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How Voluntary Information Sharing Systems Form: Evidence from a U.S. Commercial Credit Bureau

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Abstract

We use the introduction of a U.S. commercial credit bureau to study when lenders adopt voluntary information sharing technology and the resulting consequences for competition and credit access. Our results suggest that lenders trade off access to new markets against heightened competition for their own borrowers. Lenders that do not share initially lose borrowers to competitors that share, which ultimately compels them to share and leads to the formation of an information sharing system. We find access to credit improves but only for high-quality borrowers in markets with greater lender adoption. Our results offer the first direct evidence on when financial intermediaries adopt information sharing technologies and how sharing systems form and evolve.

Keywords: information sharing, access to credit, financial intermediation, fintech, SMEs.
JEL Codes: G21, G23, G32

1. Introduction

Recent advances in financial technology have led to a significant expansion of voluntary information sharing among lenders in private credit bureaus, both within and across economies (World Bank, 2019a,b).[1] Information sharing has the potential to improve access to credit for creditworthy borrowers and increase economic growth (Djankov, McLiesh, and Shleifer, 2007), but can be difficult to explain from the perspective of individual lenders because it increases competition (Padilla and Pagano, 1997). Therefore, credit bureaus may not form if competition deters lenders from adopting sharing technology.

In this paper, we study four central questions about the voluntary adoption of information sharing technology. First, when do individual lenders choose to adopt information sharing technology? Second, how does information sharing adoption interact with competition among lenders? Third, how do sharing systems form? Fourth, do these systems have positive real effects on the agents whose information is shared?

Empirical evidence on these questions has been encumbered by multiple challenges. Researchers rarely observe individual lenders' decisions to adopt information sharing or their behavior before and after sharing. Even when lender data are available, one needs to be able to separate individual lender decisions from aggregate economic motives for sharing. Moreover, each lender's adoption decision is guided by strategic considerations including adoption by competitors, which will affect the likelihood that an information sharing system will form. Last, turning to access to credit, one must separate the treatment effect of information sharing on borrowing from the selection effect of a borrower having its information shared.

To investigate our research questions, we use data from PayNet, an equipment finance credit bureau with the greatest coverage of small business loans and leases in the U.S. PayNet was established to fill a gap in the commercial credit market, in which, unlike in the consumer credit market, lenders had limited access to loan performance data from other lenders. As we further explain in Section 3.1, other commercial data providers such as Dun & Bradstreet or Experian did not collect loan performance

[1] Although developing markets receive much attention in the academic literature, private credit bureaus now cover the entire population in six of the ten largest economies, up from just two economies 15 years ago.

data or require reciprocal information sharing by lenders (Kallberg and Udell, 2003).[2] Indeed, information frictions in this market are acute: most borrowers are small and opaque, and do not access the syndicated loan or bond markets commonly studied in banking research. The quarterly probability of a borrower switching lenders is only 3%, less than half the prevailing switch rate in credit card markets and retail banking.

Our data include 218 lenders, including eight of the ten largest lenders in the market, that adopted the bureau in a staggered fashion between 2001 and 2014. Our randomly drawn contract sample provides a representative snapshot of the borrowers and lenders in the U.S. equipment finance market. Upon joining, members must share both ongoing and past contract data. Therefore, we can study a lender's adoption decision by empirically modeling the trade-offs that the lender faces in the period before adoption while controlling for aggregate effects.

Our main findings are as follows. Lenders' business models and the information structure of credit markets are central to understanding information sharing technology adoption. Early adopters are large, dispersed, model-based lenders that can take advantage of information sharing to improve credit modeling and reduce costs. Lenders adopt later when the threat of competition is high and earlier when adopting helps them enter new credit markets. We also find that the bureau is procompetitive. Borrower switch rates rise with bureau membership. This creates participation externalities for lenders, even if they initially choose not to join, because they lose borrowers and experience a decline in market share. These participation externalities ultimately compel nonmembers to join and therefore are important for understanding the evolution of the bureau. Finally, we find that total credit, number of relationships, and number of collateral types financed increase for creditworthy borrowers.

We first investigate when lenders adopt information sharing. Our hypotheses are motivated by theories examining how information asymmetry between informed incumbents and uninformed entrants affects credit market structure (Dell'Ariccia et al., 1999; Marquez, 2002) and how information sharing endogenously arises (Pagano and Jappelli, 1993). A key insight from these models is that information

[2] Market leader De Lage Landen commented, "There's no question there is a need for PayNet's kind of service…. The commercial bureaus haven't done enough to provide data across all the financial industry lenders" (Jackson, 2001, p. 44).

asymmetries can inhibit competition, create entry barriers, and provide rents for incumbents, not simply because borrower credit quality is unknown but also because incumbents' proprietary information on the subset of borrowers to whom they previously lent or rejected creates an information advantage. Therefore, we predict incentives to adopt information sharing are: 1) weaker when sharing diminishes a lender's information advantage over competitors in its home (i.e., existing) markets; and 2) stronger when sharing allows a lender to overcome adverse selection problems that create barriers to entering new (i.e., potential) markets.

To model this adoption trade-off, one needs proxies for the information frictions lenders face in their home and new markets. We exploit bureau data to micro-found a measure of information asymmetry based on the propensity for borrowers to switch lenders. A broad class of models demonstrate that information frictions can dampen competition and result in hold-up problems, such that borrowers are unable to switch between lenders (Sharpe, 1990; Rajan, 1992; Petersen and Rajan, 1995). Therefore, greater information asymmetries between lenders in a market should be associated with less switching. Switch rates have the additional advantage of being more precise and timelier than institutional- or country-level measures typically used in the literature, such as the availability of information sharing mechanisms. Switch rates can vary across a lender's markets and evolve with the competitive environment.

We define a credit market as the intersection of one of 23 collateral types and one of nine U.S. census divisions (henceforth "regions"). A lender's home markets are those collateral type–U.S. region pairs in which it lends prior to joining the bureau. New markets are those a lender does not have exposure to within its collateral expertise. For example, for a lender only financing trucks in the Northeast, we presume the plausible new markets include those involving trucks in other geographic areas. The rationale for this classification is that collateral expertise provides a comparative advantage in secured finance because of similarities in contract terms, default probabilities, resale markets, and enforcement mechanisms within an asset class (Carey, Post, and Sharpe, 1998; Benmelech, Garmaise, and Moskowitz, 2005; Eisfeldt and Rampini, 2009; Loutskina and Strahan, 2011; Murfin and Pratt, 2019). Nevertheless, we conduct robustness tests that consider alternative market definitions and alternative information friction proxies.

We start by descriptively studying early adopters because the bureau's success depends on their participation. Early adopters have less to lose in terms of already facing high switch rates in their home markets, and also face low switch rates (i.e., more adverse selection) in new markets. Early adopters are larger and more diversified lenders that arguably have the most to gain from participating because they traditionally employ monitoring technology that relies more on credit models than on private information (Berger et al., 2005; Loutskina and Strahan, 2011; Berger, Minnis, and Sutherland, 2017). Public statements from early adopters attest that the bureau is suited for their model-based approach.

We then use a hazard model to estimate time to adoption as a function of market switch rates, lender expansion decisions, and lender characteristics for the full set of lenders. Lenders adopt earlier when they face high switch rates in home markets and low switch rates in new markets. This finding is consistent with our prediction that market information frictions in both home and new markets influence adoption. Further, lenders delay adoption when they expand more without accessing the bureau, suggesting they face weaker incentives to participate when they can expand without sharing. Post adoption, lenders enter more markets and these markets have lower switch rates. Last, smaller and specialized lenders, who face higher costs to sharing given their expertise in evaluating credit risks and collecting proprietary information, adopt later.

Our second set of tests explores how information sharing affects competition. Because information asymmetries inhibit competition (Sharpe, 1990; Dell'Ariccia et al., 1999), we predict that competition in a given market will intensify with the number of lenders sharing information in that market. We find that as bureau membership grows, market-level switch rates increase and concentration declines. The effects are not confined to members: as membership increases, nonmember lenders lose more borrowers and experience a decline in their market share and portfolio quality.

Third, we investigate the effect of increased competition on the incentives of nonmember lenders to adopt information sharing. Our hypothesis is that heightened competition creates a participation externality that strengthens nonmembers' incentives to share information. This externality should affect the status quo, such that a lender who initially did not participate is exposed to heightened competition and becomes less capable of protecting its rents and retaining high-quality borrowers. Lenders' stated motives for adoption support this hypothesis. As Citibank explains, "The competitive forces at work are quite similar to those behind the ATM networks such as Cirrus and NYCE: in order to provide your bank's customers with ATM access at other banks' machines, your bank had to agree to provide ATM access to their customers at your machines. Reciprocity is the key. The result is that any competitor that joins the network has an advantage over any competitor that doesn't, quickly resulting in almost universal adoption" (Ware, 2002, p. 29).

To test this hypothesis, we exploit time-series variation in the breadth of bureau membership across markets. We find that, on average, greater bureau membership in home markets accelerates adoption. This effect is stronger for lenders experiencing higher switch rates in their own portfolio. Thus, participation externalities are critical to the formation of information sharing systems.

Fourth, we examine the bureau's effects on access to credit. Our setting helps estimate the treatment effect of information sharing on access to credit for several reasons. Lenders, not borrowers, decide to join the bureau, so credit information sharing is exogenous to the borrower. Lenders adopt in a staggered fashion, and we observe borrowers' contracts with them even before joining occurs. Furthermore, the micro-unit of analysis allows us to control for industry-quarter fixed effects to account for contemporaneous changes in the demand for credit within a sector and borrower fixed effects to account for time-invariant borrower characteristics.

We find that the sharing of a borrower's credit information leads to an improvement in their access to credit, as measured by total credit, the number of lending relationships, and the number of collateral types they secure financing against. These results are strongest for borrowers revealed to be higher quality, based on their payment histories shared in the bureau, which is consistent with a reduction in adverse selection that consequently enables lenders to enter new markets.

We further link our evidence to reciprocal sharing by conducting within-borrower-time tests that demonstrate that borrowers' access to credit improves more in markets with greater lender participation. When combined with our earlier results showing that adoption hinges on borrower switch rates, our borrower-level evidence points to information sharing affecting credit access through the extensive margin of better borrower selection, which can lead to improvements in economic growth and productivity (e.g., Bertrand, Schoar, and Thesmar, 2007; Bai, Carvalho, and Phillips, 2018). However, we also find that lenders reallocate credit away from their existing borrowers revealed to have worse payment histories, consistent with an intensive margin channel.

To our knowledge, our study provides the first direct evidence of the trade-offs behind voluntary information sharing and how sharing systems form. There is limited evidence on voluntary information sharing, despite continued growth in sharing among intermediaries in most markets. Prior work has focused on how competition shapes incentives to share information but has been limited to studying aggregate correlations between sharing and competition in developing countries (Bruhn, Fazari, and Kanz, 2013) or providing evidence from experimental settings (Brown and Zehnder, 2010; de Janvry, McIntosh, and Sadoulet, 2010). Our U.S. setting allows us to study individual lender sharing in a developed financial market, thereby offering new and generalizable evidence.

