Learning about Competitors: Evidence from SME Lending

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Abstract

This paper estimates the effect of lenders learning about competitors' contract terms using micro-data from an information sharing platform. Exploiting the staggered entry of lenders into the platform, we find that upon entry, lenders adjust their terms toward what others are offering. We address two key confounders: unobserved common shocks to fundamentals and endogenous timing of entry into the platform. Lenders' reaction appears to be driven by strategic complementarities: incentives to match rivals in order to preserve market share. We also find evidence that this increased competition increases delinquencies during the recent crisis.

Keywords: competition, information sharing, credit bureau, corporate loans

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Introduction

Information plays a fundamental role in markets and strategic behavior. Indeed, in many settings information is *dispersed*: market participants do not have full information about their counterparties or their competitors' actions. Strategic and information considerations are linked: agents' optimal actions depend on their information about competitors' actions or beliefs. A key implication is that the market equilibrium depends on how much market participants know about each other. Housing and equity markets are prominent examples, and there is extensive theoretical work demonstrating the broad implications of this idea.[1] However, empirical work has lagged behind the theory. In particular, estimating the effect of learning about competitors is complicated by two factors. First, in many market settings the information revealed, such as a change in stock or house prices, is public, making it difficult to construct an uninformed control group. Second, when new information is private, it is not typically possible to jointly observe the information and behavior of market participants.

We address these challenges by studying the introduction of an information sharing platform in credit markets for small and medium enterprises (SME) in the United States. Unlike many consumer credit bureaus, the platform provides information on previous contract terms received by borrowers and not simply current payment status or debt balances. We therefore exploit the staggered entry of lenders into the platform to estimate the effects of learning about competitors. We find evidence that upon entry, lenders adjust their terms toward what others are offering. This behavior appears to be driven by a strategic motive to match competitors in order to preserve market shares. This *strategic channel* of information sharing in credit markets operates separately from more conventional channels, such as the revelation of a borrower's payment history and creditor runs.

We document this effect in the context of maturity dynamics for SMEs' equipment financing contracts from 2001 to 2014. This setting is relevant for multiple reasons. Because of their implications for firms' liquidity positions and investment behavior, maturity cycles became a concern during the recent crisis and recovery: maturity on loans lasting over a year fell by 30% between 2007 and 2010 before slowly recovering.[2] Moreover, with over $1 trillion of annual volume, equipment financing is a major component of corporate investment, and lending to SMEs is particularly important for policy makers.[3] In our context of financing a

[1]See: competition with imperfect monitoring (Green and Porter, 1984), coordination failures (Morris and Shin, 2002), price informativeness (Grossman and Stiglitz, 1980; Hellwig, 1980), amplification of shocks (Townsend, 1983), and rational herding (Banerjee, 1992; Bikhchandani et al., 1992).

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

[3]Chairman Bernanke argued in a 2010 speech that "making credit accessible to sound small businesses is crucial to our economic recovery and so should be front and center among our current policy challenges."

specific piece of equipment, it is natural to focus on maturity as it is negotiable, while contract size is largely dictated by the equipment needed, and by design, interest rates are not shared in the platform.[4] Moreover, because these contracts involve fixed monthly payments, maturity has a drastic effect on firms' debt burden: for the median contract in our sample, reducing maturity by a year implies up to 25% larger monthly payments.

Our empirical strategy is designed to address key empirical challenges associated with estimating how lenders react to observing information about others. 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 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 the staggered entry of lenders into the bureau 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 bureau.[5] The key idea is that, while a lender's terms track the bureau average before entry, they should track it relatively *better* after entry. We therefore study how, within a relationship, maturity changes relative to what others are offering over a short window around the lender's entry into the bureau.

In our main specification, we show that the gap between the maturity offered by a lender and what others in the bureau are offering shrinks by 7% after the lender joins the bureau. Lenders' terms therefore track the bureau average relatively better after entry. In economic terms, this corresponds to a 2% change in monthly payments, a change in debt burden that is comparable to a 2 percentage point change in APR. We measure average maturity within collateral type-quarter for members, and control for borrower size, credit history, and contract type. Importantly, this empirical strategy allows for arbitrary comovement of fundamentals unobserved by the econometrician. We make the argument formal by embedding our regression model into a canonical equilibrium model with dispersed information. We therefore interpret our estimate as the effect of observing others' behavior, net of any other existing information correlated across lenders. Nevertheless, an important caveat is that the

Moreover, information sharing can be particularly valuable when lending to these firms: their repayment behavior is erratic and their size and opacity make tailoring contracts costly.

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

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

timing of entry is not randomly assigned. We address this concern in detail in robustness tests discussed below.

Why do lenders react to the information in the bureau? In theory, the welfare and policy implications of information sharing crucially depend on what competitors are learning about.[6] While there is no single answer, and a comprehensive welfare analysis is beyond the scope of this paper, we provide additional cross-sectional tests to gauge the relative importance of different underlying mechanisms.

We find evidence for a *strategic channel* of information sharing. Specifically, market participants are often uncertain about what others are offering. Prior to PayNet, there was no comprehensive source of information on contracts offered in this market. This uncertainty made it difficult for market participants to determine their own best response to preserve or grow their market share. If contract terms are strategic substitutes, observing new information about others implies a convergence in terms. However, this effect should be muted for lenders in a dominant position and whose market share is less sensitive to competitors. Indeed, we find that the effect is entirely driven by the most-competitive market segments. The effect of entry on contract terms is strong only in markets for which there is a low level of concentration, where markets are defined as a collateral type x census region pair, and concentration is measured using the HHI index. These results are consistent with a strategic channel of information sharing, whose strength depends on the degree of market power over borrowers.

We put this result in perspective with more conventional effects of information sharing in credit markets and show that they cannot fully account for our findings. Specifically, a key role of credit bureaus is to create credit files that reduce information asymmetries between lenders and borrowers, and affect the composition of credit. This effect has been documented in many settings, including our own (Sutherland, 2018; Liberti et al., 2017), and takes various forms: rejection of low-quality applicants, higher rates of borrower switching, termination of borrowers with poor credit records, or extension of lending into new markets. However, by design, our tests keep the composition of borrower-lender pairs constant by including relationship fixed effects. Moreover, we find equally strong effects when looking at single-relationship borrowers for which the credit file contains no new information. This last result also is contrary to explanations based on run-like behavior of creditors, as the incentives to run are muted for borrowers with a single lender.[7] In addition, it does not appear that

[6]See Vives (2006) for a survey of the subtle interaction between information sharing and market competition.

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

lenders shorten their maturity systematically upon entry, nor that the effect is stronger for borrowers of low credit quality. Another possible explanation is information aggregation: lenders react to others' terms because they reveal some of their private information about credit risk or borrower demand in the economy (Hellwig (1980)). However, specialist lenders with expertise in a specific market segment do not appear to react less than nonspecialist lenders, according to various measures of specialization.

These results shed light on the implications of information technology for credit markets. Interestingly, because terms offered to a borrower are influenced by what others received and not simply by its previous credit record, information can potentially lead to spillovers *across* borrowers and spread through market segments. These spillovers are likely to grow in importance going forward, as large pooled databases and improvements in data mining techniques are increasingly used for credit underwriting. More generally, the link between information technology and competition is at the center of policy makers' attention. In the words of European Commissioner for Competition Margrethe Vestager, "the future of big data is not just about technology. It's about things like [...] competition".[8] At a general level, the implications for consumer welfare or production efficiency are not obvious. In our setting, contracts originated after entry are more likely to end up repeatedly delinquent during the recent crisis relative to contracts originated before, suggesting that a desire to match competitors can backfire if lenders give less attention to fundamental sources of risk.

