design, interest rates are not shared in the platform, just as they are typically not shared in consumer credit bureaus. Finally, there is evidence consistent with oligopolistic competition in this market (Murfin and Pratt, 2017).

Our empirical strategy is derived from a simple model of dispersed information, and is designed to address the key challenges associated with estimating the effect of learning about competitors. 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 relationship, we observe contracts made before and after the lender joins the platform.[2] Our empirical tests do not take a stand on the direction of the response. The key idea is that, while a lender's terms may track the bureau average before joining, whether they track it relatively *better* or *worse* afterward reveals the sign of the response.

For each contract, we model the gap between its maturity and the bureau average maturity for similar contracts as a function of whether the lender is a bureau member, contract

[2] 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. Nonmembers cannot access the system or its scores and reports.

size, borrower risk, and contract type as well as borrower-lender relationship and collateral type-year fixed effects. We show that the gap shrinks by 7% after the lender joins the bureau. Lenders' terms therefore track the bureau average relatively better after joining, consistent with a partial matching of rivals. Economically, this average effect corresponds to a 10% probability of a six-months or larger change in contract maturity. Such changes in maturity are important in their own right considering that in our sample, 18% of borrowers experience a change in their delinquency status over the next six months, therefore substantially affecting rollover risk. Additionally, for a fully amortized loan with median characteristics, our main result is comparable to a 2 percentage point change in APR. Interestingly, the effect is symmetric: sometimes lenders match rivals by increasing maturity, sometimes by shortening it. Finally, we find similar evidence of convergence to competitors when we study contract size instead of maturity, or if we base our empirical strategy on proxies for lenders' private information.

Further evidence suggests that imperfect competition is a key driver of these findings as opposed to more conventional channels of learning about fundamentals. Our results are strongly mediated by the distribution of market shares. Specifically, lenders competing in concentrated markets (measured by the HHI) or with larger market shares react much less or not at all to observing competitor information. This pattern is not sensitive to the manner in which we define market shares and concentration or to using relationship-switching rates as an alternative proxy for competitive pressure. Our evidence is consistent with oligopoly models in which lenders react to competitors to preserve their market share: joining PayNet gives more information on what it takes to compete.[3] Dominant lenders have less incentive to match rivals, as their market share is less sensitive to competing offers.

Evidence in favor of learning about fundamentals is less compelling. A first alternative channel is the revelation of a borrower's repayment history (Pagano and Jappelli, 1993). However, we do not find that the effect is smaller for borrowers with a single relationship, for which the credit file contains no new information for the lender. Another possibility is rooted in information aggregation or other social learning models. Rivals' offers may reveal their private information, which in turn could help lenders learn about fundamentals. Yet we do not find that specialist lenders react less, although they plausibly have better signals about fundamentals and thus would put less weight on others' terms. Overall, our interpretation is not that fundamentals are irrelevant for lenders' terms, but instead that rivals' maturity is not that informative a signal about fundamentals relative to other sources of information available in the market we study. We therefore emphasize a novel channel of learning about competitors, which operates incrementally to more conventional channels.

[3] For example see Li (1985) for an early model of oligopoly and information sharing.

For robustness, we address several remaining threats to identification. Specifically, there could be shocks either to the borrower or lender that coincide with joining the platform and drive maturity independently of observing rivals' offers. On the borrower side, our results hold when comparing contracts made to the same borrower by two lenders with different information sets: one that has joined the platform and the other that has not. Specifically, we include borrower-time fixed effects (Khwaja and Mian, 2008) and find the member lender of PayNet offers a maturity closer to the bureau average than the nonmember lender in the same period.

On the lender side, joining the platform might coincide with a business model shift correlated with the propensity to offer specific contract terms. For example, a lender's joining could accompany their plans to expand or conserve their capacity, which might have its own effect on maturity. To address this concern, we implement two additional tests that exploit the behavior of *other lenders*. First, we show our results hold within lender-year across different market segments. Specifically, our information coverage measure is lender-specific in that it counts only contracts shared by rivals and not the lender itself. Thus, coverage for some segments grows faster than others due to the number of new members joining each period, and such joining decisions (and coverage changes) are beyond the incumbent member's control.[4] Including lender-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. Second, we isolate large shocks to bureau information arising from new members joining and show that incumbent lenders' contract terms better track those of their rivals once this extra information is available to them. These additional tests support the interpretation that lenders adjust their contract terms in reaction to the information revealed on the platform.

Finally, we investigate a key implication of our learning results. While a full welfare analysis is beyond the scope of this paper, we examine the link between learning from competitors and the incidence of delinquencies during the financial crisis. This episode is revealing in that it consisted of a large wave of unexpected delinquencies. For a group of lenders joining the platform before the financial crisis, we compare the crisis-period delinquencies for contracts originated just before versus just after joining. Controlling for collateral type-quarter, region-quarter, and lender fixed effects as well as borrower observables, we find that matching competitors is associated with an increase in delinquencies. An interpretation in line with our main findings is that lenders neglected future risk, either because of greater competition

[4] 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 lend against trucks.

or because they relied more on shared information at the expense of their own information collection. In general, these findings echo those of Murfin and Pratt (2018) and Goldstein and Yang (2019), who argue that technologies that increase the availability of competitor information can have unintended consequences.

Related Works

This paper relates to a growing body of empirical literature studying how information and lender coordination affect credit market outcomes. Murfin and Pratt (2018) 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 lack the power to trace out paths of influence as they do, we nevertheless find suggestive evidence that learning about competitors led to more frequent delinquencies during the financial crisis. Hertzberg et al. (2011) illustrate the role of public information in credit market coordination. 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 channel independent of creditor runs.

Gorton and He (2008) show that public information about rivals can generate credit cycles as banks update their beliefs on the viability of a collusive arrangement. Kang et al. (2019) study the introduction of loan-level reporting requirements for the ECB repo borrowers that mandate the disclosure of all contract terms, including prices. They find convergence for price and non-price contract terms across different locations of the same bank.

In credit card markets, Liberman et al. (2018) study the equilibrium effects of information deletion on the allocation of credit and risk, while Foley et al. (2018) show the impact of the information environment on competition. Fuster et al. (2018) study the distributional consequences of machine learning techniques for screening borrowers. Compared to these works and much of the earlier literature on information sharing in credit markets, we focus on learning about competitors as opposed to sharing information about borrowers.

We also contribute to the literature that studies the drivers of loan terms–maturity in particular. Hertzberg et al. (2018) examine an online consumer lending platform and show that loan maturity can be used to screen borrowers based on their private information. In the auto loan market, Argyle et al. (2019) 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.

The literature on information sharing and credit bureaus is vast and includes works by Jappelli and Pagano (2006), Doblas-Madrid and Minetti (2013), Sutherland (2018), Liberti et al. (2020), Giannetti et al. (2017), Brown et al. (2009), Kovbasyuk and Spagnolo (2018), and Balakrishnan and Ertan (2019). Equally vast is the literature studying the role of information in lending markets more broadly (Hertzberg et al. (2010), Liberti et al. (2016), Hauswald and Marquez (2003), Liberti (2017), and Berger et al. (2017). Finally, an extensive body of literature has studied the role played by public firms and public markets in diffusing information.[5] In contrast, we study private credit markets for which no centralized price exists, making information technology the primary channel of information diffusion.

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.[6] Since PayNet's 2001 launch it has attracted eight of the ten 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, reliable, and timely. PayNet has developed these products using 25 million contracts for over $1.7 trillion in transactions collected from members. Lenders are anonymous in the system.

Prior to PayNet, lenders generally had access to very limited information about new borrowers and other lenders. Competing data providers, such as Experian, offered partial (and rarely timely) information about trade liabilities, which were much smaller than the typical equipment financing contract. Public UCC filings documented the existence of a contract but did not detail whether the borrower paid on time or the terms 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.

[5] See for instance Sockin and Xiong (2015), Chen et al. (2006), Foucault and Fresard (2014), Dessaint et al. (2019), Kurlat and Veldkamp (2015), Veldkamp (2006), Leary and Roberts (2014), Badertscher et al. (2013) Bustamante and Frésard (2017), Iyer et al. (2015), Broecker (1990), and Breuer et al. (2019) .

[6] Murfin and Pratt (2017) provide an explanation for the existence of captives in equipment financing.

This development was particularly relevant for small borrowers, who typically lacked audited financial statements or public information about their creditworthiness (Berger et al., 2017; Berger and Udell, 2006). Jackson (2001) describes PayNet's value proposition to lenders: "With richer data you get much better predictive models [. . .]. There's no question there is a need for PayNet's kind of service. The commercial bureaus haven't done enough to provide data across all the financial industry lenders."

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 by Doblas-Madrid and Minetti (2013) and the online appendix of Sutherland (2018).

Crucially, unlike many consumer credit bureaus, the platform includes detailed information about contracts offered by competitors. Figure 1 illustrates the 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 with all lender members of PayNet. In Figure 1, the borrower has 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 rates are not recoverable from their data, to reduce concerns about both proprietary costs and the potential for collusion. On the one hand, this choice is revealing and supports our hypothesis that information about competitors can have important effects on credit market outcomes. On the other hand, it means that we cannot directly trace the pricing implications of our hypothesis in this setting. As we discuss in Section 2.2.3, we expect prices to respond in a similar manner as maturity. But we cannot empirically verify this using our data, and this represents a limitation of our study.

1.2 Sample

We construct our sample from the quarterly credit files of 20,000 borrowers randomly chosen from PayNet's database. The 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 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.

We restrict the sample of contracts used for our main analysis to a relatively short window around the lender 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 our sample.

Sample statistics: Table 1 describes the lenders and borrowers that meet our regression sample requirements described above. 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 assets depreciate and new ones with updated features are released. The typical borrower maintains two relationships; however, because borrowers occasionally switch lenders, we observe more relationships across the full sample period. 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 collateral types. 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.

Oligopolistic competition: As in other credit markets for durable goods (cars, real estate, etc.), borrowers in the equipment financing market transact at regular intervals and search for and negotiate with lenders. For this reason, these markets tend not to be defined by a single market-clearing price (Argyle et al., 2018). Relationships are prevalent and lenders can exercise some degree of market power, with the degree of competition affecting borrowers (Rice and Strahan, 2010). Nevertheless, market power likely varies across market segments. There is evidence of product market power in equipment sales (Murfin and Pratt, 2017; Mian and Smith Jr., 1992; Bodnaruk et al., 2016), which potentially can lead to financing market power if producers are captives or tend to work with a limited number of lenders. Consistent with financing market power, the equipment finance market is highly concentrated.[7] Defining market segments as census district-collateral type pairs (henceforth "region-collateral type pairs"), 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%.[8] The median number of lenders in each segment is 12, with an interquartile range of 5 to 31.