Our results add to a growing body of literature exploring the effects of information sharing on credit markets and lender behavior. Research demonstrates that sharing borrowers' credit histories affects the design of lending organizations (Paravisini and Schoar, 2016; Liberti, Seru, and Vig, 2017), increases lender coordination (Hertzberg, Liberti, and Paravisini, 2011; Darmouni and Sutherland, 2021), creates incentives for lenders to manipulate shared information (Giannetti, Liberti, and Sturgess, 2017), reduces the appeal of relationship lending (Sutherland, 2018), prevents overlending (Bennando, Pagano, and Piccolo, 2015), and decreases delinquencies (Doblas-Madrid and Minetti, 2013).[3]

The small commercial borrowers we study are crucial to job creation and economic growth but face information frictions that can result in them being credit rationed (Stiglitz and Weiss, 1981). Despite existing theory and significant policy interest in both developed and developing markets (e.g., World Bank, 2019a,b), there is scarce micro evidence on how information sharing has real effects on the economy through commercial borrowers' credit access. Research related to ours documents a positive correlation between country-level sharing systems and commercial lending (Jappelli and Pagano, 2002; Djankov, McLiesh, and Shleifer, 2007; Brown, Jappelli, and Pagano, 2009). But these studies do not identify a causal effect of information sharing on access to credit, and focus on developing

[3] Related literature examining consumer credit demonstrates that the deletion of negative information from borrowers' files already shared in a bureau can lead to higher borrowing limits for these same borrowers. See Musto (2004), Liberman (2016), Herkenhoff, Phillips, and Cohen-Cole (2018), Liberman et al. (2018), and Dobbie, Goldsmith-Pinkham, Mahoney, and Song (2019).

markets undergoing wide-reaching reforms concurrent with information sharing. Our setting allows us to identify the causal effects of sharing on borrowing in a developed commercial credit market in which the role of sharing is less clear because of contract enforcement and alternative information sources. Our results support theories predicting that voluntary information sharing can improve credit access for creditworthy borrowers.

Finally, our paper also contributes to the literature on financial technology adoption. Recent studies have examined the development of online lenders in the mortgage market (Buchak, Matvos, Piskorski, and Seru, 2018; Fuster, Plosser, Schnabl, and Vickery, 2019), ATM networks (Higgins, 2020), and other financial service providers (Philippon, 2016). We provide evidence not only on how financial technology adoption affects the market for credit but also on when lenders adopt financial technology and how technology networks form.

2. Theoretical framework and empirical predictions

2.1 Theoretical framework

It is unclear when private information sharing regimes should develop. Unlike mandatory information sharing arrangements in which lenders are required to share credit files, private arrangements such as credit bureaus rely on lenders' voluntary participation. We consider how lenders trade off the benefits and costs of participation, which we refer to interchangeably as the "participation trade-off" or the "participation condition."

The role for information frictions in the participation trade-off will depend on the market structure of lending and, in particular, the market power of incumbents and the ability of entrants to compete with them. Pagano and Jappelli (1993) present a model of a credit market with information asymmetries between lenders to analyze when information sharing endogenously arises. Although Pagano and Jappelli (1993) study a static model of information sharing, the key insights from their theory illuminate the trade-offs we study surrounding when lenders individually share information over time. Specifically, they show that lenders have stronger incentives to share information when they lend in markets with borrowers on which they have no credit information, but that sharing is discouraged by the fear of heightened competition. In addition, they show that information sharing benefits from economies of scale because the incentives to share increase as more lenders participate, and that technological innovations foster sharing.[4]

Dell'Ariccia et al. (1999) and Marquez (2002) explore how information asymmetry between informed incumbents and uninformed entrants affects the structure of credit markets, which in turn can help explain lenders' incentives to share information. Their key insight is that information asymmetries can inhibit competition and create information rents because incumbents' proprietary information on the subset of borrowers to whom they previously lent or rejected creates an information advantage. This helps incumbents determine whether credit applicants are new borrowers who are unknown to all lenders, or "bad type" borrowers who they have rejected previously. Potential entrants, on the other hand, cannot distinguish between the two types. Therefore, entrants face an adverse selection problem when competing with incumbents, which can create entry barriers in credit markets. Information sharing can increase a lender's ability to compete in new markets but also decrease a lender's ability to protect rents in their existing markets.

The key theoretical insights are that incentives to share information are: 1) weaker when sharing reduces the lender's information advantage over competitors in home markets; and 2) stronger when sharing allows lenders to overcome adverse selection that creates entry barriers in new markets.

2.2 Empirical predictions

Motivated by our theoretical framework, we investigate four empirical predictions surrounding 1) when individual lenders participate in information sharing; 2) competition; 3) participation externalities; and 4) borrower credit access.

2.2.1 Individual lender participation and early adopters

Lenders face an individual participation condition that determines whether they adopt information sharing. To understand how market information structure affects participation decisions, one needs to observe information frictions faced by lenders in home and new markets. In the absence

[4] As Pagano and Jappelli explain, after a subset of lenders participate, "there is a tendency for the system to encompass the whole of the market… the extension of the system's coverage itself enhances its effectiveness. In this sense, the credit bureau is a natural monopoly" (p. 1701).

of direct measures, researchers often use the presence of information sharing mechanisms, such as the bureau we study, as a proxy for the depth of credit information in a market. Our setting allows us to exploit relationship-level data to micro-found a measure of information asymmetry based on the propensity of borrowers to switch lenders. Information frictions between lenders can dampen competition and result in hold-up problems for borrowers such that they are unable to switch lenders (Sharpe, 1990). Therefore, greater information asymmetries between lenders in a market should manifest in less frequent switching.

The participation condition will therefore depend on the switch rates in both a lender's home (i.e., existing) markets and its new (potential) markets. We predict that a lender will have stronger incentives to participate when it faces higher switch rates in its home markets, and when new markets exhibit greater adverse selection and higher potential rents (which result in lower switch rates). Equivalently, lenders stand to gain less from sharing information when they seek to enter markets with fewer adverse selection problems because entry is feasible without bearing the costs of sharing. Thus, lenders' expansion plans are important to understanding adoption. Lenders not planning to expand into new markets may adopt later. Further, lenders capable of expanding without sharing information, particularly in markets with more adverse selection, have less need for bureau information and adopt later.

Theory implies that those lenders with the most to gain from information sharing are lenders with model-based screening and monitoring technology. For example, these lenders will not only be best able to use credit data in lending decisions but will also require data to improve credit modeling and decrease costs. In contrast, lenders that collect proprietary information on borrowers or markets should be less able to leverage information sharing (Rajan, 1992; Sharpe, 2000; Stein, 2002).

Therefore, we predict that larger and more diversified lenders should adopt information sharing technology sooner because sharing enhances both their data and models (Berger et al., 2005; Berger and Frame, 2007; Liberti and Mian, 2009; Loutskina and Strahan, 2011; Berger et al., 2017). Specialized lenders that earn rents because of their specific expertise in evaluating credit risks and collecting proprietary information (Winton, 1999; Acharya, Hasan, and Saunders, 2006; Liberti, Sturgess, and Sutherland, 2020; Paravisini, Rappoport, and Schnabl, 2020) should adopt later.

2.2.2 Competition and participation externalities

Sharing by a subset of lenders in a market creates an information advantage for members over nonmembers, which increases competition for borrowers. Therefore, we predict competition in a specific market will intensify with the number of members. This should lead to elevated switch rates and lower concentration. Additionally, delinquencies are expected to decrease with the growth of the bureau because information sharing mitigates adverse selection and moral hazard concerns (Padilla and Pagano, 2000; Doblas-Madrid and Minetti, 2013).

The increase in competition creates a participation externality that strengthens nonmembers' incentives to share information. This externality affects the status quo, such that a lender who initially did not participate is exposed to heightened competition and becomes less capable of protecting its rents and retaining high-quality borrowers. Therefore, as the number of lenders sharing information in a given market grows, we predict nonsharing members will be more compelled to share as well.

2.2.3 Borrower access to credit

Information sharing improves lenders' screening and monitoring. Therefore, borrower access to credit will depend on the extent of information sharing in the market and the payment histories revealed in credit files. Our hypothesis is that credit access will improve once a sufficient number of lenders in the borrower's market are sharing information. Then, financing increases for creditworthy borrowers but not for those with a history of delinquent payments (Padilla and Pagano, 1997). This effect is driven by new information about borrower credit quality rather than an increase in competition alone (e.g., Bertrand et al., 2007; Bai et al., 2018), although these two channels can have complementary effects on originations.

Information sharing can affect credit access along both the extensive and intensive margins. Extensive margin channels result in borrowers switching to new lenders and having more outstanding credit relationships. Sharing should also facilitate a better match between borrowers and lenders because lenders can better screen borrowers and borrowers can raise credit against new collateral types. Along the intensive margin, information sharing can help lenders monitor existing borrowers, reduce hold-up, and strengthen incentives for timely repayment (Padilla and Pagano, 2000).

3. Institutional setting

3.1 The information environment pre-PayNet

PayNet was founded in 2001 to fill a gap in the U.S. small business lending market: although delinquency and contract information has been voluntarily shared among consumer lenders for decades, until 2001 lenders in the U.S. equipment finance market regularly originated contracts without knowing whether the borrower had previously serviced similar obligations (Ware, 2002). Repositories such as Dun & Bradstreet and Experian had limited coverage of the market and therefore lacked timely, detailed information about borrowers' outstanding obligations, the contract terms they receive, or the length and quality of their payment history.

Other information sources that lenders typically access also lack the obligations and payment histories of small borrowers. For example, borrowers can provide lenders with financial reports, but these lack payment history details and are rarely timely or verified by auditors (Berger et al., 2017). Small borrowers attract virtually no credit rating agency or analyst coverage. Although Uniform Commercial Code (UCC) public collateral filings document the existence of a secured claim on a borrower's assets, they do not provide any information about payments and usually omit contract terms. Finally, lenders regularly review macroeconomic and industry data as well as the performance of peer firms. However, small firms are idiosyncratic in that their repayment behavior often differs from contemporaries in their sector or region.

Equipment finance lenders retain the overwhelming majority of contracts they originate (Goukasian and Miller (2012) report that securitization is very rare), so they bear the costs of bad approval decisions and monitoring problems. Therefore, the pre-PayNet gap in obligation and payment history information created significant information frictions in this market comprised primarily of opaque borrowers.

3.2 PayNet

PayNet credit reports offer three innovations over other information sources commonly used by lenders in the early 2000s. First, reports contain a borrower's detailed payment history, including historical credit payments and delinquency status. Second, PayNet provides contract-level detail of all equipment term loans and leases. This was an important feature because before PayNet, lenders could only observe payment records for much smaller obligations (e.g., utility bills or trade credit) for most borrowers (Ware, 2002). Third, for a fee, PayNet's members can query the credit file, proprietary credit score, and probability of default for each borrower.[5] Fig. 1 provides a credit report example to illustrate these features.