We conduct a number of robustness tests to address several important remaining threats to identification. Specifically, the decision to join the information sharing platform is voluntary and can therefore depend on a number of factors that could potentially affect maturity independently of the information revealed by the bureau. On this front, note first that Liberti et al. (2017) show that the key driver of lenders' entry into the PayNet platform is access to new markets, while our main test is exclusively within existing borrowers. Nevertheless, in principle there could be shocks either to the lender or borrower that exactly coincide with the entry decision. We therefore conduct two additional tests. On the borrower side, our results hold when comparing contracts made to the same firm by lenders with different information sets. Specifically, we study firms with two lenders, one sharing information and one not. We find that after entry the lender who shares information offers a maturity closer to the bureau average relative to the other lender in the same period. We show this by following Khwaja and Mian (2008) and including borrower-time fixed effects for the subset of borrowers with multiple lenders. That would alleviate the concern that our results are driven by borrower demand shocks that coincide with lenders' entry decision.

On the lender side, joining the bureau might coincide with a shift in business model

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

and be potentially correlated with its propensity to offer specific contract terms. However, our result holds when we include lender x year fixed effects by comparing contracts made by the same lender in this same period, across different market segments. Specifically, the information coverage in the bureau depends on contracts made by *other lenders* and thus varies by collateral type over time in a way that is not directly driven by the decision to enter.[9] We show that, for a given lender entering in a specific quarter, the maturity of collateral types with higher coverage tracks the bureau average better than collateral types with low coverage. This supports the interpretation that lenders adjust their contract terms in reaction to the information revealed in the bureau.

Related Works

This paper is related to various strands of the literature at the intersection of information and market interactions. Hertzberg et al. (2011) provides clean evidence of the role that public information plays in coordination in credit markets. They find that lenders react strongly to the public revelation of information they already possess about a borrower. This publicity effect triggers "run-like" behavior by creditors and financial distress for firms with multiple lenders. In comparison, we study the effect of observing information about other lenders and find evidence of a strategic channel independent of creditor runs.

Bustamante and Frésard (2017) argue that managers are imperfectly informed about their investment opportunities and rationally use peers' investment as a source of information. They share our identification challenge of empirically isolating firms' active responses to their peers from correlated decisions that arise because firms have common information. Instead of using a direct change in the information environment like we do, they exploit variation across space and product markets to construct an instrument and show investment complementarity between firms due to learning from peers.

Murfin and Pratt (2017a) study comparable pricing in the syndicated loan market. They find that past transactions impact new transaction pricing, but a failure to account for the overlap in information across loans leads to pricing mistakes. Given the local nature of equipment financing markets, our data lacks the power to trace out paths of influence of comparable individual contracts over time like they do, making heuristics difficult to directly detect. We nevertheless do find suggestive evidence that entry into the platform could have lead to more frequent delinquencies during the recent crisis.

More generally, this paper relates to the work on information sharing and credit bureaus, including Liberman et al. (2018), Doblas-Madrid and Minetti (2013), Jappelli and Pagano

[9]For example, after a truck captive joins there is a large increase in the bureau's coverage of truck contracts, but no new contracts for copiers.

(2006), Giannetti et al. (2017), and Balakrishnan and Ertan (2017), and more broadly on the role of information in lending markets (Liberti et al. (2016), Hauswald and Marquez (2003), Liberti (2017), Liberti and Mian (2009) , Berger et al. (2017), Ryan and Zhu (2018), and Hertzberg et al. (2010)).

While public firms and public markets play a role in information diffusion (Foucault and Fresard (2014), Dessaint et al. (2018), Kurlat and Veldkamp (2015), Veldkamp (2005), Veldkamp (2006) Sockin and Xiong (2015), and Badertscher et al. (2013)), we focus on SMEs (Rice and Strahan (2010)) due to their opacity. We also relate to the large body of literature studying the interaction between information and strategic complementarities in other settings.[10]

1 Information Sharing and Equipment Financing in the United States

1.1 The PayNet Platform

Our data come from PayNet, a information sharing platform focusing on the U.S. equipment finance market and SMEs. Equipment financing is a major component of corporate investment, and lending to SMEs is particularly important for policy makers. In addition, information sharing can be particularly valuable when lending to these firms: their repayment behavior is erratic and their size and opacity make tailoring customer-specific contracts costly.

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.[11] Since PayNet's 2001 launch, it has attracted eight of the 10 largest lenders in the market, as well as several hundred others as members. Like other credit bureaus, PayNet operates on the principle of reciprocity: members must share information, and only members can purchase the credit files, credit scores, and default probability products offered. PayNet gathers its data by directly connecting into lenders' IT systems, ensuring that the information shared in comprehensive and reliable. PayNet has developed these products using 24 million contracts for over $1.6 trillion in transaction collected from members.

[10]In industrial organization, see for example Brown and Goolsbee (2002) and Bonatti et al. (2017). In macroeconomics, see the survey of Angeletos and Lian (2016) or Afrouzi (2017), Amador and Weill (2012), Schaal and Taschereau-Dumouchel (2015), Angeletos and La'O (2010), Veldkamp (2011) and Van Nieuwerburgh and Veldkamp (2006). For an application to mutual funds, see Chen et al. (2010)

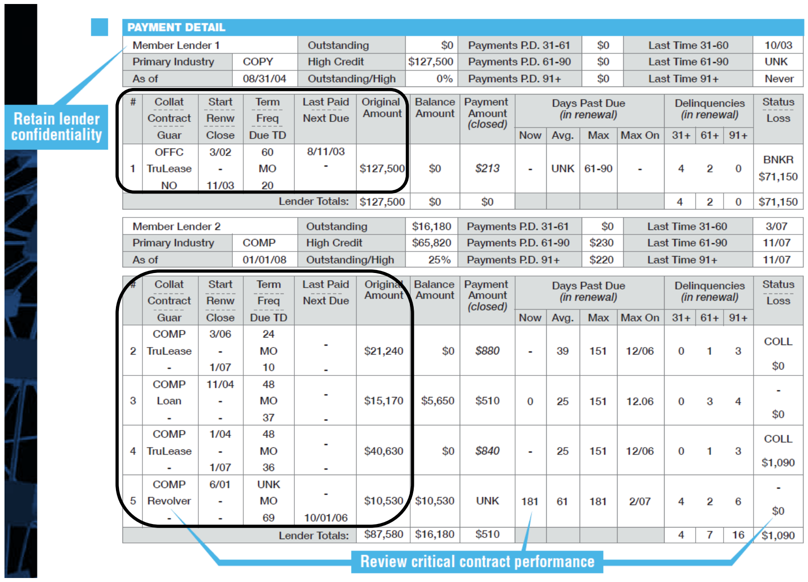
[11]Murfin and Pratt (2017b) provide an explanation for the presence of captives in equipment financing.

Prior to PayNet, lenders generally did not have access to payment history information when new borrowers applied for equipment finance loans and leases. Competing data providers such as Experian offered limited (and rarely timely) information about trade liabilities, which were much smaller than the typical equipment contract. Public UCC filings documented the existence of a contract, but did not detail whether the borrower paid on time or the terms they received. Thus, PayNet provided equipment finance lenders with a source of timely, contract-level information about a borrower's ability to service similar liabilities. This development was particularly relevant for small borrowers, who typically lacked audited financial statements or public information about their creditworthiness (Allee and Yohn, 2009; Berger et al., 2017). Although PayNet does not allow lenders to mine its data (e.g., by accessing all credit files for a given industry or zip code), lenders can observe how their counterparts contract: when they access individual credit files, they can see the terms other lenders are providing or have provided a given firm in the past. PayNet's data collection and verification process is further detailed in Doblas-Madrid and Minetti (2013) and the Online Appendix of Sutherland (2018).

Figure 1 illustrates the detailed information available exclusively to PayNet members. The figure displays a snapshot of a (fictitious) borrower's credit file accessible on the platform in return for a fee. While the first page of the credit file contains a summary of past payments as well as the borrower's state, industry, and age (omitted), subsequent pages reveal the terms of past and current contracts offered by all lenders in PayNet. In the example of Figure 1, the borrower had two lenders and five contracts in total. For each contract, the maturity, amount, and delinquency status are reported in great detail. Similar to other credit bureaus (e.g., the consumer bureaus in the United States), PayNet does not collect or distribute interest rate information.