1.3 Contract Terms

Table 2 describes the terms for the typical contract in our regression sample. The median (average) contract size is $20,300 ($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.[9] The overwhelming majority of contracts require fixed monthly payments. 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.

Our analyses study contract maturity, for two reasons. First, maturity impacts firms' liquidity and investments. During the financial crisis, maturities on loans lasting over a year fell by 30% between 2007 and 2010, before recovering slowly (Survey of Terms of Business Lending). Figures 4 and 5 show that contracts in our sample also display considerable time variation throughout the business cycle. Kalemli-Ozcan et al. (2018) provide evidence that short maturities and rollover risk were responsible for a large share of the drop in firm investment during the financial crisis. Milbradt and Oehmke (2015) also argue that loan maturity has real effects by distorting firms' decisions toward inefficiently short-term investments.

Second, maturities are regularly negotiated, and play an important role in managing risk and allocating credit. Shorter maturities may protect lenders from a deterioration in the borrower's financial position, but can impose liquidity costs on borrowers. Indeed, the corporate finance literature has shown that, in the presence of frictions, non-price loan terms are key to credit access, with maturity being a prominent example (see Section 5.2 of

7 According to a 2018 industry report, the top five (10, 25) lenders in the equipment finance market constitute 40% (55%, 82%) of industry assets.

8 Throughout this paper, we use the term "region" to refer to one of the nine census divisions, described at https://factfinder.census.gov/help/en/division.htm.

9 The borrower's choice between a lease or a loan can depend on 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 (2017) highlight the fundamental similarities of leases and loans.

Tirole (2010) for a summary).[10] By contrast, in our context of financing a specific piece of equipment, observed payment frequencies and contract types vary little. And even though interest rates are not reported in our data, contract maturity is relevant since maturity and prices are not perfect substitutes. As for contract sizes, we cannot observe the specific model or quantity of equipment being financed, but offer evidence in Section 3.1 that contract amounts and maturities respond similarly to competitor information.

Moreover, 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 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.

1.4 Lender Participation in PayNet

When a lender joins PayNet, it gains access to information about others' contracts but must share information about its own contracts, *including past ones*. 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. This allows us to study changes in contracting between the same firm and lender during a relatively short window around the lender joining PayNet.

Another key feature of our setting is that lenders join in a staggered pattern over the sample period. This variation offers 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 non-systematic pattern. Thus, members regularly experience shocks to the information

[10] Hertzberg et al. (2018) document 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.

coverage in their markets driven by other lenders joining, which is outside of their control.[11] We leverage these additional sources of variation in our main specification and robustness tests.

Table 3 shows the variation in entry timing for lenders meeting our sample criteria described in Section 1.2. Sample lenders join in all years between 2002 and 2014 except one. While large lenders tend to join earlier than small ones, in most years, a variety of lenders join. At the same time, joining PayNet is voluntary, and the timing of joining the platform is not randomly assigned. In Section 3.3 below, we perform a series of tests to ensure that our results are not driven by lender or borrower shocks coinciding with the timing of joining. Note also that Liberti et al. (2020) study in detail the decision to join PayNet. Their main finding is that, when deciding to participate, lenders trade off the greater ability to enter new markets against the threat of losing existing borrowers. In other words, PayNet helps lenders screen new borrowers, which presents both benefits (it reduces adverse selection problems associated with expansion) and costs (it increases the likelihood that the lender loses clients). Because our tests are conducted within the borrower-lender relationship in the short period around the lender's entry to PayNet, we abstract away from these extensive margin effects. Note also that our sample of lenders differs from that of Liberti et al. (2020) given our narrow event window and the sample requirements described in Section 1.2.

2 Hypothesis Development and Empirical Strategy

Lenders' optimal contract terms depend on a variety of factors. These include not just fundamentals, such as the borrower's credit risk or the lender's portfolio performance, but also rivals' offers. With imperfect competition, a lender's optimal contract depends on what competitors are offering. Moreover, the information environment plays a role. Lenders have access to public information (industry reports, macroeconomic news) as well as private signals about both fundamentals and their rivals' offers. Conceptually, joining PayNet can be thought of as receiving an additional signal that is informative about the distribution of rivals' terms. This learning about competitors can operate through two broad, non-mutually exclusive channels.

Learning about fundamentals: First, lenders may react to rivals' terms because they reveal private information about the state of the economy or industry. The rational expectations version of this information aggregation effect is canonical in the context of financial markets (Hellwig, 1980) but has been much less explored within credit markets.

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

Importantly, at this stage, we want to include under this broad channel other social learning models that are less "rational" or "efficient" in nature, such as information cascades or naive herding (Murfin and Pratt, 2018) as well as rational models with endogenous information acquisition (Goldstein and Yang, 2017).[12] This class of models would predict convergence in terms across lenders. However, the predicted impact of market structure is less clear, as these models are typically framed in a competitive market or a sequence of decision-making problems.

Learning about what it takes to compete: A second potential channel relates to imperfect competition. 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. The profit-maximizing contract terms balance a higher probability that a contract is accepted with a lower profit margin on that contract. Learning about competitors helps lenders determine the appropriate contract terms and preserve or grow market shares. The sign of the effect, however, is ambiguous. On the one hand, contract terms can be strategic complements: matching rivals' offers is necessary to attract demand, and we can expect convergence in terms. On the other hand, the industrial organization literature has also raised the possibility that rivals choose to differentiate themselves through product choice, as in Shaked and Sutton (1982). Our empirical tests do not take a stand on the direction of the response and can tease out whether strategic complementarities or the differentiation motive dominates. Nevertheless, the predictions regarding market structure are more clear-cut: lenders in dominant positions have weaker incentives to respond as their market share is less sensitive to rivals' offers.

An illustrative framework: To illustrate our empirical strategy, we sketch a simple framework in which lenders have dispersed information about their borrowers as well as their competitors. We use the model to describe the effect of joining the platform on contract maturity, as well as how we empirically account for some important confounders. However, because of data limitations, we do not explicitly provide microfoundations for the market game nor for the joint optimization of maturity and pricing. The main text is limited to notation and key ideas, while the Appendix contains more details.[13]

A lender's optimal contract terms depend on both fundamentals ϕ, such as borrower

[12] Note also the difference from the canonical effect of credit files, in which lenders learn about a specific borrower from its payment history. Instead, here lenders use the bureau information to extrapolate to other similar borrowers (e.g., with respect to size, sector, or collateral type).

[13] Our mathematical notation borrows from canonical "beauty contest" models exemplified by Morris and Shin (2002). Note, however, that we use it for a different purpose and the underlying economics and microfoundations differ.

credit risk and the lender's risk tolerance, as well as the lender's competitors' terms m_{-l}, due to imperfect competition. A lender's information I_l consists of some public information as well as private signals about fundamentals and competitors' terms. We can decompose lender l's choice of maturity m to firm f, which is part of a group of similar firms g, linearly as follows:

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

The degree to which lenders respond to their competitors' terms is denoted by α and summarizes the nature and degree of competition faced by the lender for this borrower. Strategic complements imply $\alpha > 0$, while $\alpha < 0$ if the differentiation effect dominates. Finally, the idiosyncratic term $\eta_{l,f}$ captures factors that are specific to this borrower-lender relationship. Crucially, lenders are uncertain about both fundamentals and their competitors' actions. Before joining PayNet, lenders have two sources of information in I_l: (i) public information about fundamentals or competitors' terms that can be gleaned from, for instance, forecasts of local and national economic conditions or industry reports, summarized in $m_0 = (m_0^\phi, m_0^m)$, and (ii) private signals $s_l = (s_l^\phi, s_l^m)$, 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 ($\bar{m}_{-l}^g$) to similar borrowers.[14] In equilibrium, the maturity choice depends on the information available to the lender at the time. Before joining, lenders put some weight on their own private signals, depending on their respective precision. After joining, lenders place less weight on their own private signals and place some weight on the bureau average. Importantly, note that reacting to the information in PayNet implies two things: lenders care about rivals' offers and they did not have complete information about them before joining.

The framework also makes clear that lenders can react to the information through the two non-mutually exclusive channels described above. First, the bureau average $\bar{m}$ contains information about fundamentals ϕ because each lender's term is partly influenced by their private signal s_l^ϕ about fundamentals. Second, $\bar{m}$ is information about rivals' terms m_{-l}, which the lender cares about for strategic reasons. The Illustrative Theoretical Framework section of the Appendix further develops this model to more formally illustrate the empirical strategy introduced below. Section 4 will re-examine our evidence in the context of the

[14] Concretely, lenders can learn about others' terms by purchasing individual credit files from PayNet. This makes it unlikely they can learn the entire distribution of competitors' terms or that they can leak this information easily.

model and discuss the potential efficiency implications.

2.1 Empirical Strategy

The main identification threat in isolating the effect of learning about competitors is the existence of unobserved common shocks. Maturity choices are naturally correlated across agents due to public information m_0 as well as private signals $\{s_l\}$, independent of the information revealed by the bureau. Then lenders might start offering certain 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.

To address this challenge, we exploit the time dimension associated with the lender joining PayNet. Joining leads to a shift in the lender's information set. Importantly, lenders join in a staggered fashion over 14 years. Our main specification measures how maturity changes within a relationship over a short window around the lender joining. While a lender's terms may track the bureau average before joining, we ask whether they track it relatively *better* or *worse* afterward.

Figure 2 provides a graphical illustration of this idea, focusing on the case of convergence for simplicity. Because of common shocks, the lender's terms are correlated with competitors' terms even before joining the platform. However, they track the bureau average relatively better after joining. This would be consistent with lenders mimicking competitors. A divergence in terms would generate the opposite pattern, with lenders' terms generally tracking the bureau average worse after joining. In the data, we can follow lender-borrower relationships over time, including the time before the lender joined the platform. We can also observe rivals' offers before and after the lender joins. This allows us to test this prediction directly within a fixed effect regression framework. To illustrate, Figure A.3 studies the average maturity for a large lender in the retail equipment market, and shows how they better track the bureau average after they join.