Like other voluntary credit bureaus, PayNet operates on the principle of reciprocity. Lenders can participate only if they agree to share all past, present, and future credit files with the bureau. The mandatory sharing of past data allows us to observe lender behavior before joining.

Several features of PayNet and the U.S. equipment finance market help enforce mandatory sharing and ensure the accuracy of shared information. To become a member, lenders must make significant investments in technology to allow PayNet to pull information directly from their internal systems. Then lenders are subject to PayNet's initial testing and ongoing audits to verify that shared information is complete and accurate. Additionally, PayNet cross-checks data against several sources, including the information shared by other lenders with similar exposures, the lender's prior information, trade and macroeconomic data, and public UCC collateral filings.[6] Finally, PayNet punishes misreporting with exclusion from the bureau. Misreporting also exposes lenders to litigation from borrowers and other bureau members. Together, these features help ensure complete sharing and prevent the form of manipulation documented by Giannetti et al. (2017) in a mandatory information sharing setting.

PayNet does not sell or otherwise make bureau information available to nonmembers. As members of the bureau, lenders must purchase *individual* credit files for applicants or existing clients. PayNet's interface does not allow members to perform bulk downloads of credit files or data mine (e.g., by industry, location, or collateral type). For similar reasons, lenders cannot join, download all credit files, and then quit. Lender identities are anonymous in the bureau, such that credit reports do not

[5] Proprietary credit scores and default probabilities are estimated using all ongoing and past contract information for each borrower across all contracts in the bureau, as well as macroeconomic, industry, and other information. Credit scores and default probabilities are not included in our sample.
[6] In the U.S., lenders make UCC financing statement filings to establish their legal right to collateral if a borrower defaults. Because these filings are public and Secretaries of State maintain searchable online records dating back to the 1990s or earlier, PayNet can verify that a lender has shared a given contract.

disclose the lender for each of the borrower's contracts. Likewise, credit report queries are not observable to lenders.

From PayNet's 2001 launch to the end of our sample in 2014, over 200 lenders joined, including eight of the ten largest lenders in the segment as well as a number of smaller captives and regional banks. As of 2021, PayNet's database contained $1.7 trillion of current and past obligations from 25 million lease and loan contracts. PayNet claims to have the "largest proprietary database of small business loans, leases, and lines of credit in existence," and this database is the source of the Thomson Reuters/PayNet Small Business Lending Index regularly mentioned in the business media.[7]

3.3 Sample

We construct our data set from a panel of 20,000 randomly chosen borrowers' credit files. The data include detailed records for over 400,000 contracts between 1998 and 2014, totaling nearly six million contract-quarter observations. Although we do not observe all PayNet contracts, constructing our sample from such a large set of contract-quarter observations reduces concerns about power and generalizability.

We observe each borrower's entire credit file containing all contracts with PayNet lenders during this period, including contracts beginning prior to when the lender joined PayNet.[8] The sample is constructed by randomly selecting borrowers throughout the time series and then tracing all contracts for these borrowers across all lenders and all time periods. Sampling in this way avoids survivorship bias. For example, had we selected all borrowers from a single year and traced them forward or backward, then any relationship between the bureau's formation and borrower outcomes we study in Section 5 could be generated by survivorship rather than information sharing.

For each contract, we observe the amount, collateral type, maturity, payment frequency, guarantor requirement, and payment history as well as the state, industry, and age of the borrower.[9] PayNet classifies contracts as one of 23 collateral types. Agricultural equipment, construction

[7] "Transforming commercial lending," PayNet, August 1, 2020. Accessed at https://paynet.com/about/.
[8] Naturally, we cannot observe the contracts of lenders that never share information with PayNet.
[9] Like other credit bureaus including the consumer bureaus in the U.S., PayNet does not collect or distribute interest rate information.

equipment, computers, copiers and fax machines, and trucks are the most commonly observed collateral types in our sample. Using PayNet's collateral categories, we define a credit market as the intersection of one of 23 collateral types and one of nine U.S. census divisions (which we refer to as "regions").[10] We construct lender portfolios and market structure measures using the borrower micro-data.

To assess the generalizability of our lender sample, we compare our lenders to the U.S. population of equipment finance lenders using reports from *Monitor*, the leading industry publication. Each year, *Monitor* collects lender size information and compiles a ranking of the top 100 lenders (the "Monitor 100"). They do not collect borrower- or contract-level data. Their ranking covers all the largest lenders in the market, not just those participating in PayNet.

Studying the last year of our sample (2014), we find a similar concentration for U.S. exposures in the two data sets. The top ten lenders in the PayNet (Monitor 100) sample are responsible for 60% (58%) of total lending. We find similar figures for 2002, the first year of PayNet, which reinforces how the sharing of past contracts provides us with a representative sample regardless of when individual lenders join. Such concentration levels are comparable to that in the broader U.S. banking sector (the FDIC reports that as of 2020 Q4, the ten largest banks control 66% of total assets in the United States).

We also compare the distribution of the PayNet and *Monitor* data sets using a two-sample Kolmogorov–Smirnov test, for both 2002 and 2014. We cannot reject the null hypothesis of equality in distribution functions for the two data sets in either year: the p-value for the Kolmogorov–Smirnov test statistic is 0.36 for 2002 and 0.46 for 2014. Fig. 2 shows the two distributions are highly similar. Overall, the evidence implies that our sample of 218 lenders, including eight of the ten largest, provides a representative snapshot of the entire equipment finance market.

Finally, we confirm our findings are not unique to the random sample of borrowers we draw. We select a second random draw of 10,000 borrowers from our initial sample, re-construct our lender and market measures, and re-estimate our lender and borrower tests with similar results (Table A1).

[10] The divisions include the Northeast, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific Divisions. See http://www2.census.gov/geo/docs/maps-data/maps/reg_div.txt for state-to-division mappings.

3.4 Descriptive statistics

Table 1 describes the borrowers (Panel A), markets (Panel B), and lenders (Panel C) in our sample. Borrower characteristics are averaged throughout our sample period. The mean (median) borrower has \$579,832 (\$66,204) of credit outstanding across 1.7 (1.2) lender relationships. The mean (median) borrower finances 1.5 (1.1) collateral types. In terms of payment performance, the mean (median) borrower is delinquent 19% (12%) of the time. However, the majority of delinquencies are mild: the mean borrower is late by more than 30 days (90 days) only 6% (2%) of the time.

Our market and lender characteristics are measured in the second quarter of 2001, the quarter before the bureau's launch. Panel B shows that the typical market, defined as a collateral type–region pair, exhibits relatively high levels of information asymmetry and low levels of competition. Borrowers seldom switch lenders and often contract exclusively with one lender. The median switch rate, defined as the probability that a borrower stops contracting with a lender this quarter after contracting with it last quarter, is 3%. Approximately one-fifth of borrowers have an exclusive relationship with a single PayNet lender. This underscores how information frictions are acute in the small business lending market we study. By comparison, quarterly switch rates in the retail banking, credit card, and wireless service market each average around 6%.[11]

Panel C demonstrates that before PayNet's launch, the typical lender operated in nine markets across three regions and three collateral types. Like other commercial credit markets, market power is concentrated among a few lenders: the mean (median) lender's equal weighted average market share was 5.3% (0.8%). The mean (median) lender had \$172 (8.4) million of credit outstanding across the 20,000 randomly chosen borrowers in our data.

4. Voluntary information sharing adoption

4.1 Measuring lender participation conditions

To investigate the trade-offs behind a lender's participation condition, we examine the market information structure, lenders' expansion decisions, and lenders' screening and monitoring technology.

[11] "Customer churn: Everyone hates it but can you prevent it?" Benchmark ONE, Feb 22, 2017. Blog post accessed at https://www.hatchbuck.com/blog/customer-churn/.

To capture the market-level information asymmetries facing lenders, we use the average market switch rate in the markets the lender competes in (*Home Market Switch Rate*) and the markets in which the lender has no prior exposure but into which it potentially could expand (*New Market Switch Rate*). We define a *Home Market* as a market the lender has exposure to when it first appears in the data; that is, we fix each lender's portfolio weights before it joins the bureau. We define a *New Market* as one the lender does not have exposure to within its existing collateral types. For example, for a lender that finances only trucks in the Northeast, we presume the plausible new markets include those involving trucks in other geographic areas. The intuition is that collateral expertise provides a comparative advantage in secured finance (Carey et al., 1998; Benmelech et al., 2005; Eisfeldt and Rampini, 2009; Loutskina and Strahan, 2011; and Murfin and Pratt, 2019) and lenders expand within their expertise when entering new markets (Liberti, Sutherland, and Sturgess, 2020).

To estimate lender home and new market switch rates, we combine a lender's home and new portfolio weights with market-level switch rates measured in 2001, before the bureau's launch. This approach provides lender-specific market switch rates that capture the information structure of markets independently of how the bureau's evolution affects information asymmetry. Both the lender's home and new market switch rates are measured as the equal-weighted market switch rate.[12]

We also examine each lender's expansion patterns in the "interim" period between the bureau's launch and their adoption year. For each lender, we measure whether it does not expand (*No Interim Expansion*), the number of new markets it expands into per year (normalized by the number of home markets) (*Interim Market Count*), and the average switch rate of these interim markets (*Interim Market Switch Rate*).

Finally, we also examine screening and monitoring technology. To capture whether a lender is likely to use model-based lending or develop expertise through proprietary information, we focus on the size of the lender and span of its portfolio measured by the number of unique collateral types and region exposures.

[12] Alternatively, one could apply value-weighted switch rates. Unfortunately, no such weights exist for new markets, in which the lender has no exposure by design.

4.2 Descriptive evidence on early adopters

There are two potential impediments to the bureau's initial formation: 1) the early adopters share information without knowing what information they will access in return; and 2) the bureau might fail if an insufficient number of lenders participate in the initial period. Therefore, explaining the bureau's evolution hinges on understanding not only each lender's participation trade-off but also understanding early adopters' motives.

We begin our analysis by graphically examining how each lender's adoption year varies with its initial home and new market switch rates. Fig. 3 plots the mean home and new market switch rates for adopters (right y-axis) and the fraction of lenders adopting in each year (left y-axis) against the adoption year (x-axis) from the launch of the bureau in 2001 through 2014.

The figure demonstrates that early adopters face higher home market switch rates and lower new market switch rates. These early adopters likely face stiff competition in their existing markets but information asymmetry problems in accessing new markets, which implies they have the most to gain from sharing. This pattern is consistent with information frictions, rather than other entry barriers such as regulation or geography, explaining market switch rates. As the bureau grows, lenders with initial lower home market switch rates and higher new market switch rates join. In addition, the staggered timing of adoption indicates that bureau participation was unlikely triggered by a single credit event, business cycles, or overall growth in the equipment financing market.

The evidence in Fig. 3 not only highlights the participation trade-off but also that this trade-off is dynamic. Therefore, the formation of the bureau hinges on the first group of lenders that adopt, who share without knowing what information they will gain access to in return.