1.2 Sample

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



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

This implies that an estimate of the bureau average contract terms, although unbiased, is measured with error. Such measurement error biases our estimates toward zero and in general reduces the statistical significance of our results.

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

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

1.3 Contract Terms

Table 3 describes the terms for a typical contract in our sample. The median contract size is \$20,300, with an average of \$101,000. The median maturity is 37 months from origination; the average is 44.3 months. Eighty-one percent of contracts are some form of lease (including true leases, conditional sales, and rental leases) while the remaining 19% are loans.[12] The overwhelming majority of contracts require fixed monthly payments. Seventeen percent of contracts involve some form of guarantor. The level of these contract terms are broadly similar before and after a lender joins the platform, although these levels are affected by changes in lender and borrower composition over time.

In this paper, we focus on contract maturity as our key variable for three reasons. First, maturity cycles became a concern during the recent crisis and recovery because of their implications for firms' liquidity positions and investment behavior. The Survey of Terms of Business Lending suggests that maturity on loans lasting over a year fell by 30% between 2007 and 2010 before recovering slowly. Figures 3 and 4 show that contracts in our sample also display considerable time variation across the business cycle. Second, in the context of financing a specific piece of equipment, maturity is negotiable but contract size is largely dictated by the equipment needed. In addition, by design, interest rates are not shared in the platform for fear of collusion, and similar to many other credit bureaus (i.e. consumer loans in the United States). Finally, because these contracts involve fixed monthly payments, maturity has a drastic effect on firms' debt burden: for the median contract in our sample, reducing maturity by a year implies up to 25% larger monthly payments.[13]

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 14 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 between its maturity and

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

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

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 12 months, which is a substantial fraction of the underlying variation in maturity choice.[14]

1.4 Entry into PayNet

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

Another key feature of our setting is that lenders enter at staggered times over the entire sample period. This variation in entry times brings two benefits. First, the platform information is not publicly revealed: in the same period, some lenders have access to it, while others competing in the same market do not. This within market-period, across-lender variation allows us to distinguish the effects of the new information from other events affecting lenders or borrowers in a given year. Second, the information revealed to entrants by the platform varies over time as a function of what *other lenders* are offering. Indeed, lenders often specialize by collateral type; therefore the bureau coverage across collateral types evolves in a nonsystematic pattern. Thus, members regularly experience shocks to the information coverage in their markets driven by the entry of other lenders, which is by construction outside of their control.[15] We leverage these additional sources of variation in our main specification and robustness tests.

Table 4 shows the variation in the timing of entry into the platform for lenders meeting our sample criteria described in Section 3. Lenders enter in all years between 2002 and 2014 except one. While large lenders tend to join earlier than small lenders, in any given year, a variety of lenders enters. At the same time, joining PayNet is voluntary and the timing of entry into the platform is not randomly assigned. Below, we leverage the variation in our data to ensure that results are not driven by lender or borrower shocks coinciding with the timing of entry. Note also that Liberti et al. (2017) study in detail the decision to join PayNet and show that a key driver of lenders' entry is access to new markets, but our tests

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

[15]Figure 6 in the Online Appendix shows there is considerable time variation in the volume of contracts in the bureau across collateral types.

are performed exclusively within an existing relationship.

2 Empirical Strategy

2.1 Overview

The central objective is to estimate the effects of observing others' contract terms. Such an effect is plausible from the large class of models relating information to market behavior, but designing credible empirical tests of this effect involves dealing with several identification challenges. This section provides an overview of our empirical strategy, and in the following sections we make the arguments more precise before discussing implementation and limitations.

The key empirical challenge associated with estimating how lenders react to observing information about others is the existence of unobserved common shocks.[16] Two lenders can offer similar contract maturities not because they react to what each other is offering, but simply because they react to the same fundamentals. For instance, a positive macro shock in a sector could induce two lenders to offer longer maturities independently of what they know about each other. This is a crucial issue because it is likely that at least some of these fundamentals cannot be observed by the econometrician and therefore, cannot be controlled for. The takeaway is that an estimation strategy relying only on cross-sectional correlation between agents' choices suffers from large potential bias.

In this paper, we address this issue by exploiting the time dimension associated with lenders' entry into the bureau. Specifically, the staggered entry of lenders in the information sharing platform leads to shift in information set *within* each lender. The key idea is that, upon entry, the lender's terms should track the bureau's terms better relative to before. A test based on this relative change is not confounded by the existence of correlated shocks independent of the bureau information, an argument we make precise below in the context of a canonical equilibrium model with dispersed information. Our data allows us to follow lender-borrower relationships over time, including the time before the lender joined the bureau. Our main specification therefore studies how maturity changes within a relationship over a short window around the lender's entry into the bureau.

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

2.2 An Illustrative Model

The economics of information aggregation with private signals is complex due to the presence of feedback loops and equilibrium effects: Agents' choices and the informativeness of the aggregate signal are fundamentally intertwined. In order to make the identification argument precise, we back up our empirical strategy with a canonical equilibrium model with dispersed information in the line of the "beauty contest" popularized by Morris and Shin (2002).[17] We use the model to transparently describe: (1) the effect of joining the platform and (2) how we empirically account for some important confounders.

Lender i's choice of maturity m to firm f can be decomposed in the following way:

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

When deciding what maturity to offer, lenders are influenced by their beliefs about borrower fundamentals, that is any force that influences its ability to repay. However, lenders also care about their competitors' terms. The strength of this strategic motive depends on how much market power lenders have over their borrowers. Lenders in dominant positions have little incentive to match their competitors' offers: in this case, the degree of strategic complementarities α is small, while the opposite is true in more competitive markets. The idiosyncratic term η_{if} includes borrower characteristics, news about its creditworthiness, or shocks to the lender's balance sheet that affect its propensity to lend.

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

After joining the platform, lenders can also observe an additional signal: the average terms offered by competitors $\bar{m}$.[18] This signal is potentially informative about both fundamentals and competitors' terms. Intuitively, in equilibrium, the maturity choice depends on

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

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

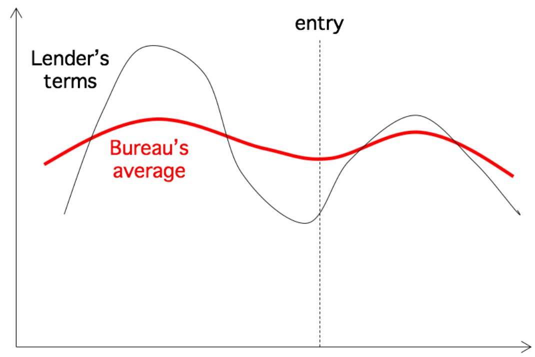


Figure 2: Hypothesis: lender's terms track bureau average better after entry

the information available to the lender at the time. Before entry, lenders weight their own private signals depending on how precise their prior and signals are about fundamentals and their competitors' terms. After entry, lenders place less weight on their own private signals and place some weight on the bureau average. Importantly, note the clear identification challenge in cross-sectional data. Maturity choices are naturally correlated across agents due to public information m_0 as well as private signals $\{s_i\}$, independent of the information revealed by the bureau. Our empirical strategy is specifically geared toward accounting for these unobserved common components.

Specifically, we exploit the time dimension associated with the lender's entry into the bureau. The staggered entry of lenders into the information sharing platform leads to a shift in the lender's information set. Our main specification measures how maturity changes within a relationship over a short window around the lender's entry into the bureau. An intuitive prediction of the model is that, while a lender's terms track the bureau average before entry, they track it relatively *better* after entry. Such a reduction of "tracking error" is likely to identify the effect of learning about competitors.[19] Figure 2 provides a graphical illustration of this idea, and a formal proof within the context of the model is provided in the Appendix.