Other empirical strategies are consistent with our illustrative framework. For example, if there exists a good proxy for a lender's private or public information, one could test whether the lender's contracts are less sensitive to this proxy after they join. By comparison, our approach does not require specifying the type or functional form of public or private information. Instead, we test whether lenders' contracts are more similar to their rivals' contracts after joining the platform, which is consistent with lenders placing less weight on their other information sources. To estimate learning, our approach only requires constructing a proxy for what lenders can observe in the platform. Given that we observe contracts by other

PayNet participants, we can compute a natural proxy: the characteristics of competitor contracts for the relevant collateral type in the bureau. This is significantly less noisy than constructing a proxy for the public or private information lenders observe outside the platform. Nevertheless, we show below that our main results are similar when using a proxy for lenders' private information instead.

2.2 Addressing Confounders

By construction, our empirical strategy is not confounded by the existence of a number of factors: public information unobservable to the econometrician m_0, other sources of information outside of the platform s_l, or idiosyncratic loan terms $\eta_{l,f}$. Indeed, all of these forces exist in the framework above, and our tests based on comparing maturities before and after joining are valid. This is the main advantage of our approach. However, a necessary assumption for identification is that shocks to other sources of public information or to idiosyncratic loan terms are uncorrelated with individual lenders' decision to join. While this assumption is considerably weaker than assuming that no such shocks exist, it cannot be taken for granted. Specifically, the identification strategy creates the possibility of two important confounders. Lenders' responses might be driven by (i) information in the platform other than rivals' offers, namely, the revelation of the borrower's repayment history, 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 address them as best we can.

2.2.1 Revelation of borrower past repayment history

The contract terms offered to a borrower can be influenced by what a lender learns from the borrower's PayNet credit file. Note, however, that we restrict attention to lending to previous borrowers, for which the credit file is not necessarily informative. Additionally, we show that our main result holds for borrowers with a single relationship, for which the credit file carries no additional information.

2.2.2 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 affect maturity, independent of the information revealed by the bureau. On this front, note that Liberti et al. (2020) show that lenders joining PayNet are motivated by a desire to enter new markets. However, our main test is exclusively within existing markets. In addition, in Section 3.3 we conduct within borrower-time tests (Khwaja and

Mian, 2008) and show that borrower shocks coinciding with the timing of joining cannot explain our results. We also exploit the decision of other lenders to join PayNet in order to address any bias coming from a business model shift, such as a plan to expand or conserve lending capacity

2.2.3 Price adjustments

Finally, one limitation of our empirical setting is that interest rates are not shared in the platform. This implies that we cannot measure price adjustments when we trace the effect on maturity. In this section, we investigate the effect of rate changes in a setting in which firms compete on both rates and maturity by offering a menu of different contracts. Under standard assumptions about credit market competition, our tests based on maturity alone are valid even if rates also react.

Figure 3 provides an illustration.[15] We assume that the rate-maturity pairs offered by a lender (dashed line) potentially differ from what rivals are offering (solid line) due to dispersed information and market power. We also make a standard assumption for commercial credit markets: a positive relation between rates and maturity (an upward-sloping yield curve) and that all else being equal, borrowers prefer longer maturities and lower rates.

This lender's market share is larger for segments in which it offers a better rate. In the example depicted in the figure, the lender's long-term contracts are more appealing and in equilibrium, their maturity is larger than the rivals' maturity. After joining, the lender updates his entire menu offering by adjusting both rates and maturities in the same direction. A convergence in menus implies more competitive short-term contracts, leading to a reduction in the maturity gap. Other reactions seem less plausible: lenders that reduce maturities but raise rates after joining will lose clients, while those that increase maturities and cut rates would leave money on the table. In other words, inferences based on maturity are still likely to be valid with unobservable price adjustments.

3 The Effects of Learning About Competitors

3.1 Main Specification and Findings

We design our main specification to answer the following question: does the contract maturity for the same borrower track the lender's rivals' maturities more or less 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

[15] We thank our discussant Andrew MacKinlay for suggesting this illustration.

transactions. The variable of interest is a "Post" indicator, equal to 0 for contracts issued before the lender joins PayNet and 1 for those issued after. A negative coefficient on δ_{post} implies that lenders react to the bureau information by offering terms more similar to those of competitors.

Specifically, the main specification estimates the following regression:

$$\log |m_{l,f,c,t} - \overline{m_{c,t-1}}| = \delta_{post} + \eta_{l,f} + \alpha_t + \nu_{contract} + \varepsilon_{l,f,c,t}. \quad (1)$$

The unit of observation is a contract originated between firm f and lender l at quarter t to finance a piece of equipment. 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.[16] We show robustness to using different measures of the bureau average below.

The parameter of interest is the coefficient δ_{post}. To control for heterogeneous deviations from the average maturity, we add a series of fixed effects. $\eta_{l,f}$ is a borrower-lender fixed effect that accounts for idiosyncratic time-invariant maturity at the relationship level, including industry and regional variation. Given that lenders join at different times, we include time fixed effects α_t to allow for aggregate time series patterns in the maturity gap. Finally, we include controls $\nu_{contract}$ for each of the three contract size categories, whether the contract is classified as a lease or a loan, and each borrower risk category based on prior delinquencies.[17] Because the decision to join PayNet is made at the lender level, we cluster our standard errors at the lender level.[18]

Table 4 presents the main result of estimating Equation 1. It shows that, upon joining PayNet, the gap between a lender's maturity and the bureau average falls by 6% to 7% in absolute value. This effect reveals that observing new information about competitors leads lenders to offer maturities closer to what others are offering. The effect is virtually unchanged whether we use quarter, year, or collateral-year fixed effects to account for aggregate time variation.

Table 5 shows that the effect is symmetric in that maturity itself does not change on average–only the gap relative to rivals changes. Column 2 confirms that lenders adjust terms in both directions. Panel A of Figure 6 plots the coefficients of a version of Equation

[16] Excluding the lender's own contracts and using a lag helps address the mechanical aspects of the reflection problem of Manski (1993).

[17] Specifically, the three contract size categories are: small ticket (below \$250k), medium ticket (between \$250k and \$5M), and big ticket (above \$5M). The three delinquencies categories are: no missed payments, missed payments 90 or fewer days late, and default or missed payments over 90 days late, all measured over the last three years.

[18] Our results are similar if we double cluster by lender and collateral type x year.

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 plot shows that the change in maturity happens the quarter after the lender joins PayNet and is unlikely to be driven by pre-trends.

Economically, the effect on borrowers is sizeable. While the coefficient implies roughly a one-month change in contract maturity for the average borrower, maturities are typically set in six-month increments. Our results correspond to a 10% probability of a six-months or larger change in contract maturity. This is notable considering that in our sample, 18% (24%) of borrowers experience a change in their delinquency status over the next six months (one year). Moreover, for the subset of borrowers with fully amortizing contracts, a back-of-the-envelope calculation suggests a 2% change in monthly payments, equivalent to a 2 percentage point change in APR.[19]

Table 6 subjects our main result to a series of robustness tests. To account for heterogeneous shocks to collateral types across regions, column 1 calculates the bureau average by collateral type-region-quarter, instead of collateral type-quarter, and yields a similar estimate. Table A.5 in the Appendix also reveals convergence not just toward the mean, but also to other central moments of the distribution of rivals' terms. We then perform two placebo tests. First, in column 2, we calculate the bureau average using contracts from one year ago instead of current contracts. We expect lenders to react less to stale information. Second, in column 3, we calculate the bureau average using an unrelated collateral type, based on the relatedness measure introduced in Liberti et al. (2018). For both placebo tests, we find null results.

Next, we measure the contract-bureau gap for contract sizes rather than maturity. In our setting, there is drastically more variation in contract sizes than maturity or payment frequency. In some collateral types (such as copiers), contract sizes are often just a few thousand dollars, whereas others (such as aircraft) contracts regularly exceed seven figures. Moreover, within collateral type, there is significant heterogeneity in borrower size, and therefore, contract size. To mitigate the influence of outliers on our estimation we assign each contract's size to a decile within a collateral type-year, and calculate the absolute gap between each contract's decile and the bureau's average decile. In column 4, we find that after the lender joins the bureau the contract size gap shrinks by roughly 10% of its pre-period mean.

[19] 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). Since we cannot directly observe interest rates nor any embedded options in our data, this calculation relies on Schalheim and Zhang (2017)'s estimate of the mean annualized interest rate of 15% during this period.

Finally, column 5 implements an empirical approach based on a proxy for lenders' private information: borrower-lender relationship length. According to our theoretical framework, lenders should put less weight on their private information after joining the bureau.[20] To test this, we regress Maturity on Post, Borrower Risk, Relationship Length and their interactions. We find evidence consistent with our main results. In the pre-joining period, Relationship Length mediates the link between Borrower Risk and Maturity (risky borrowers can get longer maturity if their lender has known them longer), but this link disappears in the post-joining period. While the statistical power is limited by the noisiness of our private information and credit risk proxies, this alternative strategy adds credibility to our main results.

We make two comments regarding the implications of our main results. First, note that for econometric reasons, our tests are restricted to existing borrower-lender relationships. However, in principle, this effect would apply to new borrowers as well. For example, better information about competitors' offers is particularly valuable when trying to poach borrowers. Nevertheless, cleanly isolating this effect for new borrowers is particularly challenging.

Second, it is plausible that the change in lender behavior upon joining PayNet in turn affects other lenders, implying that there can be knock-on effects that propagate, either through competition or learning. For instance, Murfin and Pratt (2018) document pricing mistakes by tracing out "paths of influence" across syndicated loans and show how these mistakes are propagated across time. However, the fact that we do not observe the universe of lenders and contracts limits our ability to study propagation.

3.2 The Role of Market Structure

A natural question is whether the effect of learning about competitors is mediated by market structure. To investigate this, we construct different measures capturing the distribution of market shares. We first measure market concentration using the HHI. We define a "market" either at the collateral type-contract size category level or at the collateral type-contract size category-region level because lenders might compete locally or nationally. To alleviate concerns 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 considerable variation in concentration across market segments: moving from the 25th to the 75th percentile of the distribution implies a 0.15–0.20 increase in the HHI. 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

[20] We thank an anonymous reviewer for suggesting this alternative approach.

unique degree of product differentiation, specialization, or other switching costs. Finally, we also construct a within-market across-lender measure that flags lenders that are among the five largest in a collateral type-region-quarter. This classification allows us to distinguish between dominant lenders and the competitive fringe. Table A.3 presents summary statistics for these measures.