To better understand early adoption, we compare early adopters with late adopters in Fig. 4. For the 218 lenders we study, we classify the 23 that joined in 2001 and 2002 as early adopters. Next, we rank all lenders based on market and portfolio characteristics in 2001, with a lower rank representing a larger value. We focus on comparing the median characteristics of early and late adopters, to understand the typical lender in each group.

We find early adopters have a higher switch rate in both their own portfolio and their home markets, and face a lower switch rate in new markets. Early adopters exhibit less expansion into new markets prior to information sharing (their interim market count is lower), and the switch rate for these interim markets is higher. Early adopters also hold larger lending portfolios that span more regions and more collateral types.

We view this exercise as descriptive and more rigorously study adoption timing in the next section. Nevertheless, the evidence points to information asymmetries, expansion patterns, lender size, and business models affecting the early participation trade-off in a manner consistent with our broader theoretical framework. Early adopters face higher switch rates in home markets and lower switch rates in new markets. They enter fewer markets per year before joining, suggesting they have a greater need for bureau information to expand. Further, lenders that enter interim markets with high switch rates face lower costs of sharing information and therefore adopt earlier. Early adopters rely most on model-based lending technology, in which data quality and scale are important. Indeed, public statements by early adopters confirm that data coverage, credit risk modeling, and costs were all central to their adoption decision. De Lage Landen Financial Services, one of the 15 largest equipment finance lenders stated:

> There's more pressure to wring out costs from the origination process. If lenders instill models from this data, and thus make better decisions, they'll have a competitive advantage over other lenders (Jackson, 2001, p. 49).

Volvo Commercial Finance, the captive finance arm of Volvo commented:

> It will certainly streamline the process and reduce the man-power involved (Jackson, 2000, p. 56).

Further, there is evidence that large lenders understood the importance of their adopting early if the bureau were to succeed. Wells Fargo commented:

> [PayNet] will work so long as the companies contributing information are significant. . . . But somebody has to take a leap of faith. We will because, if everybody waits, what's the good in that? (Jackson, 2000, p. 61).

Finally, PayNet's website markets better data, credit risk modeling, cost savings, and growth to encourage lenders to join:

In many financial institutions, portfolio management is a time-intensive and resource-consuming activity that is neither efficient—nor always accurate. PayNet turns a reactive and cumbersome process into a predictive model of efficiency.

Small business credit data is the engine for institutional growth. With PayNet, you'll be better equipped to come at higher profits from both directions:

- Cost reductions – from lowered costs of risk and reduced borrower touch time.
- Revenue gains – from more applications, more wins, and more accurate pricing. Lending managers can capitalize on underserved markets to bump up growth.

4.3 A hazard model of individual lender participation

To formalize the descriptive evidence from Section 4.2, we estimate a hazard model of lender bureau adoption. To study bureau adoption, we consider the period from the 2001 introduction of PayNet until adoption for each lender. We track 218 lenders until the year they joined PayNet, giving us 1,694 lender-year observations. The hazard rate, $h(t)$, is the likelihood that a lender adopts the bureau at time t, given that the lender has not adopted by that time. In Fig. 5, we plot the Kaplan–Meier estimator of the hazard rate.[13] The hazard rate increases over the period of our sample, consistent with the incentives for bureau adoption increasing over time.

To model the time to adoption, we must decide what structure, if any, to impose on the hazard function. To approximate the shape of the hazard function presented in Fig. 5, we estimate a Weibull proportional hazard model using the accelerated failure-time metric, in which the log of time to adoption is modeled as a linear function of time-varying covariates. The dependent variable is the log of *Time to Adoption,* which measures the number of years from the current year until the year the lender joins. A positive coefficient implies that an increase in the covariate delays adoption. To facilitate the economic interpretation of our results, we standardize our continuous independent variables to mean zero and a standard deviation of one. All continuous variables are winsorized at the 1% level.

[13] The Kaplan–Meier hazard ratio is estimated as the ratio of lenders that enter in year t to the number of lenders that have not yet entered in year t.

We estimate *Time to Adoption* as a function of a lender's home and new market switch rates, preadoption ("interim") expansion decisions as defined above, and business model characteristics. Our business model characteristics include size (*Log Portfolio Credit*), market share (*Lender Market Share*), and specialization in geography (*Regional Specialist*) and collateral types (*Collateral Specialist*). We define region (collateral) specialists as those with exposures to two (three) or fewer regions (collateral types); using other thresholds does not affect our inferences. Tracking the *Time to Adoption* for each lender allows us to include year fixed effects to absorb common factors within each year, such as credit cycles or business cycles (e.g., Granja, Leuz, and Rajan, 2018) that might explain adoption. We cluster our standard errors at the lender level because the adoption decision is at the lender level.

We present our hazard model results in Table 2. In line with the unconditional analysis presented in Fig. 3, the conditional results in column (1) demonstrate that lenders competing in home markets with higher switch rates adopt earlier. Comparing lenders in the cross-section, a one standard deviation increase in *Home Market Switch Rate* accelerates adoption by 29.0%. The mean number of years until adoption in our sample is 5.2, so this implies that a one standard deviation increase in *Home Market Switch Rate* accelerates adoption by 1.5 years. The evidence is consistent with lenders having stronger incentives to participate when they face more competition in home markets.

Confirming our Fig. 4 evidence, column (1) also shows that lenders relying upon private information, such as smaller lenders, those with a greater market share, and those that specialize in fewer collateral markets, join later. Combined with our findings on market switch rates, this evidence is in line with lenders adopting later when they have more private information to protect.

In column (2), we introduce our *New Market Switch Rate* variable. Lenders facing lower new market switch rates adopt significantly earlier, consistent with the bureau helping lenders overcome information asymmetry problems associated with expansion. Economically, a one standard deviation increase in *New Market Switch Rate* delays adoption by 1.6 years.

In column (3), we examine how adoption timing relates to the lender's expansion patterns during the interim period. The overall decision to expand (*No Interim Market Expansion*) does not appear to significantly influence adoption timing. However, we find that lenders delay adoption when they exhibit higher expansion intensity in the interim period (*Interim Market Count* is positive and significant), consistent with lenders having weaker incentives to adopt when they can expand without incurring the costs of sharing.

The particular markets a lender expands into during the interim period also matter for adoption. In column (4), we show that adoption occurs sooner when the lender's interim markets have higher switch rates (*Interim Market Switch Rate* is negative and significant). Intuitively, lenders adopt sooner when they compete in markets with higher switch rates because they face greater competition, regardless of whether these are home markets or markets they enter before adopting. Reintroducing our *New Market Switch Rate* variable in column (5) does not affect our inferences surrounding market characteristics, interim expansion, or lender business models. Overall, the evidence in columns (1)–(5) is consistent with lenders having weaker incentives to adopt when they face less competition for their existing borrowers, and stronger incentives to adopt when they face information barriers to expansion into new markets.

We also examine new market entry to reinforce how lender adoption decisions are influenced by information barriers to expansion. First, we find that lenders enter 20% more new markets per year after adoption. Second, lenders enter markets with switch rates roughly one-sixth lower in the post-adoption period than the pre-adoption period. Both of these findings illustrate how the bureau helps lenders expand by reducing adverse selection problems. Third, prior to adoption, later adopters enter markets with lower switch rates compared to early adopters, consistent with lenders delaying adoption when they can expand without bearing the cost of information sharing.

Next, to confirm our findings, we present robustness tests examining alternative estimation specifications for our Table 2, column (2) analyses.

First, our main tests use a Weibull proportional hazard model. To ensure our results are not sensitive to our choice of estimator, we use a cross-sectional, lender-level OLS test, in which all lenders are included in the estimation once and all market and lender characteristics are measured prior to PayNet. Column (1) shows that our inferences surrounding market switch rates are the same despite a much smaller sample.

Second, adverse selection might only matter to lenders that join early because these lenders face the greatest adverse selection problems. If so, the generalizability of our results could be questioned. In column (2), we exclude lenders that joined before 2004. Our results hold.

Third, aggregate economic events might explain adoption patterns. Although our tests include year fixed effects, a particular event could create a spurious correlation between adoption timing and market characteristics. One such event might be the financial crisis. We define 2008–2010 as the crisis period and eliminate all crisis observations (column (3)) and all observations from lenders that joined during the crisis, including their precrisis observations (column (4)). Again, we find similar results.

Fourth, our measure of *New Market Switch Rate* in Table 2 defines new markets as those in which the lender does not have exposure in its collateral expertise. In column (5), we re-estimate our base model specification but instead define new markets to be the complement of a lender's *Home Markets*. This much broader *New Market* measure ignores a lender's collateral expertise and allows for expansion into any new market. Our results hold with this less precise measure of new markets, but as expected, the coefficient on *New Market Switch Rate* is smaller than in column (2) of Table 2.

Fifth, our baseline estimation uses 2001-based market measures. In column (6), we use dynamic market measures, which capture competition changes induced by the bureau. Our results are similar.

Last, to mitigate the concern that adoption decisions relate spuriously to market characteristics, we add indicators for each lender's modal collateral type. Column (7) shows that our results remain.[14]

4.4 Competition and participation externalities

As outlined in Section 2.2.2, we expect the bureau to be procompetitive if information sharing decreases adverse selection for new entrants. We examine this hypothesis using the following OLS regression:

$$y_{m,t} = Member\ Count_{m,t} + \ \alpha_m + \alpha_t + \varepsilon_{m,t}, \tag{1}$$

[14] We also note that our results are similar when we employ alternative information asymmetry proxies based on the proportion of borrowers contracting with just one lender (*Exclusive Share*) or market concentration ratios (*HHI*).

where $y_{m,t}$ is a competition variable measured in each market m in year t. $Member\ Count_{m,t}$ is the number of members in market m in year t. We estimate the effect of information sharing on market competition with market α_m and time α_t fixed effects that absorb heterogeneity across markets and aggregate changes in competition, respectively. Continuous dependent and independent variables are standardized to have a mean of zero and a standard deviation of one. We cluster standard errors by market.

The competition variables are *Switch Rate, HHI*, *Share of Top 1*, *Share of Top 3*, *Share of Top 5*, and *Delinquencies,* measured at the market-year level. *Switch Rate* measures the proportion of borrowers in the market that switch lenders. *HHI*, *Share of Top 1*, *Share of Top 3*, and *Share of Top 5* measure the degree to which lending is concentrated among a few lenders. *Delinquencies* measures the fraction of borrowers that are delinquent in a given market-year. The competition measures are estimated across all lenders in each market, not just members, because our data allow us to observe lenders' exposures prior to their joining the bureau.

In column (1) of Table 4, we find the market-level switch rate increases with the growth of bureau membership, consistent with the bureau being procompetitive. A one standard deviation increase in membership is associated with 12% of a standard deviation increase in *Switch Rate*. Next, in column (2), we demonstrate that market *HHI* decreases with the growth of information sharing. A one standard deviation increase in member count is associated with 5.4% of a standard deviation decrease in HHI. Likewise, in columns (3)–(5), we find information sharing decreases *Share of Top 1*, *Share of Top 3*, and *Share of Top 5*. The results imply that information sharing not only decreases market concentration but also diminishes dominant lenders' market power.