The model also makes clear that there are, broadly speaking, two classes of channels at play. To see this, recall that the bureau is potentially informative about *both* fundamentals and competitors' terms. The traditional view of information sharing in credit markets emphasizes this first aspect: Lenders' update their beliefs about fundamentals and adjust their offers. On the other hand, a *strategic channel* of information sharing may also exist. Additional information about others makes it easier for a lender to determine its best response to preserve or grow its market share. If contract terms are strategic substitutes, observing new

[19]In Section 3 below we address the issue of nonrandom timing of entry into the platform.

information about others implies that lenders will adjust their terms towards what others are offering. The first part of the empirical analysis takes a broad view and estimates the total effect of joining the platform. The second part conducts additional cross-sectional tests to tease out what the platform is likely most informative about.

2.3 Regression Implementation

Importantly, the prediction that a lender's terms track the bureau average relatively better after entry can be tested within a fixed effects regression framework. While Section 3 provides details on sample selection and variable construction, at a general level we run regressions of the form:

$$|m_i^* - \bar{m}| = \delta_{post} + FE + \varepsilon$$

The absolute value of gap $|m_i^* - \bar{m}|$ measures the dispersion in maturity relative to the bureau average at the collateral type-quarter level. The coefficient of interest is δ_{post}: It is the coefficient on a dummy variable equal to 0 prior to entry and 1 after. It measures how much better lender's terms track the bureau average after entry relative to before entry. A negative coefficient $\delta_{post} < 0$ implies that lenders react to the bureau information by offering terms more similar to competitors.

We account for heterogeneous deviations from average maturity by including a series of granular fixed effects. For instance, time fixed effects absorb aggregate time variation, while the variation at the collateral type-time level is differenced out in the left-hand side variable. Moreover, we control for relationship idiosyncratic features with lender-borrower fixed effects, keeping the composition of borrower-lender pairs constant. This is key in isolating the effects of information sharing that work specifically through learning about competitors as opposed to other channels. Indeed, there is plenty of evidence that the revelation of borrowers' payment history affects the composition of credit and contract terms as worse borrowers are screened out or offered harsher terms, while better borrowers receive better offers. We also include controls for contract type, contract size, and risk category, which can vary across lenders. In additional robustness checks, we also control for borrower-time or lender-time fixed effects to account for shocks coinciding with the timing of entry.

2.4 Discussion

By construction, our empirical strategy is not confounded by the existence of:

- Public information unobservable to econometrician m_0

- Other sources of learning s_i
- Idiosyncratic loan terms $\eta_l f$

Indeed, all of these forces exist in the model, and our tests based on entry are valid independent of the sequence of realization of any of these shocks. However, a necessary assumption for identification is that their precision or dispersion is constant around the time of entry within fixed effects groups. This assumption is much weaker than requiring that all common shocks are observable to the econometrician. Nevertheless, it is strong enough that it cannot not be taken for granted in our setting. Indeed, the timing of a lender's entry is not randomly assigned. For instance, if entry coincides with a change in the lender's business model or with a change in borrower characteristics, this would create a bias in our estimate.

In Section 3 below, we provide additional tests that explicitly relax these assumptions. To account for borrower-level shocks, we compare maturities offered to the *same* firm at the *same* time by lenders with different information sets. To account for lender-level shocks, we employ lender x year fixed effects and exploit the shift of information caused by entry of *other* lenders in the bureau. We compare terms offered by the same lender in market segments with different coverage depth in the bureau.

3 Learning about Competitors

The main specification estimates the following fixed effect regression:

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

The unit of observation is a contract signed between firm f and lender l to finance a specific piece of equipment. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type.[20]

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. Importantly, recall that our data set is constructed from a random sample of 20,000 borrowers' quarterly credit files. We therefore cannot observe the universe of contracts in the bureau. Although our estimate of the bureau average is unbiased, this implies that it is measured with error. Such measurement error biases our estimates toward zero and reduces the statistical significance of our results.

[20]Our results are the same if we instead restrict the sample to borrower-lender relationships with at least one contract before and one contract after the lender's entry.

The parameter of interest is the coefficient δ_{post} on a post-entry dummy, equal to zero if the contract is originated before entry and 1 if it is originated afterward. To control for heterogeneous deviations from average maturity, we add a series of fixed effects. η_{lf} consists of a set of borrower-lender fixed effects to account for idiosyncratic time-invariant maturity at the relationship level, including industry and regional variation. Given that lenders join at different times, we can include a set of year fixed effects α_t to absorb aggregate time variation in maturity across firms and lenders. Note also that the variation at the collateral type-quarter level is differenced out in the left-hand side variable. Finally, we include contract characteristic controls $\nu_{contract}$ such as indicators for one of three contract size categories, whether the contract is classified as lease or a loan, and indicators for one of three borrower risk categories based on prior delinquencies.

To lend support to the empirical strategy, Table 5 reports pre-trends for contract terms before entry into the bureau. For the entire distribution of loan size and maturity, there is virtually no difference a quarter before entry relative to a year prior to entry. The distribution of the gap relative to the bureau average also does not display any particular trend..

Table 6 presents the main result of estimating equation 1. The last column includes all controls and shows that upon joining the bureau, the gap between a lender's maturity and the bureau average falls by 7% in absolute value. This effect reveals that observing new information about competitors leads lenders to offer maturities closer to what others are offering. Economically, this information effect implies a notable change in borrowers' debt burdens. To get a sense of economic magnitudes, we translate our main estimate into a change in implied monthly payments.[21] While we cannot directly observe monthly payments or interest rates in our data, Schalheim and Zhang (2017) estimate the mean annualized interest rate to be 15% in this market. Moreover, our main estimate corresponds to a one-month change in contract maturity. Taken together, this corresponds to a 2% change in monthly payments, which is equivalent to a 2 percentage point change in APR.

Table 7 shows that this result is robust to a number of alternative specifications, both in terms of economic magnitude and statistical significance. To account for heterogeneous shocks to collateral types across regions, column 1 calculates the bureau average by collateral type-region-quarter categories instead of collateral type-quarter and yields a very similar estimate. Column 2 shows that results are unchanged if we drop contracts originated during the crisis years of 2008-2010. Column 3 shows that the result is not driven by small collateral types that consist of less than one hundred observations in the whole sample, for which the bureau average is likely measured with a significant amount of error. Unreported results also show that the effect does differ significantly across borrower or lender size. Nevertheless, an

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

important identification concern remains: given that entry is not randomly assigned, it is necessary to rule out entry decisions driven by a change in borrower or lender characteristics. Sections 3.2 provides additional tests to account for such potential endogenous entry decisions.

3.1 The Role of Market Concentration

What mechanism is behind the previous result? Why do lenders react to others' terms? As described above, one possibility is a *strategic channel* of information sharing. Specifically, because market participants are often uncertain about what other are offering, it is difficult to determine their own best response to preserve or grow their market share. If contract terms are strategic substitutes, observing new information about others implies that lenders will adjust their terms toward what others are offering. However, this effect should be muted for lenders in a dominant position and whose market share is less sensitive to competitors' actions.

To test this hypothesis, we construct measures of market concentration based on the local HHI.[22] Table 15 in the Appendix shows summary statistics for these measures. We define a "market" either at the collateral type-contract size level or at the collateral type-contract size-census region level. To alleviate any concern that local market concentration is directly affected by information sharing, we compute market concentration at the beginning of 2001, before PayNet was introduced. There is a considerable variation in concentration across market segments: across contracts, moving to the 25th to the 75th percentile of the distribution implies a .15 to .20 increase in the HHI index. Moreover, Figure 7 in the appendix reveals that concentration levels are remarkably stable during our sample period.