Table 7 shows that our learning results are mediated by market structure. All market structure measures point in the same direction. The first two columns show that the effect is driven by markets with low levels of concentration. In these less-concentrated markets, the gap between the lender's maturity and the bureau average falls by 8% after joining, while it is statistically unchanged in markets with high concentration levels.[21] Column 3 confirms these findings by showing that the effect is driven by markets with high relationship-switching rates. Finally, column 4 suggests the same interpretation: lenders in the competitive fringe are more responsive to information about their competitors, although the distinction is statistically weaker in this specification.

Figure 6 illustrates the full dynamics of the effect across subsamples with high and low market concentrations, respectively. Panel B shows that, in the most-concentrated markets, the gap between a lender's terms and the bureau average is unaffected by joining. Panel C presents a different pattern for the least-concentrated 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.[22]

3.3 Other Shocks Coinciding with the Lender Joining PayNet

Joining PayNet is voluntary and not randomly assigned. Therefore we cannot ignore the possibility that our results are due to factors that drive both the decision to join and equilibrium maturities. Recall that access to new markets is the key driver of lenders' joining PayNet (Liberti et al., 2020). 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 Figure 6 Panel A reveals no discernible pre-trends in our dependent variable prior to joining. Moreover, Table A.4 shows that the effect is similar in magnitude across cohorts of lenders joining PayNet in

[21] We also find a similar pattern for other terms including contract size: there is more convergence in competitive markets.

[22] In principle, the speed of learning might be slower in less competitive markets. However, when we extend our event window, we continue to find null results for these markets.

different years. 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, we exploit the fact that, in a given period, some lenders to the same borrower have access to the platform, while others do not. We can use this 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:

$$\log |m_{l,f,c,t} - \overline{m_{c,t-1}}| = \delta_{post} + \eta_{l,f} + \zeta_{f,t} + \nu_{contract} + \varepsilon_{l,f,c,t}. \quad (2)$$

Table 8 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 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 our 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 business model shift, which is potentially correlated with the propensity to offer specific contract maturities. For example, lenders may alter the maturities they offer to support their efforts to increase total lending. This possibility is important to consider because we do not observe lender identities, and therefore cannot rely on public financial statements or other sources to develop business model controls. To address this concern, we design two additional tests that exploit 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 one's own decision to join. For example, after lenders join, they have no control over how the bureau's membership or collateral market coverage evolve. 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.

In the first test, we leverage this variation driven by other lenders to check whether our result holds within lender-year across different collateral types. We can ask 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 as follows:

$$\log |m_{l,f,c,t} - \overline{m_{c,t-1}}| = \delta_{post} * Volume_{c,t-1} + \gamma Volume_{c,t-1} + \eta_{l,f} + \xi_{lt} + \nu_{contract} + \varepsilon_{l,f,c,t}. \quad (3)$$

The main coefficient of interest is now the Post×Volume interaction, where Volume is defined as the number of open contracts in the bureau of the same collateral type as of the previous quarter. We include a lender-year fixed effect ξ_{lt} that absorbs any change in lenders' credit supply that is constant across collateral types within a year.

Panel A of Table 9 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. Columns 3 and 4 also include borrower-year fixed effects for robustness and arrive at the same results.

In the second test, we ask whether lenders react to large information shocks due to others joining PayNet. We implement this test in three steps. First, for each lender, we identify its primary collateral type—the one that lender most frequently finances. Second, for each lender, we identify an event quarter *after the lender joined* when the bureau experiences the largest increase in contract coverage for the primary collateral type. Although some lenders will share primary collateral types, their staggered joining results in different event quarters. Third, for each lender, we estimate a variant of Equation 1 around the event quarter, where the Post dummy is now defined relative to each lender's event quarter.

Panel B of Table 9 shows the results for this alternative specification. Consistent with our interpretation that lenders react to information about competitors contained in the platform, contract maturities are closer to rivals' average following a large information inflow after the lender has joined PayNet. Overall, these additional results alleviate the concern that our main findings are purely driven by factors behind the decision to join.

4 Interpreting the Findings and Implications

4.1 Conventional Channels of Information Sharing

The previous section provides robust evidence that lenders react to learning about their competitors. 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 some of them are operating in our setting (Doblas-Madrid and Minetti (2013), Sutherland (2018), Liberti et al. (2020)). We argue only that our findings cannot be fully explained by these conventional channels.

4.1.1 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 amount 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 previously tried to keep secret.

If this channel were driving our result, we expect that it would be smaller or absent for borrowers with (i) a single relationship, because for them the credit file would contain no new information, and (ii) a good credit history. However, Table 10 reveals that there is no significant difference in the effect for single relationship borrowers or borrowers with bad credit records.

4.1.2 Creditor runs

Alternatively, lenders can react to observing others' terms due to the fear of a creditor run.[23] For instance, Hertzberg et al. (2011) illustrate 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.

Several factors suggest that a run-based explanation is not behind our results. First, the institutional setting is not conducive to front-running: contracts are attached to a specific piece of equipment and typically have monthly payments. Second, recall from Table 5 that lenders do not shorten their maturities systematically upon joining: lenders adjust their terms toward what others are offering, in both directions. Third, the aforementioned findings in Table 10 contradict 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.

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

4.2 Learning about Competitors: Revisiting the Channels

The illustrative framework presented in Section 2 suggests two potential non-exclusive channels of learning about competitors: learning about what it takes to compete and learning about fundamentals. We revisit them in light of our main results and offer further tests aiming to differentiate between the two. Nevertheless, discriminating among all alternative models is difficult, given that market power and beliefs are not directly observable.

Learning about what it takes to compete: Under this channel, lenders respond to competitors' offers to preserve or grow their market share. Interestingly, industrial organization models can disagree on the sign of the effect. Lenders might try to preserve the demand for their contracts by matching rivals' terms (strategic complementarities) or by trying to differentiate themselves (Shaked and Sutton, 1982). Our evidence of lenders adjusting maturities toward what others are offering is consistent with the first view. This result can have important implications because it is well known that strategic complementarities help propagate shocks throughout the economy (Angeletos and Lian, 2016). Strategic complementarities are also crucial to determining the total effect of lifting barriers to entry, as they dictate the strength of incumbents' response to entrants contesting the market. Our findings that maturity adjustments are mediated by market structure are in line with this channel. Lenders in a dominant position and whose market share is less sensitive to competitors face little pressure to respond to what others are offering. Conceptually, lenders' "market power" should predict the strength of the effect (Bebchuk and Goldstein, 2011).[24]

Learning about fundamentals: There can also be an inference effect: competitors' actions partly reveal their private signals, which are informative about fundamentals such as credit risk or borrower demand in the economy. As opposed to learning about a specific borrower's credit file, this channel postulates that lenders look at the bureau information to extrapolate to similar borrowers. The rational expectations version of this effect has been studied extensively, but at this stage, other social learning models, such as information cascades or naive herding (Murfin and Pratt, 2018), are equally plausible. The unifying theme is that learning about competitors reduces the lender's reliance on its own private information.

We cannot directly measure lenders' beliefs, so instead we look for additional cross-sectional evidence consistent with learning about fundamentals. Conceptually, this learning channel does not suggest a clear-cut prediction with respect to the role of market structure. The main reason is that the canonical models tend to be cast in terms of a com-

[24] 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.

petitive financial market or through a sequence of decision-making problems. Recent work has incorporated elements of strategic behavior, and a consensus has yet to emerge (Vives, 2011; Bernhardt and Taub, 2015; Rostek and Weretka, 2015). Empirically, Bustamante and Frésard (2017) study how public firms respond to peers' investment, and document that, consistent with their learning model, peers only influence public firms' investment in more concentrated industries. This prediction of a learning channel is the opposite of the pattern we document above.

We perform several additional tests to look for direct evidence in support of learning about fundamentals. First, we compare the behavior of specialist lenders to others joining the platform. Although specialization is an imperfect proxy for differences in information, the idea is that specialist lenders may have more precise private information and thus put less weight on others' terms when deciding what to offer.[25]

We include five definitions of lender specialization, with the intent of capturing lenders that have expertise in a market segment. The first two define specialization based on the number of quarters since the lender's first contract originated in this collateral type or collateral type-region category. The next two 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. Finally, we define a lender as a specialist for a collateral type if that collateral type constitutes at least 30% of its lending portfolio.

A potential concern is that specialization measures could be mechanically correlated with market concentration measures, because to some extent they both rely on lenders' origination volume in different markets. To address this, our first two measures of specialization do not rely on volume; instead, they measure experience length. Additionally, recall that earlier we present results using the relationship-switching rate as an alternative proxy for market power that is not constructed based on volume. Moreover, the average univariate correlation between the HHI and our five specialist measures is below 0.1. This is consistent with specialization and market concentration not being mechanically related. A lender can be specialized in a collateral type without competing in a concentrated market. Likewise, a diversified lender can compete in concentrated markets without being a specialist in any. Overall, we acknowledge that our market structure and specialization measures are imperfect, and assess the sensitivity of our results to approaches that do not directly depend on origination volume.

If learning about fundamentals drives our main results, then specialists should adjust their terms relatively less upon observing others' terms. However, the specialist interaction

[25] Stroebel (2016), Kurlat and Stroebel (2015), and Loutskina and Strahan (2011) also exploit heterogeneity in expertise in the context of real estate markets.

is typically small, of the wrong sign, and insignificant, as displayed in Table 11.

Second, learning about fundamentals suggests that lenders might not converge toward the raw average of all other comparable contracts, but instead to other types of averages. For instance, a natural model of information aggregation implies convergence to the average of others' average. Moreover, specialists or lenders with the best portfolio performance might act as "thought leaders" that other lenders try to mimic. Table 12 however finds little evidence in favor of these hypotheses. The convergence to the average of others' average is strong, but not statistically different from our baseline effect (repeated in column 1 for convenience). In addition, there is no statistical convergence toward the average of specialists or low-delinquency lenders. Recall that lender identities are not disclosed to PayNet members, making it difficult to distinguish, say, specialists from others. So, in our setting, it may be less practical for lenders to track the average term of specific rivals than the term from all contracts they observe from a given market.

Finally, we test whether the effect is stronger in market segments in which fundamentals are more persistent. The idea is that rivals' actions are more informative when there is more persistence. We calculate the persistence of both maturity and delinquencies for each collateral market. Specifically, we fit separate AR(1) models of the quarterly average of maturities and delinquencies on the previous quarterly average for the same collateral type. We obtain the AR(1) coefficient and sort collateral types according to the coefficient. However, Table 13 reveals no significant difference across markets with different persistence for either maturity or delinquencies.[26] Of course, one limitation of this test is that persistence is measured with error.