In column (6), we examine how the bureau's growth affects market-level delinquencies. We find a one standard deviation increase in *Member Count* is associated with 41% of a standard deviation decrease in *Delinquencies*. This is consistent with information sharing mitigating adverse selection and moral hazard concerns and improving lenders' screening and monitoring.

To understand how the effects of bureau evolution on market competition create a participation externality, we examine how bureau membership in a lender's markets affects nonmembers. Intuitively, if the growth of information sharing creates competition externalities for nonmembers, then they should lose borrowers as other lenders in their markets adopt the bureau and information sharing expands.

We first study how the bureau affects competition by examining switches by borrowers away from nonmembers. We estimate the following OLS regression:

$$y_{i,l,t} = Shared\ by\ Competitor_{i,t} + \alpha_i + \alpha_{l,t} + \varepsilon_{i,l,t}, \tag{2}$$

where $y_{i,l,t}$ is an indicator for whether borrower *i* does not contract with lender *l* in this quarter *t* after contracting with them in last quarter *t-1* (*Borrower Switch)*. *Shared by Competitor* is an indicator for whether the borrower's credit file has already been shared in the bureau by *another* lender as of quarter *t*. We include borrower α_i and lender-time $\alpha_{l,t}$ fixed effects. These account for time-invariant borrower attributes and time-varying lender attributes (including their decision to not yet adopt) that independently affect switching. Because we are interested in the externalities of bureau adoption, our sample is limited to nonmember lender-year observations.

To illustrate our test, consider a borrower contracting with two lenders, A and B. Lender A begins sharing information in 2005, while Lender B begins in 2009. Our tests focus on Lender B before 2009 and examine whether its borrowers are more likely to switch once their credit file is shared by *another* lender (in this illustration, Lender A starting in 2005). If the bureau creates competition externalities, we expect the switch rate between a nonmember lender and a borrower to increase after information on the borrower has been shared in the bureau.

We present the results in Table 5. Column (1) demonstrates that borrowers are more likely to switch from nonmember lenders after their credit file has been shared. In column (2), we control for relationship length to mitigate survivorship bias concerns. The results maintain. Economically, information sharing raises the quarterly probability that a borrower will leave a lender by 0.7%, an increase of nearly one-fourth over the unconditional average switch rate.

Second, we build on our borrower micro-level evidence by examining how the bureau's evolution affects nonmember lender portfolio exposures using the following OLS regression:

$$y_{l,t} = Log\ Member\ Count_{l,t} + \alpha_l + \alpha_t + \varepsilon_{l,t}, \tag{3}$$

where $y_{l,t}$ is the *Lender Portfolio Switch Rate*, *Lender Market Share*, or *Portfolio Delinquency* for lender *l* in year *t*. *Log Member Count* is the natural logarithm of the number of bureau members, averaged across the lender's home markets. We include lender α_l and time α_t fixed effects to control for time-invariant lender business model features and aggregate economic conditions. Because we are interested in the externalities of bureau adoption, our sample is limited to the same nonmember lender-year observations studied in Table 2. We cluster standard errors by lender.

In column (1) of Table 6, we find results analogous to the borrower-level evidence presented in Table 5: portfolio switch rates for nonmembers rise with bureau membership. A nonmember's switch rate increases by 0.5 percentage points for a doubling in bureau membership.

In column (2), we demonstrate that nonmembers' *Log Market Share* declines by approximately one-eighth for a doubling in bureau membership. In column (3), we examine whether the increase in information sharing is associated with a decline in portfolio performance. The results again present evidence consistent with a participation externality. For lenders not electing to share information, their delinquency rate increases by 0.5 percentage points for a doubling in bureau membership in their home markets. Thus, lenders not only lose market share but also lose some of their better quality borrowers when they do not participate in information sharing and their competitors do.

Overall, the results in Tables 4, 5, and 6 demonstrate that the bureau is procompetitive and that the change in competition affects all lenders, not just those that join. This effect on competition creates a participation externality, which affects nonmembers adversely in terms of both market share and borrower quality.

4.5 Participation externalities, and bureau adoption

In light of our evidence on how competition creates a participation externality, we revisit lender adoption decisions to examine how the externality impacts adoption through a lender's own portfolio.

First, building on the switching evidence in Table 5 and Table 6, column (1), we study how lender-specific switch rates influence adoption decisions. Table 7, column (1) finds that lenders adopt sooner when their portfolio switch rate is higher, consistent with the evidence using market-level switch rates in column (1) of Table 2.

Second, column (2) adds *Log Member Count* and finds lenders adopt sooner when there are more bureau members in their home markets (i.e., more competition creates a participation externality). Column (3) examines how the participation externality interacts with a lender's own participation trade-off. Intuitively, the externality should accelerate adoption through interacting with the switch rates a lender faces in its own portfolio. This is precisely what we find: the participation externality interacts negatively with *Lender Portfolio Switch Rate*. In other words, as the bureau expands, nonmembers with the least to lose by participating (those facing high switch rates) ultimately adopt faster.

In summary, the results in Section 4 demonstrate that lenders participate later when the threat of competition deters them from sharing information on their own borrowers, and earlier when adverse selection problems inhibit their entry into new markets. We also find that the bureau is procompetitive in that membership intensifies competition in individual markets. Thus, nonmember lenders face participation externalities that lead to a decline in their own market share and portfolio quality. These externalities are important for understanding the formation of sharing systems and illuminate why sharing can prevail, even when competition concerns initially deter participation.

5. Borrower access to credit

We have demonstrated that lenders join the bureau to use information shared by competitors in new markets, even if doing so means they must reveal proprietary information. Consequently, competition increases. Is the information shared of sufficient quality and the competition sufficiently meaningful to affect credit access? If so, how and for whom?

Our next set of tests investigates these questions by studying borrowers around the time they first appear in the bureau. Specifically, we model borrowers' total credit and number of lending relationships around when their credit file first appears in PayNet, as follows:

$$y_{i,t} = Shared_{i,t} + \alpha_i + \alpha_{k,t} + \varepsilon_{i,t}, \quad (4)$$

where $y_{i,t}$ is the log total credit, log relationships, log collateral types, or delinquency status for borrower i in quarter *t*. $Shared_{i,t}$ is an indicator equal to one for quarters after borrower i's file has been included in the bureau. α_i and $\alpha_{k,t}$ are borrower and industry-quarter fixed effects, respectively.

We restrict the sample to an event window spanning three years before to three years after the *Shared* date. Our results are robust to using alternative windows. Standard errors are clustered at the borrower level.

Several features of our tests provide for reliable estimates of the effect of information sharing on access to credit. First, lenders, not borrowers, adopt the bureau, so the decision to share credit files is exogenous to the borrower. Second, borrowers' credit files are included in the bureau in a staggered fashion determined by when their lenders join. Third, the micro-unit of analysis allows us to control for industry-quarter fixed effects to account for contemporaneous changes in the demand for credit within a sector and borrower fixed effects to account for time-invariant borrower characteristics.[15] Therefore, the coefficient on *Shared* compares the treatment effect for borrowers included in the bureau for the first time with a control group of borrowers in the same industry and time period not included in the bureau.

Column (1) of Table 8 demonstrates that a borrower's credit increases by 3.2% more than peers after its file has been shared with other lenders. Next, we examine the effect on relationships. Column (2) demonstrates a statistically and economically significant 5.2% increase in the number of lending relationships. To better understand the positive effect on credit and relationships, we examine whether better credit access affects the menu of assets borrowers use as collateral. In column (3), we find that the number of distinct collateral types the borrower finances increases by 3.0%, on average, after their inclusion in the bureau. This effect translates into 5% fewer borrowers with just one collateral type in the *Shared* period.

In the final column of Table 8, we examine whether information sharing affects delinquency rates. As we highlighted earlier in Section 2.2.2, there are two main channels through which sharing improves lending efficiency: 1) mitigating adverse selection, and 2) mitigating moral hazard. In within-borrower tests that hold borrower selection constant by design, we find that delinquency rates decline by 2.4%, consistent with information sharing reducing borrower moral hazard by acting as a disciplining device.

[15] We control for industry effects rather than collateral-type effects here because many borrowers have more than one collateral type.

In Table 9, we add an interaction between *Shared* and *Good Record* to differentially identify the treatment effects of information sharing on borrowers revealed to have good and bad credit records. Although we do not observe PayNet's proprietary credit rating for each borrower, we follow industry convention and classify borrowers as having a *Good Record* based on their payment history in the three years before their credit file is shared. Our main measure considers whether the borrower has missed a payment by over 30 days. Sixty-eight percent of borrowers have no delinquency worse than 30 days in this period, while 89% have no delinquency worse than 90 days. For comparison purposes, this latter figure is similar to the share of the bond market involving investment grade issues.[16]

In Panel A (B), we classify borrowers as having a *Good Record* when they have no delinquency worse than 30 days (90 days) during the three years before their credit file is shared. Panel A finds that increases in total borrowing, the number of relationships, and the number of collateral types associated with information sharing is greater for borrowers with a good credit record. In columns (1)–(3), we find that the sum of the *Shared* and *Shared* x *Good Record* coefficients is positive and significantly different from zero (p-value <0.01). Additionally, we find that, while good credit record borrowers experience a 8.6% increase in total credit, borrowers revealed to have a bad credit record realize a decline in total credit of 9.7% (column (1)). In column (4), we find that the within-borrower reduction in delinquencies is evident only for bad credit record borrowers.

As expected, our results in Panel B follow a similar pattern but show worse effects for those with over 90-day delinquencies on their record compared to those with over 30-day delinquencies in Panel A. Credit for borrowers with over 90-day late payments on their record declines by 17.2% (versus 9.7% in Panel A using the 30-day cutoff), and there is no change in the number of relationships or collateral types. These borrowers also experience a significant decline in delinquencies. By comparison, good type borrowers experience significant increases in credit, relationships, and collateral types and relatively small improvements in payment behavior.

The evidence that aggregate lending increases and is reallocated toward borrowers with good records is consistent with information sharing improving screening and monitoring of participating

[16] "High yield bond primer" S&P Global, 2019. Accessed at https://www.spglobal.com/marketintelligence/en/pages/toc-primer/hyd-primer#sec5.

lenders. Our collection of results points to these effects happening through the extensive margin of better borrower selection: lender adoption decisions are significantly influenced by switch rates in new and home markets (Table 2). Borrowers with a shared credit file are more inclined to switch lenders (Table 5), form new and more relationships than those not visible to bureau members (Table 8), and these effects are stronger for borrowers revealed to have a good record (Table 9).

We also find that information sharing improves the allocation of credit along the intensive margin. Table 10 expands the unit of observation to include a lender dimension and control for borrower-lender relationship fixed effects. For bad-record borrowers, we find credit and delinquencies decline, consistent with lenders rationing lower quality borrowers and information sharing incentivizing these borrowers to pay on time (Padilla and Pagano, 2000). However, we find no change in credit or delinquencies for good type borrowers (*Shared* + *Shared* x *Good Record* equals zero). Given this, the increase in credit shown in Table 8 must be along the extensive margin.