Table 8 shows that the main result is entirely driven by market segments with low concentration levels. The first two columns split the sample according the median contract HHI at the collateral type-contract size-census region level. In markets with low concentration levels, the gap between lender's maturity and the bureau average falls by about 10% after entry, while it is unchanged in markets with high concentration levels. Columns 4 and 5 replicate this results with the more aggregated definition of HHI, while columns 3 and 6 use an interactive specification instead of a sample split.

Figure 5 shows the full dynamics of the effect for each subsample. Each panel plots the coefficients of a version of Equation 1 in which each quarter before and after entry has its own dummy variable. The omitted category is the quarter prior to entry and is labeled as time zero. The left panel shows that, in the most-concentrated markets, the gap between

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

a lender's terms and the bureau average is unaffected by entry. The right panel paints a different picture for the most competitive markets. After entry, there is a significant and persistent fall in the gap, implying that lenders adjust their terms towards what others are offering.

These results are consistent with a strategic channel of information sharing, whose strength depends on the degree of market power over borrowers. Lenders in a dominant position and whose market share is less sensitive to competitors face little competitive pressure to respond to what others are offering.[23] Section 4 compares this result to more conventional effects of information sharing in credit markets, such as a reduction of asymmetric information due to the revelation of payment histories or a creditor run.

3.2 Endogenous Entry

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

3.2.1 Accounting for Borrower Shocks

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

[23] One concern is that this concentration effect works through learning about borrowers' fundamentals instead. However, Bustamante and Frésard (2017) show in detail that this channel would lead to the opposite pattern: the effect should be stronger in more concentrated markets in which a fringe of smaller firms has stronger incentives to learn from larger product-market peers.

with multiple lenders:

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

Table 9 shows the results of this extended specification. As before, the gap between a lender's maturity and the bureau average falls after entry in competitive market segments, but is unchanged in others. The estimated magnitudes are naturally lower, as the average effect on the borrower is absorbed in the borrower-time fixed effects. The coefficient reflects the reduction in the gap after entry relative to other lenders of the firm in the post-entry period. This more stringent specification alleviates the concern that results are driven by shocks to borrower demand or creditworthiness that coincide with the lender's entry decision.

3.2.2 Accounting for Lender Shocks

On the lender side, joining the bureau might coincide with a shift in its business model, which is potentially correlated with its propensity to offer specific contract maturities. To address this concern, we design an additional test that exploits the entry of *other lenders*. Specifically, the information coverage in the bureau depends on contracts originated by others and thus varies by collateral types over time in a way that is not directly driven by the decision to enter. For example, a lender entering in one quarter might see many more contracts financing copiers than trucks, while another lender entering at another time might observe the opposite. This variation driven by others allows us to check whether our result holds within lender across different collateral types.

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

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

First, the main coefficient of interest is now the Post×Volume interaction, where Volume is defined as the number of contracts in the bureau of the same collateral type still open as of the previous quarter.[24] Second, we include a lender-year fixed effect ξ_{lt} that absorbs any change in lender's supply that is constant across collateral types within a year.

Table 10 shows the result for this extended specification. The estimated coefficients are consistent with our main finding. For a given lender entering in a specific quarter, the maturity of collateral types with higher coverage tracks the bureau average better than

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

collateral types with low coverage and only so in the most-competitive market segments. The magnitudes are again lower, as the average effect on the lender is absorbed by the lender-time fixed effects. Columns 5 and 6 also include borrower-year fixed effects for robustness and arrive at the same results. These tests lend additional support to the interpretation that lenders adjust their maturities in reaction to the information revealed in the bureau, as opposed to other factors that drive entry decisions.

4 Relationship to Other Mechanisms

The previous section provides robust evidence of a strategic effect of information sharing: lenders' reactions appear to be driven to match competitors in order to preserve market shares and depend on the extent of market power over borrowers. In this section, we put this result into perspective with more conventional channels of information sharing in credit markets: (1) the revelation of borrowers' payment histories, (2) creditor runs, and (3) the revelation of competitors' private information through their contract terms. Note first that the strategic channel is novel because the information shared is atypical: PayNet includes information about contract details offered by competitors that are not typically shared in consumer credit bureaus. Moreover, these channels are not mutually exclusive. We do not claim that these channels are not at play in general; in fact, previous work using PayNet data suggest they are in our setting. Simply, we argue that our specific findings cannot be fully explained by a number of forces previously documented. Next, we provide strong cross-sectional evidence supporting this view.

4.1 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 composition of credit and contract terms. Part of this channel works through a change in the composition of borrowers: worse borrowers are screened out or offered harsher terms, while better borrowers receive better offers. However, by design, our tests keep the composition of borrower-lender pairs constant by including relationship fixed effects. The effect we document is therefore a change in maturity within a relationship.

The revelation of credit histories can affect an existing relationship if a borrower has multiple lenders. Accessing the bureau can reveal negative information to the lender that the borrower tried to keep secret previously. If this channel were driving our result, we expect that it would be smaller for borrowers with (1) a good credit history, and (2) a single relationship because for them the credit file would contain no new information.[25] However, Table 11 reveals that none of these predictions hold in our setting.

4.2 Creditor Runs

Alternatively, lenders can react to observing others' terms due to the fear of a creditor run.[26] For instance, the classic contribution of Hertzberg et al. (2011) illustrates the effect of information sharing on lender coordination. In the context of maturity choice, Brunnermeier and Oehmke (2013) emphasize the risk of "maturity rat race", in which new lenders offer short maturities in an effort to front-run existing creditors. In general, these incentives to run leads to strategic complementarities in maturity choice that could explain a convergence in maturities after entry in the bureau.

Although all loans are formally collateralized, there is still significant default risk. Nevertheless, three pieces of evidence speak against an explanation based on run-like behavior of creditors. First, it does not appear that lenders shorten their maturities systematically upon entry. Table 12 runs our main specification using the level of maturity as a dependent variable instead of the gap. Entering the bureau has no effect on maturity per se; instead, lenders adjust their terms toward what others are offering, in both directions. Moreover, the aforementioned findings in Table 11 are at odds with a run interpretation: the effect is equally strong for borrowers with good credit records or with a single relationship for which the incentives to run are muted.[27]

4.3 Information Aggregation and Lender Specialization

Finally, we examine a last alternative channel based on information aggregation. In this view, lenders react to others' terms because they reveal some of their private information about credit risk or borrower demand in the economy. Note the differences with the previous channels. The strategic channel emphasizes that lenders care about others' action per se, while the information aggregation channel argues that they care because of what they represent: maturities partially reveal competitors' private information that was used to make

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

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

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

this choice. As opposed to learning about a specific borrower from its payment history, information aggregation postulates that lenders look at the bureau information to extrapolate to other similar borrowers (e.g., with respect to size, sector, or collateral type). This insight is canon in the context of financial markets (Hellwig, 1980) and the information aggregation channel is often mentioned in antitrust debates related to the benefits of information sharing, a point we will revisit.

In the context of credit markets, this is an intriguing hypothesis. Admittedly, it is difficult to fully separate from the strategic channel, as the perfect test would rely on observing beliefs or preferences. Instead, we proxy for differences in information about fundamentals across lenders. The hypothesis is that if some lenders are more informed than others, they should react less to the information in the bureau. Indeed, a lender with more-precise prior or more private signals puts less weight on others' terms when deciding what contract to offer.[28]

Toward this end, we compare the behavior of specialist lenders relative to others upon entry into the platform. We include numerous definitions of lender specialization with the intent of capturing lenders that have strong expertise in a specific market segment. Table 13 presents the results. Columns (1) and (2) define specialization as the number of quarters since the lender's first contract originated in this collateral type or collateral type-region category. Columns (3) and (4) define a lender as a specialist for a specific collateral type if that collateral type is either the most common or one of the top three originated by that lender. Columns (5) and (6) define a lender as a specialist for a specific collateral type if that collateral type makes up at least 30% or 50% of its lending portfolio. The information aggregation channel would imply that specialists adjust their terms relatively less upon observing others' terms, leading to a positive interaction term $Post \times Specialist$. However, in no specification is the interaction between entry and the specialist dummy positive. The interaction is typically small, negative, and insignificant. Given that lenders with strong expertise in a specific market segment do not appear to react less than non-specialists, these results suggest that information aggregation plays a modest role in our setting.