Overall, we do not find strong evidence in favor of the learning about fundamentals channel. Our interpretation is not that fundamentals are irrelevant for lenders' terms, but that rivals' maturity is not that informative a signal about fundamentals relative to other sources of information available to lenders.

4.3 Implications

Our findings provide a new perspective on how information shocks are transmitted within credit markets. First, we show that information about rivals matters beyond simply information about borrower or lender fundamentals. The economic magnitudes we document are not small. They imply significant changes in rollover risk, which can have a large impact on this population of SMEs with particularly volatile cash flows. Our estimates imply a 10% probability of a six month or more change in maturity. This is notable because in our sam-

[26] A countervailing force is that persistent fundamentals can also lead to strong priors, muting the reaction from observing rivals.

ple 18% of borrowers see a change in their delinquency category over the next six months. Therefore, changing the borrower's maturity could affect their ability to make required payments on time, which in turn affects the terms they will receive on their next contract or whether they get credit at all.

Second, we argue that the competitive environment is key for the transmission of these information shocks. While most existing works emphasize the aggregation of fundamental information through market-clearing prices, credit markets tend to be decentralized and imperfectly competitive.

Interestingly, the rise in big data and algorithm developments across many markets is making learning about competitors increasingly easier. Debates over the effects of information technology on market competition has therefore resurfaced recently. Our findings speak, in a novel way, to this interaction. The equilibrium effects of information flows are inextricably linked to the underlying competitive environment. Conversely, any change in the competitive landscape will influence the transmission of new information (or lack thereof) to the real economy.

Much work remains before we fully understand the implications of learning about competitors. The economic forces and welfare considerations at play are subtle. On one hand, pooling information can be beneficial: it can improve production efficiency or remove barriers to competition. On the other hand, information from competitors could facilitate collusion. Moreover, having access to more information can backfire if "mistakes" are propagated as opposed to corrected when information is shared. For instance, Goldstein and Yang (2019) argue that in general, the market quality implications of information disclosure are subtle and can crowd out the production of private information. Murfin and Pratt (2018) document in detail how the use of comparables leads to pricing mistakes in the syndicated loan market, showing for example that learning from others leads to incorporating stale information. This in turn implies that market terms will be slow to react to market fundamentals in both downturns and upturns. As often described anecdotally, this can lead to aggressive lending in the downturns, but also, not aggressive enough lending in upturns. As shown in Figure A.2, the maturity dynamics across PayNet members and non-members appears to broadly follow this pattern.

4.4 Delinquencies During the Financial Crisis

To relate the above implications to our setting, we examine delinquencies during the financial crisis. This is an interesting episode, as it led to a wave of delinquencies that was difficult to predict. Broadly speaking, there are two potential and not mutually exclusive channels that could increase delinquencies. First, enhanced competition can lead lenders to neglect risk as they aggressively compete to preserve their market share. 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. Rajan et al. (2015) document this phenomenon in the market for securitized subprime mortgages during this period.[27]

We exploit the staggered timing of lenders' joining and study how contracts that originated prior to the crisis performed 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 by reacting 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 fixed effects ensure that our results are not driven by lending to different cohorts with different (and potentially region-specific) default risk. Note however, that unlike our main specification, we cannot control for borrower-lender fixed effects or impose the same sample restrictions.

Table 14 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 overlook fundamental sources of risk.

Admittedly, this is not the only possible explanation, and although our data cannot reject alternatives with absolute confidence, we offer additional supporting evidence. First, in line with our prior results, we also find that the delinquency increase is entirely driven by more competitive markets, as shown in columns 2 and 3. Second, we identify states with the largest drop in housing prices during the crisis, where a substitution from screening to mimicking should result in worse contract outcomes.[28] Even after controlling for region-origination quarter fixed effects, columns 4 and 5 show more delinquencies for post-joining contracts only in large housing price drop states. To mitigate concerns that our delinquency evidence stems from new market entry by lenders, column 6 limits the sample to the lender's existing markets. Our results are unaffected.

Several additional untabulated results support our inference that the rise in delinquencies

[27] 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.

[28] Housing crisis states are defined as those with a greater than 30% housing price decline from their peak, according to the FHFA index (14 states).

relates to learning about competitors. We find a reduction in the average gap between the lender's contract maturity and rivals' maturity after joining PayNet, but this decline is most pronounced for contracts that end up delinquent. Finally, lenders do not seem to target riskier borrowers after joining. On the contrary, if anything, borrowers' credit records improve, consistent with the canonical information effect of credit bureaus (Doblas-Madrid and Minetti, 2013). Accordingly, we find that the effect is large for existing borrowers. Because the set of lenders joining PayNet a few years before the financial crisis instead of in other periods is small and potentially selected, we take this evidence as suggestive. Nevertheless, it supports the idea that incentives to match competitors can have a cost if they lead to the neglect of fundamental risk.

5 Conclusion

We show how contract terms and outcomes are shaped by the availability of competitor information. Using microdata from the introduction of an information sharing platform, we find that upon joining, lenders adjust their terms toward what others are offering. Further tests reveal that this effect is unlikely to be driven by lenders learning about fundamentals. Instead, we argue that imperfect competition plays a key role: information about rivals allows lenders to learn about what it takes to compete. These findings imply a new perspective on how information shocks are transmitted within credit markets, and ultimately, to the real economy. Information about rivals matters beyond simply information about borrower or lender fundamentals, and market structure is key for the transmission of these information shocks.

These results speak directly to recent trends that have attracted considerable attention from academics and policymakers. Learning about competitors is becoming increasingly easier given the rise of large pooled databases and improvements in data mining, in credit markets and beyond. Many works have also documented a rise in credit market concentration. The implications for consumer welfare, production efficiency, and policy design are open questions worthy of further investigation.

Finally, one limitation of our evidence is that, like most information sharing systems (e.g., the consumer bureaus in the United States), the bureau we study does not collect interest rates. While we point to several reasons why rates and maturities should respond similarly to competitor information in Section 2.2.3, we cannot directly test this. Therefore, future research investigating rate dynamics is warranted.

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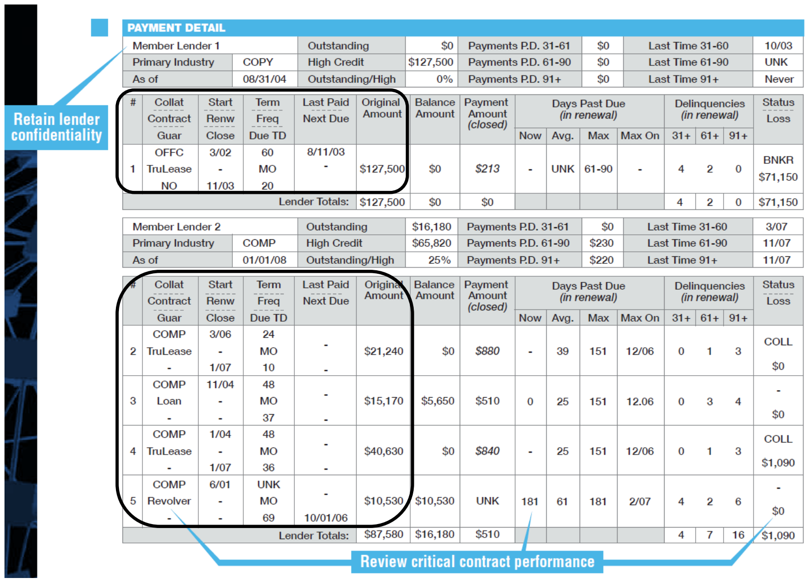
Figures and Tables



PAYMENT DETAIL

Member Lender 1		Outstanding	$0	Payments P.D. 31-61	$0	Last Time 31-60	10/03
Primary Industry	COPY	High Credit	$127,500	Payments P.D. 61-90	$0	Last Time 61-90	UNK
As of	08/31/04	Outstanding/High	0%	Payments P.D. 91+	$0	Last Time 91+	Never

#	Collat Contract Guar	Start Renw Close	Term Freq Due TD	Last Paid Next Due	Original Amount	Balance Amount	Payment Amount (closed)	Days Past Due (in renewal) Now	Avg.	Max	Max On	Delinquencies (in renewal) 31+	61+	91+	Status Loss
1	OFFC TruLease NO	3/02 - 11/03	60 MO 20	8/11/03 -	$127,500	$0	*$213*	-	UNK	61-90	-	4	2	0	BNKR $71,150
				Lender Totals:	$127,500	$0	$0					4	2	0	$71,150

Member Lender 2		Outstanding	$16,180	Payments P.D. 31-61	$0	Last Time 31-60	3/07
Primary Industry	COMP	High Credit	$65,820	Payments P.D. 61-90	$230	Last Time 61-90	11/07
As of	01/01/08	Outstanding/High	25%	Payments P.D. 91+	$220	Last Time 91+	11/07

#	Collat Contract Guar	Start Renw Close	Term Freq Due TD	Last Paid Next Due	Original Amount	Balance Amount	Payment Amount (closed)	Days Past Due (in renewal) Now	Avg.	Max	Max On	Delinquencies (in renewal) 31+	61+	91+	Status Loss
2	COMP TruLease -	3/06 - 1/07	24 MO 10	- -	$21,240	$0	*$880*	-	39	151	12/06	0	1	3	COLL $0
3	COMP Loan -	11/04 - -	48 MO 37	- -	$15,170	$5,650	$510	0	25	151	12.06	0	3	4	- $0
4	COMP TruLease -	1/04 - 1/07	48 MO 36	- -	$40,630	$0	*$840*	-	25	151	12/06	0	1	3	COLL $1,090
5	COMP Revolver -	6/01 - -	UNK MO 69	- 10/01/06	$10,530	$10,530	UNK	181	61	181	2/07	4	2	6	- $0
				Lender Totals:	$87,580	$16,180	$510					4	7	16	$1,090

Figure 1: Past Contract Terms in PayNet Credit File

Note: This figure illustrates the information contained in a borrower credit file. Contract terms are highlighted.