In our final tests, we provide more precise evidence on how information sharing affects credit access. Intuitively, credit access will only improve for a borrower if enough lenders are sharing with each other. Therefore, credit access effects should depend not only on the treatment effect of being included in the bureau (*Shared* in Table 8) but also on the number of lenders sharing and receiving information in the market (*Member Count* from Tables 4, 6, and 7).

To test this, we examine whether the treatment effect of information sharing on a borrower's credit exposure presented in Table 8 varies with the number of lenders sharing information in each market. Our specification is as follows:

$$y_{i,j,t} = Shared_{i,t}\ x\ Member\ Count_{j,t} + \alpha_{i,j} + \alpha_{i,t} + \alpha_{j,t} + \varepsilon_{i,j,t}, \quad (5)$$

where $y_{i,j,t}$ is the log total credit or relationships for borrower *i* in collateral type *j* at quarter *t*, measured in the same six-year window as in Tables 8–10. $Shared_{i,t}$ is defined as before. $Member\ Count_{j,t}$ is the number of bureau members in collateral market *j* in time *t*. $\alpha_{i,j}$, $\alpha_{i,t}$, and $\alpha_{j,t}$ are borrower-collateral type, borrower-quarter, and collateral type–quarter fixed effects. These fixed effects absorb the main effects for $Shared_{i,t}$ and $Member\ Count_{j,t}$. Standard errors are clustered at the borrower level.

Importantly, conducting analysis at the borrower–collateral type–quarter level allows us to control for borrower-quarter and collateral-quarter fixed effects to account for borrower-level demand for credit (e.g., Khwaja and Mian, 2008) as well as for contemporaneous changes in demand for credit within a collateral type. Therefore, we examine how the treatment effect varies with the level of bureau membership (*Shared x Member Count*) by comparing treated borrowers to a control group of borrowers financing the same collateral type in the same period, but whose file is not yet shared.

Table 11 presents the results. We find that the treatment effects on total borrowing and number of relationships shown in Table 8 are indeed greater in markets in which the bureau membership base is broader. The coefficient of 0.079 (0.050) on *Shared x Member Count* in column (1), (2) implies that the effect of information sharing on borrowing (relationships) depends on the number of bureau members in each market. Doubling the number of bureau members in a market increases the effect on borrowing (relationships) by 7.9% (5.0%), on average. In columns (3) and (4), we include borrower x collateral-specific trends in addition to fixed effects to account for pretreatment growth in credit demand. The results remain.

In summary, our credit access evidence directly follows from the motives for lender information sharing shown in Section 4. Credit access improves and more so for better quality borrowers, consistent with a reduction in adverse selection enabling lenders to enter new markets and match with new borrowers. Further, the channel through which information sharing impacts credit access relies on the reciprocal sharing arrangement. Access to credit improves after a borrower's file is shared in the bureau and is enhanced most when the bureau has more members.

In addition, our results help rule out an alternate motive for information sharing by lenders: collusion to protect their own rents. If collusion among lenders drove adoption decisions, we would expect adoption to be associated with less competition for borrowers, resulting in less switching, less new lending, and fewer new relationships. However, our results show information sharing leads to more switching (Tables 5 and 6), and more lending and relationships (Table 8). Additionally, collusion relies on lenders being able to communicate and enforce a tacit agreement. But in our setting, lenders' identities are withheld from PayNet credit reports. Therefore, lenders cannot easily monitor one another's behavior or detect deviations.

6. Conclusion

We offer the first direct evidence on when financial intermediaries adopt information sharing technology, how sharing systems evolve and affect competition, and whether these systems have positive real effects on the agents whose information is shared. Our evidence is based on micro-data from a U.S. commercial credit bureau with $1.7 trillion current and past obligations from 25 million lease and loan contracts. This setting allows us not only to overcome identification concerns that have hindered empirical evidence on these topics but also to offer generalizable evidence on sharing from a developed financial market.

We find that adverse selection problems resulting from information asymmetries between lenders is central to lenders' adoption decisions. Lenders adopt information sharing technology earlier when adverse selection problems inhibit their entry into new credit markets and adopt later when adverse selection protects them from competition over their own borrowers. In terms of lender characteristics, early adopters tend to be large, diversified lenders whose screening and monitoring rely more on credit models than on private information.

However, studying lenders' individual adoption decisions is insufficient for understanding how information sharing systems form. We demonstrate that information sharing by adopters increases competition for borrowers. This leads to a decline in market share and portfolio quality for lenders that initially choose not to adopt sharing technology, which ultimately compels them to adopt. Therefore, the formation of the information sharing system hinges on participation externalities. Finally, we provide evidence that credit access improves for creditworthy borrowers, consistent with bureau participation reducing information asymmetries and facilitating lender entry into new markets.

Our study is important for understanding technology adoption in financial markets. We demonstrate that adoption not only depends on a lender's own business model but also on competition and the information environment. In this regard, our paper complements Mishra, Prabhala, and Rajan (2019), who show that lender business models affect information sharing technology adoption in India. Our findings suggest that, although technological advances have facilitated lenders' collection, analysis, and sharing of information, adoption could stall if sharing opens the door to competition from technology-based fintech firms. This is particularly relevant in light of the recent expansion of digital platforms in credit markets. For example, in 2020 the European Commission unveiled its second FinTech Action Plan as part of its efforts to build a Capital Markets Union. The Action Plan includes initiatives that focus on the digitization and sharing of credit information.

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Appendix A: Variables Definitions

Variable	Definition
Time to Adoption	The number of years from 2001 until the lender's bureau adoption year. The variable is recorded as missing thereafter.
Market	A lending segment defined as the intersection of one of 23 collateral types and one of nine U.S. census divisions ("regions").
Home Market	Those collateral type–regions the lender competed in during its first quarter in the data.
New Market	Those collateral type–regions the lender did not compete in during its first quarter in the data but that involve the lender's collateral expertise. To illustrate, for a lender only financing trucks in the Northeast, we presume the plausible new markets include those involving trucks in other geographic areas.
Interim Market	Those collateral type–regions the lender enters between the launch of the bureau and their bureau adoption.
Switch Rate	The proportion of borrowers who stop contracting with their lender this period after contracting with them last period, measured across all borrowers in the market.
Home Market Switch Rate	The proportion of borrowers who stop contracting with their lender this period after contracting with them last period, measured as the average switch rate across the lender's home markets. If the lender has more than one home market, we take the equal-weighted average.
New Market Switch Rate	The proportion of borrowers who stop contracting with their lender this period after contracting with them last period, measured as the average switch rate across the lender's new markets. If the lender has more than one new market, we take the equal-weighted average.
Interim Market Switch Rate	The proportion of borrowers who stop contracting with their lender this period after contracting with them last period, measured as the average switch rate across the lender's interim markets. If the lender has more than one interim market, we take the equal-weighted average.
No Interim Expansion	An indicator variable equal to one for lenders who do not enter new markets between the launch of the bureau and their adoption, and zero otherwise.
Interim Market Count	The number of new markets the lender expands into per year between the launch of the bureau and their bureau adoption, scaled by the number of home markets.
Lender Market Share	The lender's share of total credit outstanding in home markets. If the lender has more than one market, we take the equal-weighted average.

School of Economics and Finance

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Portfolio Credit	The dollar value of all open contracts for the lender. For leases, we sum the total required payments during the contract term.
Regional Specialist	An indicator variable equal to one for lenders with exposure to two or fewer census divisions, and zero otherwise. The divisions include the Northeast, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific Divisions.
Collateral Specialist	An indicator variable equal to one for lenders with exposure to three or fewer collateral types, and zero otherwise. The collateral types include agricultural, aircraft, automobiles, boats, buses and motor coaches, computers, construction and mining, copiers, energy, fax machines, forklifts, logging and forestry, manufacturing, medical, medium- and light-duty trucks, offices, printing and photography, railroad, real estate, retail, telecommunications, vending, and waste and refuse handling.
HHI	The Herfindahl-Hirschman Index for the market that year, measured based on dollars of credit.
Share of Top 1 (3, 5)	The market share of the largest (three largest, five largest) lenders in the market.
Delinquencies	The proportion of contracts in the market that are currently delinquent.
Member Count	The number of lender members of the credit bureau in the market that period.
Borrower Switch	An indicator variable equal to one if the borrower leaves the lender this quarter after contracting with them last quarter, and zero otherwise.
Shared by Competitor	An indicator variable equal to one if the borrower's other lender(s) already shared their credit file in PayNet, and zero otherwise.
Relationship Length	The natural logarithm of the number of quarters since the borrower-lender relationship began.
Lender Portfolio Switch Rate	The proportion of borrowers who stop contracting with the lender this period after contracting with them last period.
Portfolio Delinquency	The proportion of the lender's contracts that are currently delinquent.
Borrower Credit	The total value of all open contracts for the borrower.
Relationships	The number of lenders currently providing the borrower with credit.
Collateral Types	The number of unique collateral types the borrower finances.
Delinquent	An indicator variable equal to one for borrowers who are currently delinquent on a contract, and zero otherwise.

Shared	An indicator variable equal to one if the borrower's credit file has been shared in the bureau, and zero otherwise.
Good Record	An indicator variable equal to one for borrowers who do not have a delinquency worse than 30 days during the three-year period before their credit file first appears in the bureau, and zero otherwise.

Fig. 1: Illustrative Credit File

This figure provides excerpts from a PayNet credit file. The file is illustrative in that the borrower name and contracting activity is fictitious.

BUSINESS PROFILE	
Company Name	MOBILE INTERNATIONAL, INC.
Affiliated Entities, Trade Names, and Individuals	MOBILE COM, INC. JONES, BRIAN SMITH, STEVE
Management	B. JONES, PRESIDENT
Address/Phone	1234 WEST PARK AVENUE NEW YORK, NY 12345 (212) 785-2030
Address Type	STREET ADDRESS
Metro Area	NEW YORK, NY
Tax ID	*****9999
PayNet ID	1234567
Years in Business	18
Oldest Contract	MARCH 2000
SIC Codes	3550 – MACHINERY, EXCEPT ELECTRICAL 3561 – PUMPS, PUMPING EQPT EXC FLUID PUMP 7359 – EQUIPMENT RENTAL AND LEASING, NEC 3567 – INDUSTRIAL FURNACES AND OVENS
Primary Equip	TRCK – Truck

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)				Delinquencies (in renewal)			Status / Loss
								Now	Avg.	Max	Max On	31+	61+	91+	
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)				Delinquencies (in renewal)			Status / Loss
								Now	Avg.	Max	Max On	31+	61+	91+	
2	COMP TruLease -	3/06 - 1/07	24 MO 10	- -	$21,240	$0	$880	-	39	151	12/06	0	1	3	COLL $0