4.4 Discussion and Implications

In the context of credit markets, the strategic channel appears to go beyond conventional mechanisms of the effects of information sharing. This is largely because in our setting, lenders gain access to an atypical source of information: their competitors' contract terms. Importantly, how much this information matters depends on market power: lenders in dominant positions have little incentive to match their competitors' offers. This result speaks, in

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

a novel way, to the interaction between information and market competition that has been emphasized in the literature (Jappelli and Pagano, 2006).

Interestingly, across many markets, the debate on the effect of information sharing on market behavior has resurfaced recently due to the rise in big data and algorithm developments.[29] The economic forces at play are subtle. On the one hand, information from competitors could facilitate collusion. On the other hand, there are potential benefits of pooling information: it can improve production efficiency or remove barriers to competition. European Commissioner for Competition Margrethe Vestager summarized this view at the EDPS-BEUC Conference on Big Data and Competition in 2016:

> "Because if bigger is better, then combining companies' data into a single, big pool might give you insights that you couldn't get from each one on its own. Take connected cars, for instance... They have dozens of sensors that measure the car's performance.... So just imagine if they could combine all that information, from each different make of car. That might help car companies build better cars... And there's no reason why that should harm competition... In fact, data pooling might even help competition. For example, a big online bookstore can use its data from billions of purchases, to work out which books I might want to buy. But smaller rivals, without so much data, might not be able to give me such good recommendations. So if smaller shops pool their data – in a way that complies with the privacy rules – that could help them compete. And that could be good for us all."

This perspective raises at least two sets of broad research questions. First, how can we credibly estimate the effect of learning about others? Is information about competitors used and if so how? This paper takes a step toward answering these questions by leveraging the micro-data of one of these information sharing platforms.

Second, what are the implications for efficiency and the optimal design of information sharing? Crucially, they depend on what information is shared and how it is shared, in addition to the existing market structure (Vives, 2006; Jappelli et al., 2000). Welfare implications can be positive or negative depending on whether information sharing fosters competition or collusion. Similarly, having access to more information can backfire if "mistakes" are propagated as opposed to corrected when information is shared. For instance, Murfin and Pratt (2017a) document in detail how the use of comparables leads to pricing mistakes in the syndicated loan market.[30]

[29] See for example Ferretti (2014) for a discussion of the role of information sharing from the point of view of European competition law.

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

In order to relate these questions to our setting, we provide a final set of tests linking information sharing to delinquencies during the recent crisis. Many have argued that a 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.[31] To investigate this possibility, we exploit the staggered sharing of lenders and study how contracts originated prior to the crisis end up performing during the crisis. Specifically, for each lender joining in 2005-2007, we study the 2008-2009 performance of contracts originated just before joining, compared to contracts originated just 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. 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.

We find contracts originated just after the lender joined experienced more crisis-period delinquencies than the contracts originated by the same lender just before.[32] Specifically, the post-join contracts experience approximately 0.3 more quarters of delinquency from 2008 to 2009 than the pre-join contracts. One interpretation is that a desire to match competitors can backfire if lenders give less attention to fundamental sources of risk. Consistent with this interpretation and our prior results, we also find that the effect is entirely driven by markets with low levels of market power and by states experiencing the largest drops in housing prices.

Because the set of lenders joining Paynet a few years before the crisis instead of in other periods is small and potentially selected, we take this evidence as suggestive as opposed to definitive. Nevertheless, it supports the idea that strategic incentives to match competitors behind contract design can have a cost if they lead to neglect of fundamental risk.

5 Conclusion

This paper estimates the effect of learning about competitors on the behavior of market participants. We document this effect in the context of maturity dynamics for small and medium enterprises (SME) equipment financing contracts using micro-data from the introduction of an information sharing platform in this market between 2001 and 2014. Unlike many consumer credit bureaus, the platform provides details of previous and current contracts and not simply current payment status or debt balances. We exploit the staggered

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

[32] Results are reported in Table 16 in the Online Appendix.

entry of lenders into the platform to estimate the effects of learning about competitors.

We find that, upon entry, lenders adjust their terms toward what others are offering. Crucially, we address two key confounders: unobserved common shocks to fundamentals and endogenous timing of entry into the bureau. We highlight a novel *strategic channel* of information sharing in credit markets: lenders' reactions appear to be driven by a strategic motive to match competitors in order to sustain market shares. The strength of this effect depends on the degree of market power lenders have over their borrowers. This strategic channel exists beyond more conventional channels, such as the revelation of a borrower's payment history and creditor runs. We also find that contracts originated after entry were more likely to end up repeatedly delinquent during the recent crisis relative to contracts originated before, suggesting that a desire to match competitors can backfire if lenders give less attention to fundamental sources of risk.

These results shed light on the interaction between information and market competition in credit markets, as well as many other settings. Learning about competitors is likely becoming increasingly easier, given the rise of large pooled databases and improvements in data mining techniques. The implications for consumer welfare, production efficiency, and optimal policy design are important questions for future research.

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Tables and Figures

Table 1: Sample Description

N. of borrowers	2,076
N. of lenders	44
N. of relationships	8,194
N. of contracts	54,290
N. of collateral types	23
N. of relationships per lender	94
N. of relationships per borrower	2
N. of collateral types per lender	6.1
N. of collateral types per borrower	1.7

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

Table 2: Distribution of collateral types

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

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

Table 3: Contract Characteristics

	All Contracts				Inside Bureau				Outside Bureau			
Contract Characteristics	N.	Mean	Median	SD	N.	Mean	Median	SD	N.	Mean	Median	SD
Loan size (thousands $)	54,290	101	20.3	593	37,333	104	20.7	589	16,957	93	19.7	605
Maturity (months)	54,290	44.3	37	17	37,333	44.5	39	17	16,957	43.8	37	16
Lease (indicator)	54,290	0.81	1	0.39	37,333	0.81	1	0.39	16,957	0.82	1	0.39
Monthly repayment (indicator)	51,568	0.91	1	0.28	35,410	0.90	1	0.29	16,158	0.92	1	0.26
Guarantor (indicator)	45,269	0.16	0	0.37	32,227	0.16	0	0.37	13,042	0.16	0	0.37
Personal guarantor (indicator)	45,269	0.01	0	0.10	32,227	0.01	0	0.09	13,042	0.01	0	0.11
Log |gap| (%)	54,290	2.42	2.51	0.77	37,333	2.41	2.44	0.81	16,957	2.44	2.49	0.70