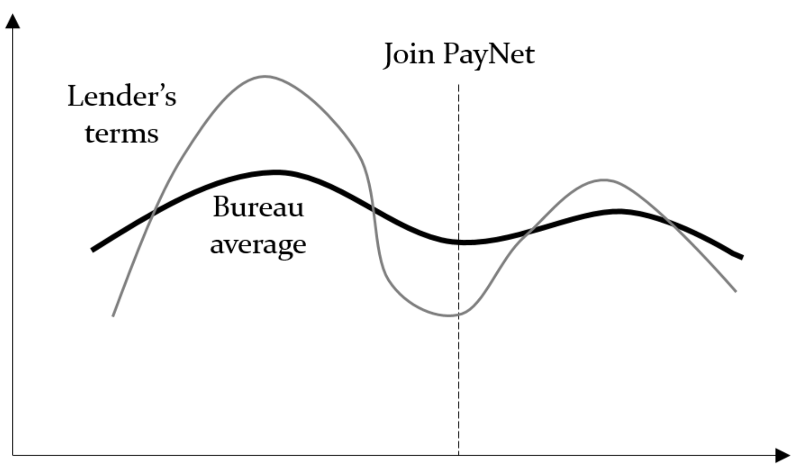
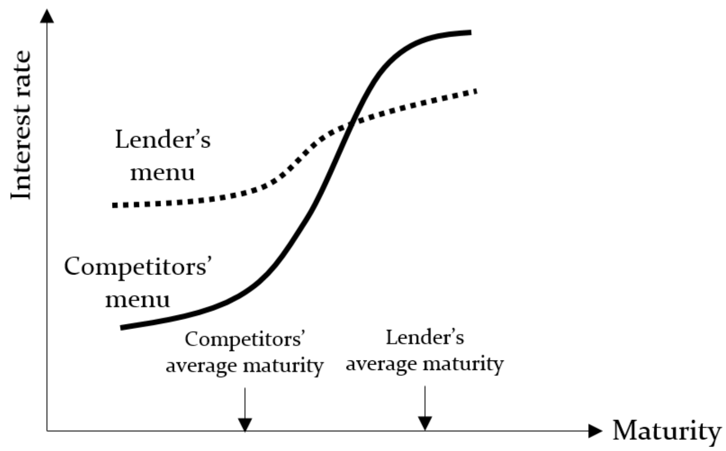


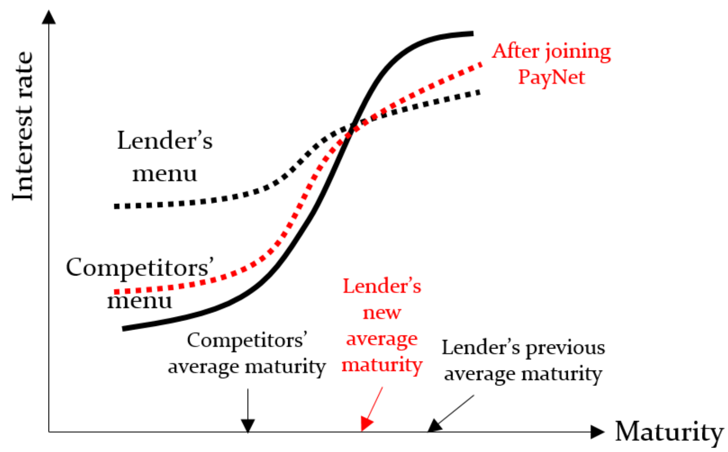
Figure 2: Empirical Strategy: Illustration

Note: This figure illustrates our empirical strategy. We assess whether a lender's maturity tracks the bureau average better or worse after they join. The case of convergence (better tracking) is illustrated.

Figure 3: Price Adjustments



(a) Before joining PayNet



(b) After joining PayNet

Note: This figure illustrates how lenders would adjust interest rates and maturities upon joining the bureau under the assumptions discussed in Section 2.2.3. Panel (a) presents the average maturity and interest rate for a given lender before they join (dashed line), alongside the same averages for bureau members (solid line). Panel (b) adds the lender's new average maturity and interest rate (dashed red line) after they join.

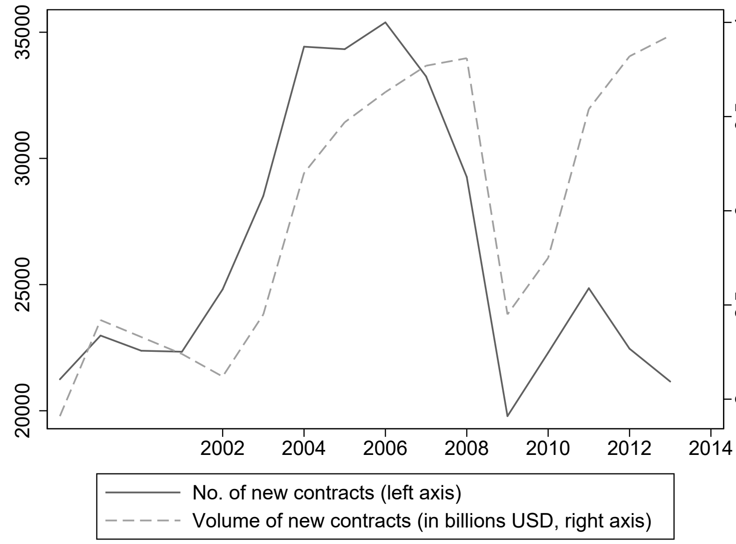


Figure 4: Contract Originations in PayNet

Note: This figure displays the distribution of contract originations by year for our random sample of PayNet contracts. The sample includes all contracts in our data.

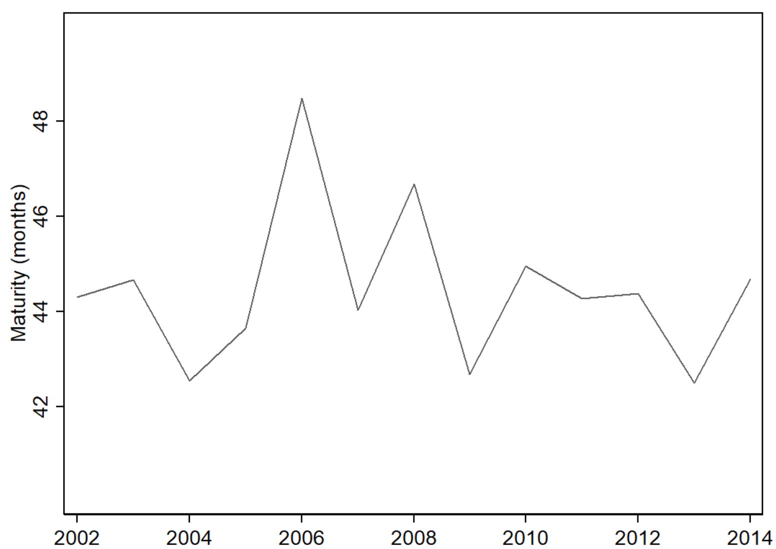
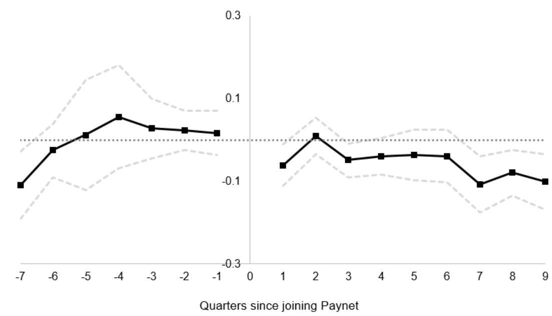


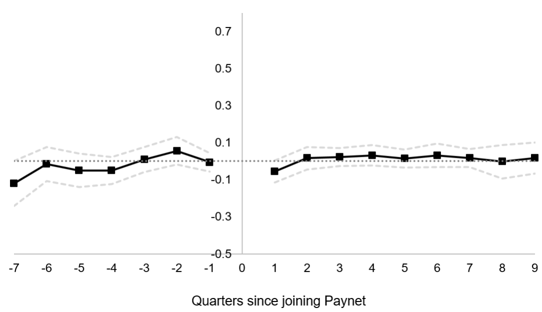
Figure 5: Contract Maturity by Origination Year

Note: This figure displays the average maturity of the contracts in our regression sample according to origination year.

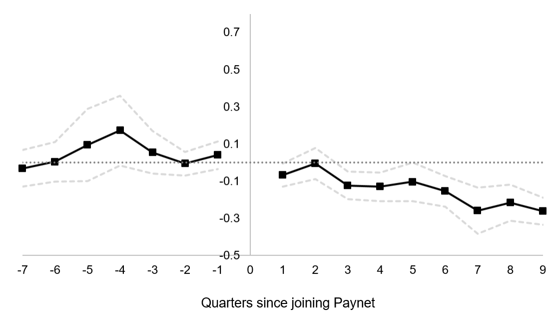
Figure 6: Joining PayNet and Contract Maturity: Dynamic Coefficient Plots



(a) All markets



(b) High HHI



(c) Low HHI

Note: This figure plots the coefficients from estimating a piecewise version of Equation (1) using event quarter indicators. For this plot, we extend the Table 4 sample to include contracts originated between the eight quarters before to eight quarters after the lender joins the bureau. The dashed lines plot 90% level confidence intervals. Panel (a) considers the entire sample. For panels (b) and (c), the sample is split according to the median HHI of the collateral type-region-contract size category.

Table 1: Sample Description

No. of borrowers	2,076
No. of lenders	44
No. of relationships	8,194
No. of contracts	54,290
No. of collateral types	23
No. of relationships per lender	94.0
No. of relationships per borrower	2.0
No. of collateral types per lender	6.1
No. of collateral types per borrower	1.7

Note: This table presents summary statistics for the borrowers and lenders in our Table 4 regression sample.

Table 2: Contract Characteristics

	All Contracts				Post=1				Post=0			
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
|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 summarizes the terms for the contracts in our Table 4 regression sample. The unit of observation is contract.

Table 3: Lender Entry to Bureau

Year	Lenders	Lender size quartile 1	2	3	4
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 Table 4 regression sample according to the size of the lender. Lender size quartiles are assigned according to total credit upon joining the bureau.