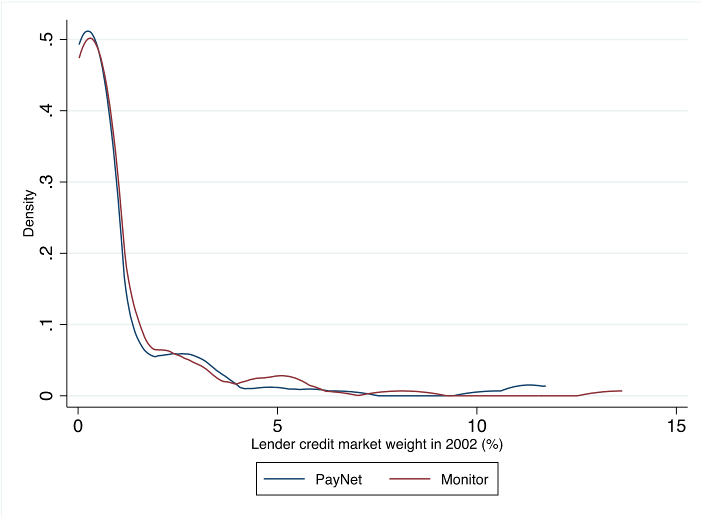
UCC DETAIL

UCCs For:	MOBILE INTERNATIONAL, INC.						
UCC Action:	CONTINUED	Date:	2005-01-10	Doc#:	0500011192	Loc:	SEC OF STATE NEW YORK
Secured Party:	COMMERCIAL BANK – TEXAS TX DALLAS 75247 8828 STEMMONS FWY STE						
Collateral:	EQUIP, AFTER ACQUIRED PROP, UNDEFINED						

Fig. 2: PayNet and Monitor Data Set Comparison

This figure plots kernel density estimates for lender credit market weights (%) in 2002 and 2014 using PayNet (blue line) and *Monitor* (red line) data. Lender credit market weights are computed as each lender's outstanding credit divided by the total outstanding credit for the largest 100 lenders. The kernel density estimate is computed using bin widths of 0.5%. We cannot reject the null hypothesis of equality in distribution functions: the *p*-value for the Kolmogorov–Smirnov test statistic is 0.36 for 2002 and 0.46 for 2014.

Panel A: Year 2002 Comparison



Panel B: Year 2014 Comparison

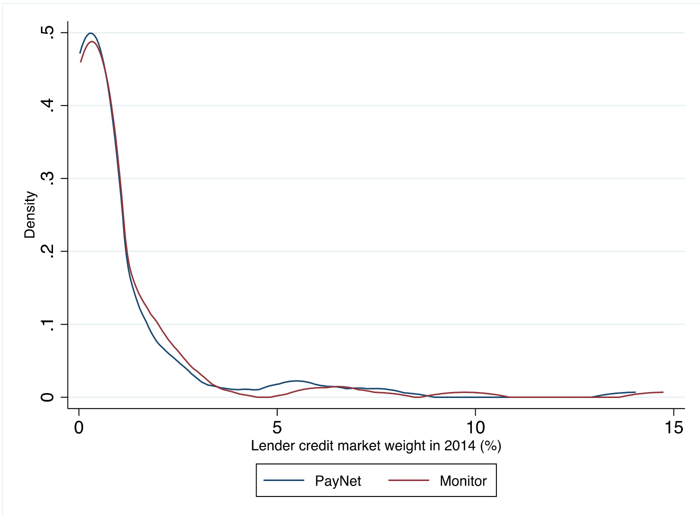


Fig. 3: Bureau Adoption Timing and Market Switch Rates

This figure plots the timing of lenders' bureau adoption as a function of initial home and new market switch rates, measured in 2001. We plot the mean home and new market switch rate for lenders joining in each year and a quadratic line of best fit across years. The left (right) axis measures the fraction of lenders adopting the bureau that year (*Home* and *New Market Switch Rate*). See Appendix A for variables definitions.

Fig. 4: Descriptive Analysis of Early Adopters

This figure presents box plots of lender characteristics for early adopters and late adopters. Early adopters are the lenders that join the bureau in 2001 and 2002. Late adopters are the remaining lenders. For each characteristic, a lower rank represents a larger measurement. We plot the median (center line in box), the 25th/75th percentiles (lower/upper end of box), and the lower/upper adjacent value (lower/upper limit on whiskers). The lower (upper) adjacent value is the furthest observation within one-and-a-half interquartile ranges of the lower (upper) end of the box.

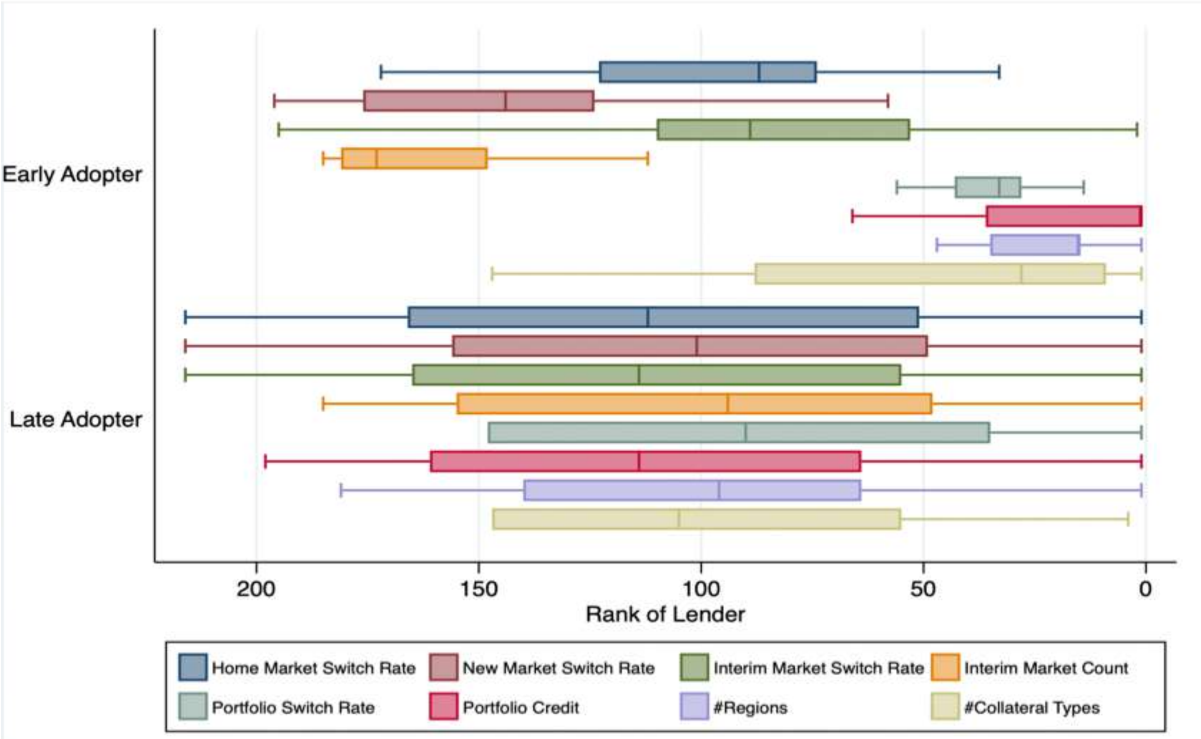


Fig. 5: Hazard Rate for Bureau Adoption

This figure plots the Kaplan–Meier estimator of the hazard rate over 2001–2014. The Kaplan–Meier hazard ratio is estimated as the ratio of lenders that adopt in year t to the number of lenders that have not yet adopted in year t.

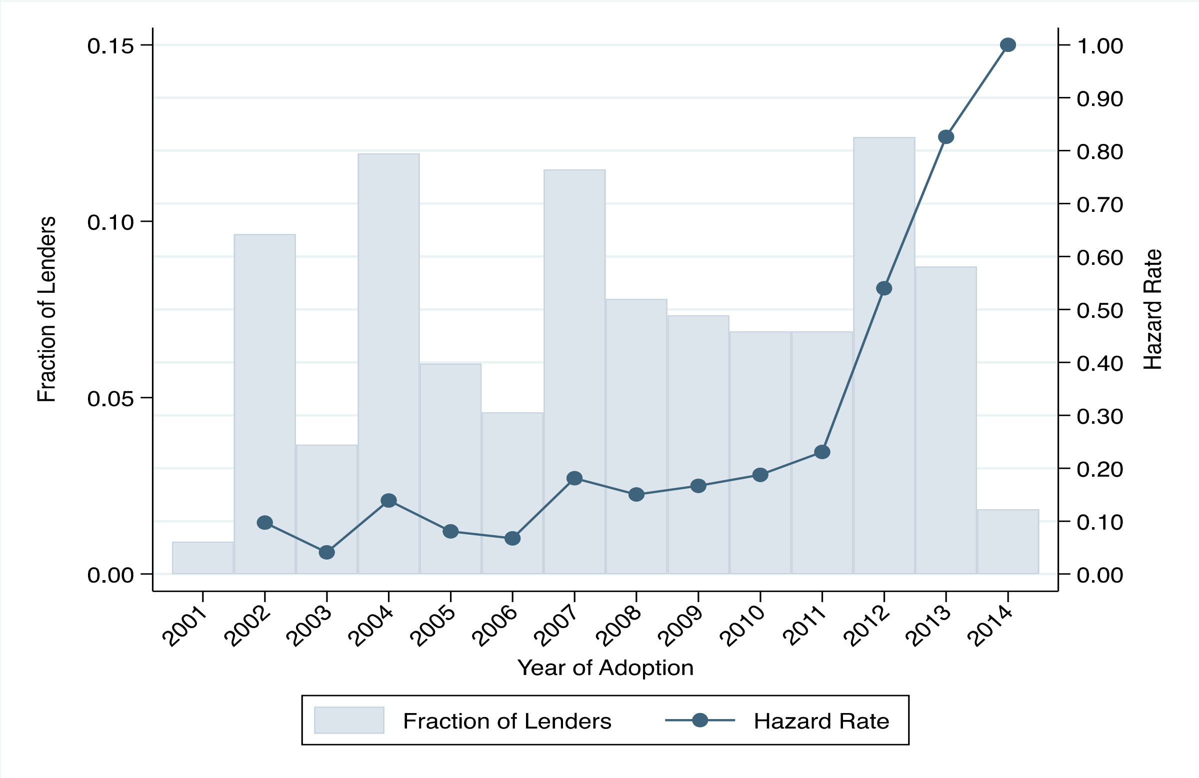


Table 1: Summary Statistics

This table presents descriptive statistics for borrowers, markets, and lenders in our sample. The unit of observation in Panel A (B; C) is borrower (market; lender). See Appendix A for variables definitions.