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

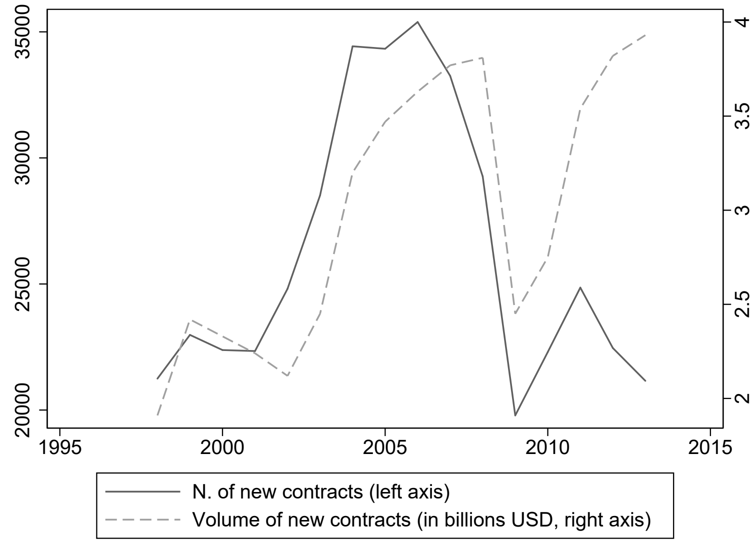


Figure 3: Origination of Contracts in PayNet

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

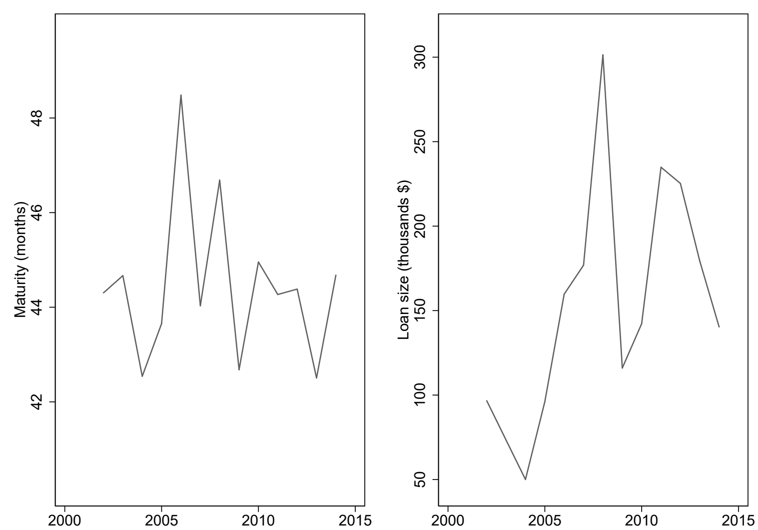


Figure 4: Contract Characteristics

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

Table 4: Lenders' Entry into PayNet

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

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

Table 5: Pre-Trends

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

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

Table 6: Entry and Contract Maturity: Main Specification

	Log |gap|			
	(1)	(2)	(3)	(4)
Post joining bureau	-0.045	-0.048*	-0.069**	-0.069**
	[-1.00]	[-1.66]	[-2.30]	[-2.34]
Year FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	No	No
Borrower FE	No	Yes	No	No
Lender-Borrower FE	No	No	Yes	Yes
Contract characteristics FE	No	No	No	Yes
N	54290	54290	54290	54290
Adj. R-squared	0.117	0.361	0.521	0.522

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

Table 7: Robustness

	Bureau average by collateral type-quarter-region	Drop crisis period	Drop small collateral types
	(1)	(2)	(3)
Post joining bureau	–0.047*	-0.078**	-0.071**
	[-1.82]	[-2.52]	[-2.38]
Year FE	Yes	Yes	Yes
Lender-Borrower FE	Yes	Yes	Yes
Contract characteristics FE	Yes	Yes	Yes
N	53231	51011	54136
Adj. R-squared	0.510	0.515	0.522

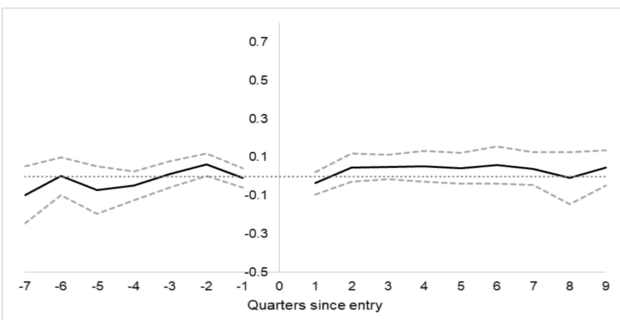
*Note: This table displays the regression results from estimating variations of Equation 1. Column (1) calculates the bureau average by collateral type-quarter-regions categories, instead of collateral type-quarter. Column (2) drops observations during the crisis period, defined as 2008 to 2010. Column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

Table 8: Entry and Contract Maturity: Split by Market Concentration

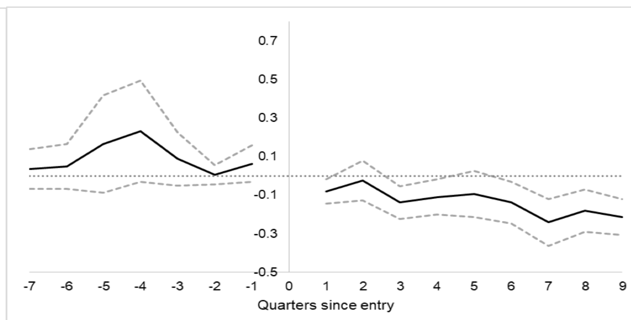
	Log |gap|					
	Collateral type- Region- Loan Size HHI			Collateral type- Loan Size HHI		
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Low	All	High	Low	All
Post joining bureau	-0.017	-0.095***		-0.012	-0.111***	
	[-0.56]	[-2.58]		[-0.34]	[-3.22]	
Post × High HHI			-0.030			-0.036
			[-0.93]			[-1.01]
Post × Low HHI			-0.116***			-0.104***
			[-2.91]			[-3.93]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender-Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Contract characteristics FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26142	27163	53305	25789	28312	54101
Adj. R-squared	0.548	0.567	0.523	0.562	0.572	0.522

*Note: This table displays the regression results from estimating Equation 1 by market concentration level. In columns 1 and 2, the sample is split according to the median HHI of the collateral type-region-contract size category measured at the contract level, or according to the median HHI of the collateral type-contract size category measured at the contract level (columns 4 and 5). Columns 3 and 6 provide interactive specifications instead of a sample split. The unit of observation is contract. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type. The dependent variable is the log absolute value of gap between the contract maturity and the bureau average maturity for that collateral type in the previous quarter (excluding lenders' own contracts). Contract characteristic controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are in parentheses and are clustered by lender. *** p<0.01, ** p<0.05, * p<0.10.*

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



(a) High HHI



(b) Low HHI

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

Table 9: Accouting for Demand Shocks: Borrower-Year FE

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

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

Table 10: Stock of Information Tests

	Log |gap|					
	(1)	(2)	(3)	(4)	(5)	(6)
			HHI		HHI	
	All firms		High	Low	High	Low
Post*Volume	-0.004	-0.005	-0.002	-0.0108*	-0.001	-0.008*
	[-1.30]	[-1.24]	[-0.59]	[-1.67]	[-0.11]	[-1.83]
Lender-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender-Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower-Year FE	No	Yes	No	No	Yes	Yes
Contract characteristics FE	Yes	Yes	Yes	Yes	Yes	Yes
N	54290	54290	26142	27163	26142	27163
Adj. R-squared	0.526	0.315	0.553	0.574	0.265	0.341

*Note:This table displays the regression results from estimating Equation 3. Volume is defined as the number of contracts in the bureau of the same collateral type still open as of the previous quarter. The sample in columns 3-6 is split according to the median HHI of the collateral type-region-contract size category measured at the contract level. The unit of observation is contract. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type. The dependent variable is the log absolute value of gap between the contract maturity and the bureau average maturity for that collateral type in the previous quarter (excluding lenders' own contracts). Contract characteristic controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are in parentheses and are clustered by lender. *** p<0.01, ** p<0.05, * p<0.10.*

Table 11: Entry and Contract Maturity: Borrower Heterogeneity

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

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

Table 12: Effect of Entry on Maturity Level

	Log maturity	
	(1)	(2)
Post joining bureau	0.024	0.016
	[1.16]	[0.71]
Year FE	Yes	No
Lender-Borrower FE	No	Yes
Borrower-Year FE	Yes	Yes
Contract characteristics FE	Yes	Yes
N	54290	54290
Adj. R-squared	0.666	0.523