Table 4: Information Sharing and Contract Maturity: Main Specification

	Log | gap |			
	(1)	(2)	(3)	(4)
Post	-0.069**	-0.069**	-0.067**	-0.059**
	[-2.30]	[-2.34]	[-2.12]	[-2.30]
Year FE	Yes	Yes	No	No
Lender-Borrower FE	Yes	Yes	Yes	Yes
Quarter FE	No	No	Yes	No
Collateral-Year FE	No	No	No	Yes
Controls	No	Yes	Yes	Yes
N	54,290	54,290	54,290	54,290
Adj. R-squared	0.521	0.522	0.524	0.524

*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 study only 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). Post is an indicator variable equal to one in quarters after the lender has joined the bureau. Controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are clustered by lender, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

Table 5: Information Sharing and Contract Maturity: Symmetry

	(1)	(2)
	Log maturity	Log |gap|
Post	0.024	
	[1.16]	
Post × Positive Gap_{t-1}		-0.103*
		[-1.68]
Post × Negative Gap_{t-1}		-0.055*
		[1.91]
Year FE	Yes	Yes
Lender-Borrower FE	Yes	Yes
Controls	Yes	Yes
N	54,290	54,290
Adj. R-squared	0.666	0.522

Note: This table displays the regression results from estimating a modified version of Equation 1. The unit of observation is contract. In column (1), the dependent variable is log contract maturity. In column (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). Positive Gap_{t-1} *and Negative* Gap_{t-1} *are defined based on the last contract in the borrower-lender relationship before the lender joins PayNet. Controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are clustered by lender, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

Table 6: Robustness

	Bureau average by collateral type-quarter-region	Bureau average for previous year	Bureau average for unrelated collateral type	Contract size: |Size gap|	Alternative specification: Log Maturity
	(1)	(2)	(3)	(4)	(5)
Post	–0.047**	-0.042	0.059	-0.238***	
	[-1.82]	[-1.03]	[0.42]	[-3.29]	
Borrower Risk × Relationship Length					0.056
					[1.15]
Post × Borrower Risk × Relationship Length					-0.055
					[-1.54]
Year FE	Yes	Yes	Yes	Yes	Yes
Lender-Borrower FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
N	53,231	41,540	22,484	54,290	54,290
Adj. R-squared	0.510	0.553	0.477	0.332	0.666

*Note: This table displays the regression results from estimating variations of Equation 1. In columns (1)-(3), 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). Column (1) calculates the bureau average within collateral type-quarter-region, instead of within collateral type-quarter. Column (2) calculates the bureau average from four quarters ago instead of one quarter ago. Column (3) uses the bureau average for an unrelated collateral type, chosen as the median of the relatedness measure defined by Liberti et al. (2018). In column (4), the dependent variable is the contract-bureau average gap for contract sizes. In column (5), the dependent variable is the log contract maturity, and the specification includes all main effects and interaction terms. Relationship Length is an indicator equal to one if it has been more than three years since the lender-borrower relationship began. In all specifications, the unit of observation is contract. Controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are clustered by lender, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

Table 7: Information Sharing and Contract Maturity: Split by Market Structure

	Log | gap |			
	(1)	(2)	(3)	(4)
	Collateral-Region-Contract Size HHI	Collateral-Contract Size HHI	Switching Rate	Top 5 Lender
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]	
Post × Top 5				-0.063**
				[-2.11]
Post × Not Top 5				-0.101**
				[-2.20]
Lender-Borrower FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	53,305	54,101	54,290	54,290
Adj. R-squared	0.523	0.522	0.523	0.523

*Note: This table displays the regression results from estimating an augmented version of Equation 1 that considers various market structure measures. In columns 1 and 2, market structure is defined according to the median HHI of the collateral type-region-contract size category and collateral type-contract size category, respectively. Column 3 uses the relationship-switching rate, defined as the fraction of relationships in the market last quarter that no longer exist this quarter. Column 4 uses an indicator for whether the lender is among the five largest in this particular collateral type-region-quarter combination. The unit of observation is contract. 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). Controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are clustered by lender, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

Table 8: Accounting for Borrower Shocks

	Log |gap|	
	(1)	(2)
	High HHI	Low HHI
Post	0.048	-0.044*
	[0.89]	[-1.79]
Borrower-Year FE	Yes	Yes
Lender-Borrower FE	Yes	Yes
Controls	Yes	Yes
N	17,615	18,175
Adj. R-squared	0.523	0.561

*Note: This table displays the regression results from estimating Equation 2. In addition to our Table 4 sample restrictions, these tests are also limited to borrowers with at least two outstanding relationships. The unit of observation is contract. 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). Controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are clustered by lender, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

Table 9: Accounting for Lender Shocks

Panel A: Volume Tests

	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
Controls	Yes	Yes	Yes	Yes
N	26,142	27,163	17,607	18,163
Adj. R-squared	0.553	0.574	0.525	0.560

Panel B: Other Lenders' Entry Tests

	Log |gap|
	(1)
Post Large Info Shock	-0.064***
	[-2.88]
Year FE	Yes
Lender-Borrower FE	Yes
Controls	Yes
N	30,498
Adj. R-squared	0.482

*Note: Panel A displays the regression results from estimating Equation 3. Volume (main effect not tabulated for brevity) is defined as the number of contracts in the bureau of the same collateral type in the previous quarter. The sample in columns 1-4 is split according to the median HHI of the collateral type-region-contract size category measured at the contract level. Panel B displays the regression results from estimating a variant of Equation 1 in which the Post dummy is defined with respect to when the lender experiences a large information shock for its primary collateral type after it has joined the bureau. In both panels, the unit of observation is contract. 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). Controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are clustered by lender, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

Table 10: Information Sharing and Contract Maturity: Borrower Heterogeneity

	(1)	(2)
	Log |gap|	Log |gap|
Post	-0.055**	-0.085***
	[-2.12]	[-2.66]
Post $\times$ Single Relationship	-0.070	
	[-1.13]	
Post $\times$ Past 90+ Days Delinquency		0.036
		[1.22]
Collateral-Year FE	Yes	Yes
Lender-Borrower FE	Yes	Yes
Controls	Yes	Yes
N	54,290	54,290
Adj. R-squared	0.545	0.545

*Note: This table displays the regression results from estimating Equation 1 by borrower type. The interaction in column (1) flags borrowers with one lender at the time of contract origination. The interaction in column (2) flags borrowers whose worst delinquency in the previous three years exceeds 90 days. The unit of observation is contract. 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). Controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are clustered by lender, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

Table 11: Information Sharing 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 types	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]
Lender-Borrower FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
N	54,290	54,290	54,290	54,290	54,290
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 measures and their interaction with Post. 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 its most common or one of its three most common in terms of originations. 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 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). Controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are clustered by lender, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

Table 12: Learning about Fundamentals: Tracking Different Averages

	Log |gap|			
	(1)	(2)	(3)	(4)
	Other lenders' average	Average of others' average	Specialists' average	Low delinquencies lenders' average
Post	-0.069**	-0.090**	-0.051	-0.049
	[-2.34]	[-2.26]	[-1.21]	[-1.59]
Year FE	Yes	Yes	Yes	Yes
Lender-Borrower FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	54,290	54,290	52,601	53,462
Adj. R-squared	0.522	0.515	0.560	0.531

*Note: This table displays the regression results from estimating Equation 1 using different versions of the bureau average for the benchmark, as labeled in the column header. Specialist lenders are those for whom the collateral type is one of their three largest. Low delinquency lenders are those who have a lower than average record of delinquencies in that collateral type. The unit of observation is contract. The dependent variable is the log absolute value of the gap between the contract maturity and the respective bureau average maturity for that collateral type in the previous quarter. Controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are clustered by lender, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

Table 13: Learning about Fundamentals: Market Persistence

	Log |gap|			
	(1)	(2)	(3)	(4)
	Persistence of maturity		Persistence of delinquencies	
Post	0.252	-0.072**	-0.105	-0.050
	[0.57]	[-2.12]	[-0.47]	[-1.58]
Post × Persistence	-0.327		0.041	
	[-0.70]		[0.16]	
Post × **1**{High persistence}		0.006		-0.043
		[0.20]		[-1.39]
Year FE	Yes	Yes	Yes	Yes
Lender-Borrower FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	54,290	54,290	54,290	54,290
Adj. R-squared	0.530	0.524	0.523	0.520

*Note: This table displays the regression results from estimating an augmented version of Equation 1. The interactions in columns (1) and (3) measure within-collateral type persistence in maturity and delinquency, respectively, as the AR(1) coefficient of quarterly regressions. The interactions in columns 2 and 4 use an indicator for collateral types with above median AR(1) coefficients. The unit of observation is contract. The dependent variable is the log absolute value of the gap between the contract maturity and the respective bureau average maturity for that collateral type in the previous quarter. Controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are clustered by lender, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

Table 14: Information Sharing and Delinquencies during the Financial Crisis

	Number of quarters delinquent in 2008-2009					
	(1)	(2)	(3)	(4)	(5)	(6)
	All contracts	High HHI market	Low HHI market	Housing crisis states	Other states	Exclude lenders entering new markets
Post	0.299**	-0.430	0.501**	0.594***	0.113	0.233**
	[2.54]	[-1.60]	[2.73]	[3.41]	[0.73]	[2.10]
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Collateral type-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	3,236	1,676	1,485	1,324	1,912	3,189
adj. R-sq	0.211	0.230	0.246	0.247	0.232	0.210

*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. The dependent variable is the number of delinquencies for the contract during 2008 and 2009. 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. Standard errors are clustered by lender, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

Online Appendix

Illustrative Theoretical Framework

Assume the following information structure:

$$\begin{pmatrix} s_l^{\phi} \\ s_l^{m} \end{pmatrix} = \begin{pmatrix} \phi \\ m_{-l} \end{pmatrix} + \begin{pmatrix} \epsilon_l^{\phi} \\ \epsilon_l^{m} \end{pmatrix}$$

and $\begin{pmatrix} \phi \\ m_{-l} \end{pmatrix} \sim N(0, \Sigma)$ and $\begin{pmatrix} \epsilon_l^{\phi} \\ \epsilon_l^{m} \end{pmatrix} \sim N(0, \Sigma_e)$, with Σ and Σ_e diagonal for simplicity. In this section, we only solve for the case where lenders adjust their terms towards rivals' terms (i.e., complementarities are sufficiently strong), as this is the canonical case studied in the literature.

We study a linear equilibrium, in which the signal from the bureau average is linear in ϕ and m_{-l}: $\bar{m} = a_0 + a_{\phi}\phi + a_m m_{-l} + \bar{\epsilon}$. The rational expectation equilibrium (REE) literature has shown that, in this simple setting, there exists an equilibrium that is linear in the lender's signals, both before and after joining. In other models, the equilibrium can take different forms in general, but in this section, we focus on the linear case as a first-order approximation. Before joining the bureau, lender l offers maturity:

$$m^*_{l,pre} = m_0 + \beta^{\phi}_{pre} s_l^{\phi} + \alpha \beta^{\phi}_{pre} s_l^{m} + \eta_{l,f}$$

After joining the bureau, lender l offers maturity:

$$m^*_{l,post} = m_0 + (\rho^{\phi} + \alpha\rho^{m})(\bar{m} - a_0) + \beta^{\phi}_{post} s_l^{\phi} + \alpha \beta^{m}_{post} s_l^{m} + \eta_{l,f}$$

In a simple REE model these optimal choices are truly linear, while in other models they can take more general forms. Nevertheless, for the sake of illustration, we focus on the linear case.