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

Table 13: Entry and Contract Maturity: Lender Specialization

	Log |gap|					
	(1)	(2)	(3)	(4)	(5)	(6)
Specialist definition	Quarters since 1st contract in collateral type	Quarters since 1st contract in collateral type-region	Lender's most common collateral type	In lender's top 3 collateral type	Collateral type >30% of lender's portfolio	Collateral type >50% of lender's portfolio
Post x Specialist	-0.002	-0.000	-0.045	-0.019	-0.038	-0.155**
	[-0.90]	[-0.14]	[-1.08]	[-0.49]	[-0.79]	[-2.00]
Post	-0.050	-0.086	-0.037	-0.062**	-0.040	-0.025
	[-0.75]	[-1.33]	[-0.78]	[-2.01]	[-0.75]	[-0.72]
Specialist	0.017	0.015	0.056	-0.250***	0.076	0.274***
	[1.19]	[1.56]	[0.51]	[-2.83]	[0.52]	[3.93]
N	54290	54290	54290	54290	54290	54290
adj. R-sq	0.523	0.524	0.523	0.525	0.523	0.526

*Note: : This table displays the regression results from augmenting equation 1 with different specialist lender variables. All specifications include year, lender-borrower and contract characteristics fixed effects. Columns (1) and (2) define specialization as the number of quarters since the first contract originated in this collateral type or collateral type-region category. Columns (3) and (4) define a lender as a specialist for a specific collateral type if that collateral type is either the most common or one of the top three originated by this lender. Columns (5) and (6) define a lender as a specialist for a specific collateral type if that collateral type makes up at least 30% or 50% of its lending portfolio. The sample includes contracts originated between the four quarters before to four quarters after the lender joins the bureau. We only study lenders with at least one contract before and one contract after joining the bureau in the given collateral type. The dependent variable is the log absolute value of gap between the contract maturity and the bureau average maturity for that collateral type in the previous quarter (excluding lenders' own contracts). Contract characteristic controls include indicators for contract size categories, leases, and the borrower's risk category. Standard errors are in parentheses and are clustered by lender. *** p<0.01, ** p<0.05, * p<0.10.*

Appendix

Omitted Proofs

Assume the following information structure:

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

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

We solve for a linear equilibrium, in which the signal from the bureau average is linear in f and m_{-i}: $\bar{m} = \phi_0 + \phi_f f + \phi_m m_{-i} + \bar{\epsilon}$. It is an elementary exercise in this literature to show that, both before and after entry, there exists an equilibrium linear in the lender's signals. Before joining the bureau, lender i offers maturity:

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

After joining the bureau, lender i offers maturity:

$$m_{i,post}^* = m_0 + (\rho^f + \alpha\rho^m)(\bar{m} - \phi_0) + \beta_{post}^f s_i^f + \alpha \beta_{post}^m s_i^m + \eta_{if}$$

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

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

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

$$\begin{matrix} \phi_f = \beta_{post}^f + (\rho^f + \alpha\rho^m)\phi_f \\ \phi_m = \alpha\beta_{post}^m + (\rho^f + \alpha\rho^m)\phi_m \end{matrix} \iff \begin{matrix} \phi_f = \frac{\beta_{post}^f}{1-(\rho^f+\alpha\rho^m)} \\ \phi_m = \frac{\alpha\beta_{post}^m}{1-(\rho^f+\alpha\rho^m)} \end{matrix}$$

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

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

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

$$d_{post} = \beta^f_{post}\epsilon^f_i + \alpha\beta^m_{post}\epsilon^m_i - (1-\rho^f-\alpha\rho^m)\bar{\epsilon} + \eta_{if}$$

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

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

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

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

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

Online Appendix: Additional Results

Table 14: Unexplained Variation in Maturity Choice

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

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

Table 15: HHI: Summary Statistics

	HHI in 2001Q1					
HHI definition	N.	Mean	S.D.	p25	Median	p75
Market-level						
collateral type- contract size- region	258	0.62	0.31	0.34	0.54	1.00
collateral type- contract size	51	0.47	0.30	0.22	0.32	0.63
Contract-level sample						
collateral type- contract size- region	53,305	0.34	0.20	0.20	0.24	0.42
collateral type- contract size	54,101	0.24	0.11	0.15	0.27	0.27

Note: This table summarizes competitive features for observations in our regression sample. The unit of observation in the top (bottom) panel is market (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.

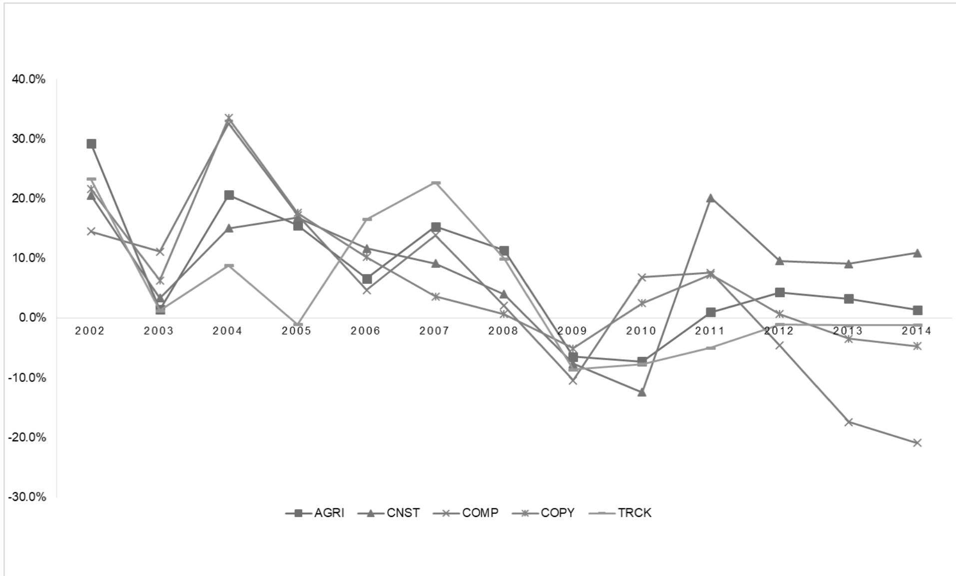


Figure 6: Annual Growth in Contracts in Platform by Collateral Types

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

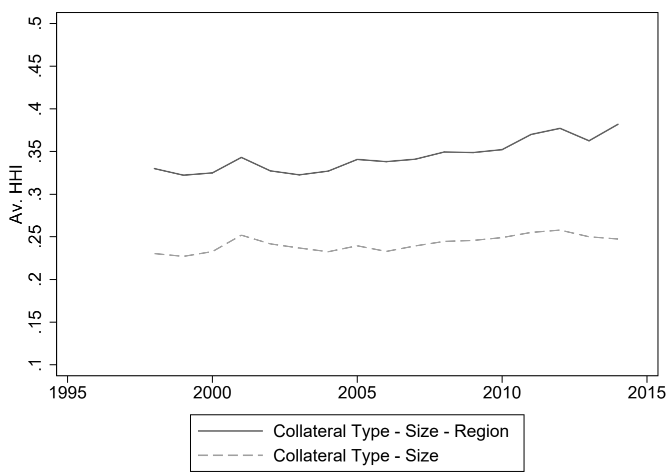


Figure 7: Market Concentration

Note: This figure plots average concentration measures for our markets according to contract origination year. HHI is the credit-weighted Herfindahl-Hirschman Index for the market. Markets are defined as a collateral type-census region-contract size or collateral type-contract size combinations.

Table 16: Entry and Delinquencies during 2008-2009 Crisis

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

*Note: This table shows the effect of joinig PayNet on deliquencies during the crisis. The sample is restricted to (1) lenders joining between 2005 and 2007, and (2) contracts originated no later than 2006 and still open in 2008-2009. The unit of observation is contract. HHI is the credit-weighted Herfindahl-Hirschman Index for the market, measured in 2001, before the bureau's inception. Housing crisis states are Arizona, California, Florida, Georgia, Idaho, Illinois, Maryland, Minnesota, Nevada, New Jersey, Oregon, Rhode Island, Utah and Washington. Standard errors are in parentheses and are clustered by lender. *** p<0.01, ** p<0.05, * p<0.10.*