The weight on the bureau's signal $\rho^{\phi} + \alpha\rho^{m}$ is decomposed in two terms to explicitly reflect that the signal is informative about both ϕ and m_{-l}. In a linear equilibrium, $\bar{m} = m_0 + a_{\phi}\phi + a_m m_{-l} + \bar{\epsilon}$. In a simple REE model, the vectors of parameters ρ, a, and β are jointly determined and depend on the signals' relative precision. In other models, other factors enter. For the sake of argument, it is sufficient to solve for a in terms of ρ and β. Importantly, it is a common prediction that $\beta_{post} \leq \beta_{pre}$ across a wide class of models: lenders put less weight on their signal after joining the bureau (or equivalently, they collect less information). Although we do not model its micro-foundations, this prediction is an important ingredient of the argument below.

The argument behind our empirical strategy can be formalized as follows (for the convergence case): the variance of the gap between the lender's maturity choice m_l^* and the bureau average $\bar{m}$ decreases after joining the bureau as long as 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 $m_{l,post}^*$ across lenders and identifying the coefficient on ϕ and m_{-l}:

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

Hence $\bar{m} = m_0 + \frac{\beta_{post}^\phi}{1-(\rho^\phi+\alpha\rho^m)}\phi + \frac{\alpha\beta_{post}^m}{1-(\rho^\phi+\alpha\rho^m)}m_{-l} + \bar{\epsilon}$. Substituting in $m_{l,post}^*$:

$$m_{l,post}^* = m_0 + \frac{\beta_{post}^\phi}{1-(\rho^\phi+\alpha\rho^m)}\phi + \frac{\alpha\beta_{post}^m}{1-(\rho^\phi+\alpha\rho^m)}m_{-l} + \beta_{post}^\phi\epsilon_l^\phi + \alpha\beta_{post}^m\epsilon_l^m + (\rho^\phi+\alpha\rho^m)\bar{\epsilon} + \eta_{l,f}$$

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

$$d_{post} = \beta_{post}^\phi\epsilon_l^\phi + \alpha\beta_{post}^m\epsilon_l^m - (1-\rho^\phi-\alpha\rho^m)\bar{\epsilon} + \eta_{l,f}$$

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

$$d_{pre} = \beta_{pre}^\phi\epsilon_l^\phi + \alpha\beta_{pre}^m\epsilon_l^m - \bar{\epsilon} + \left(\beta_{pre}^\phi - \frac{\beta_{post}^\phi}{1-(\rho^\phi+\alpha\rho^m)}\right)\phi + \left(\alpha\beta_{pre}^m - \frac{\alpha\beta_{post}^m}{1-(\rho^\phi+\alpha\rho^m)}\right)m_{-l} + \eta_{l,f}$$

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_l and $\bar{\epsilon}$ is negligible:

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

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 $\beta_{post} = \beta_{pre}$.

Supplemental Analysis

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
Computer	4,538	8.36
Construction and Mining	6,049	11.14
Copier	18,737	34.51
Energy	6	0.01
Forklift	1,520	2.80
Logging	90	0.17
Manufacturing	1,134	2.09
Medical	601	1.11
Medium Truck	2,547	4.69
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.

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 FE + Year FE	17.25	0.05
Collateral Type FE + Year FE + Lender FE	16.17	0.17
Collateral Type FE + Year FE + Lender FE + Borrower FE	13.40	0.52
Collateral Type FE + Year FE + Lender-Borrower FE	10.32	0.76
Collateral Type FE + Year FE + Lender-Borrower FE + Controls	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 and controls, using our regression sample from Table 4

Table A.3: Market Power Proxies: Summary Statistics

Market Power Proxy	N	Mean	S.D.
HHI for collateral type-contract size-region	53,305	0.34	0.20
HHI for collateral type-contract size	54,101	0.24	0.11
Top 5 lender indicator	54,290	0.48	0.50
Relationship-switching rate	53,857	0.027	0.040

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. The Top 5 indicator is equal to one if the lender is among the five largest in this particular collateral type-region-quarter combination. The relationship-switching rate is defined as the fraction of the relationships in the collateral type-region last quarter that end this quarter.

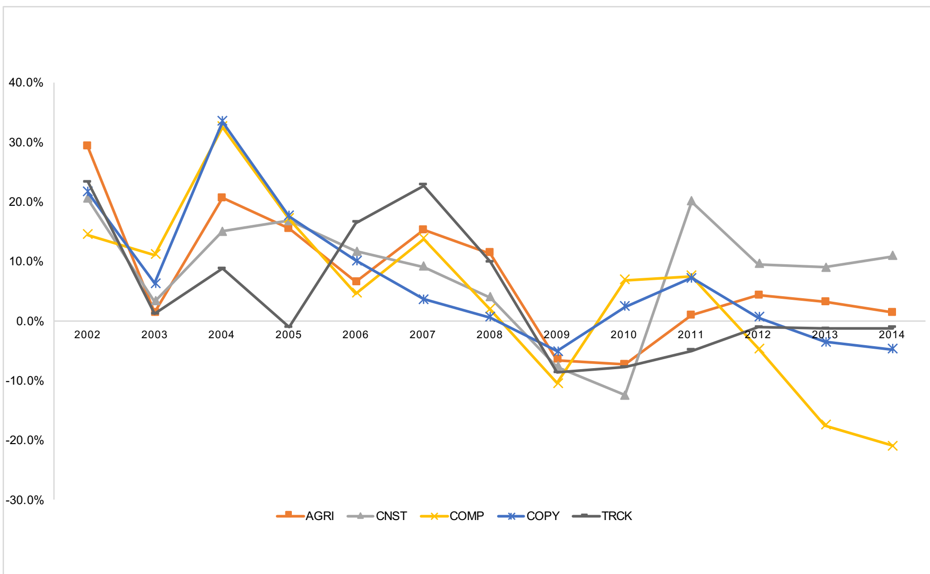


Figure A.1: Annual Growth in Bureau Contracts by Collateral Type

Note: This figure displays the annual growth rate of the number of contracts in the bureau for the five most common collateral types: agricultural equipment, construction and mining equipment, computers, copiers, and trucks. The sample includes all contracts in the data.

Table A.4: Early vs. Late Joiners

	(1) Log |gap|	(2) Log |gap|
Post	-0.065*	-0.074**
	[-1.83]	[-2.28]
Post $\times$ $\mathbf{1}\{\text{Join} \geq 2004\}$	-0.009	
	[-0.15]	
Post $\times$ $\mathbf{1}\{\text{Join} \geq 2005\}$		0.014
		[0.35]
Year FE	Yes	Yes
Lender-Borrower FE	Yes	Yes
Controls	Yes	Yes
N	54,290	54,290
Adj. R-squared	0.522	0.522

*Note: This table displays the regression results from estimating an augmented version of Equation 1. The interaction in column (1) flags lenders joining PayNet in 2004 or later, while column (2) flags lenders joining in 2005 or later. The unit of observation is contract. 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). Controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are clustered by lender, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

Table A.5: Other Parts of the Maturity Distribution

	Log |gap|							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gap w.r.t.	min	p10	p25	p50	mean	p75	p90	max
Post	0.005	0.076	-0.119**	-0.160***	-0.121**	-0.018	-0.029	0.004
	[0.08]	[1.29]	[-2.24]	[-2.92]	[-2.02]	[-0.35]	[0.41]	[0.08]
Lender-Collateral FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Collateral-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,275	5,275	5,275	5,275	5,275	5,275	5,275	5,275
adj. R^2	0.563	0.576	0.642	0.694	0.573	0.744	0.751	0.790

*Note: This table displays the regression results studying maturity convergence to various parts of the distribution, as labeled in the column header. The dependent variable is the log absolute difference between the lender's statistic (e.g., 25th percentile of maturity) to the same statistic for bureau members (25th percentile of maturity of bureau contracts). The unit of observation is lender-collateral type-quarter. Controls include indicators for contract size categories, leases, and the borrower's risk category, all averaged across the lender-collateral type-quarter. Standard errors are clustered by lender, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

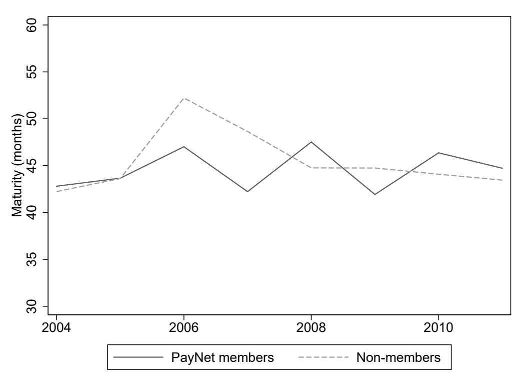


Figure A.2: Average Maturity for Members vs. Other Lenders

Note: This figure displays the average maturity for lenders that have joined PayNet versus others. Note that the sample composition of each group changes over time as new lenders join the platform.

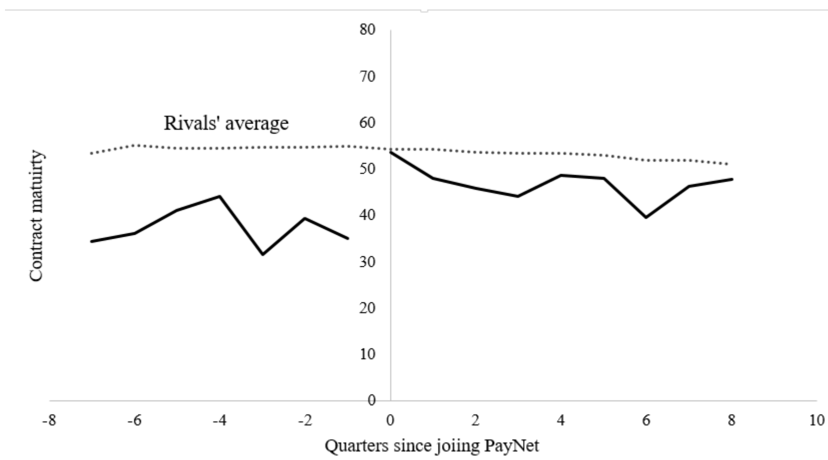


Figure A.3: Graphical Illustration: One Specific Market

Note: This figure displays the average contract maturity offered by a sample lender in the retail equipment market around the time they join PayNet. The sample lender's maturity is the solid line, and the bureau average maturity is the dashed line.