Panel A: Borrower Characteristics

	Mean	Std Dev	25%	50%	75%	N
Borrower Credit	579,832	4,201,668	25,044	66,204	206,517	20,000
Relationships	1.66	1.28	1.00	1.23	1.78	20,000
Collateral Types	1.46	0.84	1.00	1.14	1.59	20,000
Delinquent	0.19	0.21	0.03	0.12	0.30	20,000
Delinquent>30 Days	0.06	0.12	0.00	0.00	0.07	20,000
Delinquent>90 Days	0.02	0.07	0.00	0.00	0.00	20,000

Panel B: Market Characteristics

	Mean	Std Dev	25%	50%	75%	N
Switch Rate	0.03	0.02	0.01	0.03	0.04	196
Exclusive Share	0.23	0.15	0.13	0.19	0.27	196

Panel C: Lender Characteristics

	Mean	Std Dev	25%	50%	75%	N
# Regions	3.7	2.2	2.0	3.0	5.0	218
# Collateral Types	5.1	5.1	1.0	3.0	7.0	218
# Markets	19.7	27.6	3.0	9.0	25.0	218
Lender Market Share (%)	5.3	11.0	0.1	0.8	4.9	218

Table 2: Time to Bureau Adoption

This table estimates the time to bureau adoption as a function of market characteristics, lender characteristics, and expansion patterns. The dependent variable is the log number of years remaining before the lender joins the bureau (*Time to Adoption*). All columns use a Weibull accelerated failure time model. To facilitate interpretation, all continuous independent variables have been standardized to mean zero and a standard deviation of one. The sample begins in 2001 and ends when the lender joins. The unit of observation is lender-year. Reported below the coefficients are *Z*-statistics calculated with standard errors clustered at the lender level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1)	(2)	(3)	(4)	(5)
			Time to Adoption		
Home Market Switch Rate	-0.290***	-0.493***	-0.295***	-0.291***	-0.461***
	[-3.44]	[-4.25]	[-3.18]	[-3.14]	[-3.94]
New Market Switch Rate		0.298***			0.274**
		[2.76]			[2.49]
No Interim Expansion			0.035	0.157	0.128
			[0.39]	[1.52]	[1.20]
Interim Market Count			0.518***	0.521***	0.519***
			[5.30]	[5.32]	[5.23]
Interim Market Switch Rate				-0.188**	-0.139*
				[-2.40]	[-1.73]
Log Portfolio Credit	-0.683***	-0.714***	-0.669***	-0.678***	-0.689***
	[-6.27]	[-6.28]	[-6.30]	[-6.31]	[-6.20]
Lender Market Share	0.345***	0.405***	0.341***	0.357***	0.398***
	[3.55]	[4.05]	[3.60]	[3.77]	[4.09]
Regional Specialist	0.079	-0.047	0.483**	0.455**	0.343
	[0.44]	[-0.25]	[2.32]	[2.20]	[1.61]
Collateral Specialist	0.722***	0.877***	1.041***	1.050***	1.182***
	[3.92]	[4.60]	[5.36]	[5.47]	[5.88]
N	1,694	1,694	1,694	1,694	1,694
Year FE	Yes	Yes	Yes	Yes	Yes

Table 3: Time to Bureau Adoption—Robustness

This table provides robustness analyses of our Table 2 results. The dependent variable is the log number of years remaining before the lender joins the bureau (*Time to Adoption*). All columns use a Weibull accelerated failure time model, except for column (1), which uses OLS. Column (1) collapses the data to a lender-level unit of observation. Column (2) omits all observations from lenders joining before 2004. Column (3) ((4)) omits observations from crisis years (joiners), where the crisis is defined as 2008–2010. Column (5) defines *New Markets* as the complement of *Home Markets*. Column (6) employs dynamic versions of *Home Market Switch Rate* and *New Market Switch Rate*. Column (7) includes fixed effects for each lender's modal collateral type. To facilitate interpretation, all continuous variables have been standardized to mean zero and a standard deviation of one. The unit of observation is lender-year, except for column (1), in which the unit of observation is lender. Reported below the coefficients are *Z*-statistics calculated with standard errors clustered at the lender level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Time to Adoption						
	Lender level OLS	Drop Early Joiners	Drop Crisis Years	Drop Crisis Joiners	Alternate New Market	Dynamic New Market	Collateral Market FE
Home Market Switch Rate	-0.158***	-0.393***	-0.504***	-0.541***	-0.356***	-0.288***	-0.427**
	[-3.24]	[-3.46]	[-4.03]	[-4.58]	[-4.03]	[-3.29]	[-2.02]
New Market Switch Rate	0.098*	0.232**	0.338***	0.337***	0.187*	0.323***	0.324*
	[1.97]	[2.18]	[2.95]	[3.01]	[1.88]	[4.28]	[1.76]
Log Portfolio Credit	-0.088	-0.560***	-0.691***	-0.714***	-0.657***	-0.656***	-0.700***
	[-1.45]	[-4.58]	[-5.46]	[-5.50]	[-6.04]	[-5.96]	[-5.76]
Lender Market Share	-0.028	0.412***	0.296***	0.367***	0.325***	0.372***	0.276**
	[-0.50]	[3.80]	[2.71]	[3.12]	[3.47]	[3.87]	[2.29]
Regional Specialist	0.145	-0.140	-0.072	-0.069	0.044	0.107	-0.271
	[1.61]	[-0.73]	[-0.36]	[-0.33]	[0.25]	[0.61]	[-1.18]
Collateral Specialist	0.285***	0.734***	0.812***	0.968***	0.860***	0.785***	0.933***
	[3.39]	[3.84]	[3.96]	[4.61]	[4.17]	[4.37]	[4.38]
N	218	1,626	1,485	1,414	1,694	1,694	1,694
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Bureau Membership and Market Competition

This table uses Eq. (1) to model market competition as a function of market-level bureau membership. The dependent variables include various market competition measures. *Switch Rate* is the proportion of borrowers who stop contracting with their lender this period after contracting with them last period. *HHI* is the Herfindahl–Hirschman Index for the market. *Share of Top 1* (*3*, *5*) is the market share of the largest (three largest, five largest) lenders in the market. *Delinquencies* is the proportion of contracts in the market that are currently delinquent. *Member Count* is the number of lender members in the bureau for that market-year. The unit of observation is market-year. To facilitate interpretation, all continuous variables have been standardized to mean zero and a standard deviation of one. Reported below the coefficients are *t*-statistics calculated with standard errors clustered at the market level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Switch Rate	(2) HHI	(3) Share of Top 1	(4) Share of Top 3	(5) Share of Top 5	(6) Delinquencies
Log Member Count	0.120***	-0.054**	-0.057**	-0.114***	-0.112***	-0.414***
	[4.42]	[-1.98]	[-2.08]	[-3.70]	[-3.56]	[-3.45]
Adj R-Sq.	0.12	0.70	0.65	0.69	0.67	0.58
N	2,744	2,744	2,744	2,744	2,744	2,744
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Bureau Membership and Participation Externalities—Micro Evidence

This table uses Eq. (2) to model borrower switches as a function of whether the borrower's credit file has been shared by another lender. The dependent variable *Borrower Switch* is an indicator for whether the borrower stops contracting with their lender this period after contracting with them last period. *Shared by Competitor* is an indicator for whether the borrower's other lender(s) already shared their credit file in PayNet. *Log Relationship Length* measures the natural logarithm of the number of quarters since the relationship began. The unit of observation is borrower-lender-quarter. Reported below the coefficients are *t*-statistics calculated with standard errors clustered at the borrower and quarter level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Borrower Switch	(2) Borrower Switch
Shared by Competitor	0.012***	0.007**
	[2.94]	[2.21]
Log Relationship Length		0.021***
		[8.82]
Adj R-Sq.	0.071	0.076
N	621,977	621,977
Lender x Quarter FE	Yes	Yes
Borrower FE	Yes	Yes

Table 6: Bureau Membership and Participation Externalities—Lender-Level Evidence

This table uses Eq. (3) to model lender-specific switch rates, market shares, and delinquency rates as a function of bureau membership. The dependent variable in column (1) ((2)) is *Lender Portfolio Switch Rate* (*Lender Market Share*), the proportion of borrowers who stop contracting with the lender this period after contracting with them last period (the lender's share of total credit outstanding in home markets). The dependent variable in column 3 is *Portfolio Delinquency,* the proportion of the lender's contracts that are currently delinquent. *Member Count* is the average number of bureau members across the lender's markets that year. As in Table 2, the sample begins in 2001 and ends when the lender adopts the bureau (i.e., the sample is restricted to nonmembers). The unit of observation is lender-year. Reported below the coefficients are *t*-statistics calculated with standard errors clustered at the lender level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Lender Portfolio Switch Rate	(2) Log Lender Market Share	(3) Portfolio Delinquency
Log Member Count	0.005***	-0.128***	0.005*
	[6.66]	[-4.94]	[1.92]
Adj R-Sq.	0.39	0.94	0.58
N	1,694	1,694	1,694
Lender FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 7: Time to Bureau Adoption and Participation Externalities

This table estimates the time to bureau adoption as a function of lender-specific switch rates and bureau membership. The dependent variable is the log number of years remaining before the lender joins the bureau (*Time to Adoption*). *Lender Portfolio Switch Rate* is the proportion of borrowers who stop contracting with the lender this period after contracting with them last period. *Member Count* is the average number of bureau members across the lender's markets that year. All columns use a Weibull accelerated failure time model. To facilitate interpretation, all continuous independent variables have been standardized to mean zero and a standard deviation of one. The sample begins in 2001 and ends when the lender adopts the bureau. The unit of observation is lender-year. Reported below the coefficients are *Z*-statistics calculated with standard errors clustered at the lender level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1)	(2)	(3)
		Time to Adoption	
Lender Portfolio Switch Rate	-0.524***	-0.393***	-0.269***
	[-8.54]	[-6.77]	[-3.03]
Log Member Count		-0.993***	-1.023***
		[-7.73]	[-8.08]
Lender Portfolio Switch Rate x Log Member Count			-0.172**
			[-1.99]
Log Portfolio Credit	-0.502***	-0.482***	-0.505***
	[-4.13]	[-3.65]	[-3.83]
Lender Market Share	0.223*	0.089	0.097
	[1.89]	[0.72]	[0.79]
Regional Specialist	0.144	-0.419***	-0.463***
	[0.78]	[-2.58]	[-2.85]
Collateral Specialist	0.581***	0.489***	0.521***
	[3.16]	[2.58]	[2.73]
N	1,694	1,694	1,694
Year FE	Yes	Yes	Yes

Table 8: Borrower Credit Exposures

This table uses Eq. (4) to study borrower credit, relationships, collateral exposures, and delinquency status. The dependent variables in columns (1)–(3) are the log credit outstanding, number of lending relationships, and unique collateral types that quarter (*Log Borrower Credit*, *Log Relationships*, and *Log Collateral Types*), respectively. The dependent variable in column (4) is an indicator for whether the borrower is delinquent on any contract that quarter (*Delinquent*). *Shared* is an indicator equal to one for quarters after the borrower's credit file is first shared in the bureau. The sample is limited to the three years before and after the borrower's credit file is first shared in the bureau. The unit of observation is borrower-quarter. Reported below the coefficients are *t*-statistics calculated with standard errors clustered at the borrower level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Log Borrower Credit	(2) Log Relationships	(3) Log Collateral Types	(4) Delinquent
Shared	0.032***	0.052***	0.030***	-0.024***
	[3.23]	[11.94]	[7.41]	[-4.94]
Adj R-Sq.	0.86	0.75	0.73	0.37
N	281,914	281,914	281,914	281,914
Borrower FEs	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes

Table 9: Borrower Credit Exposures by Credit Record

This table uses an augmented version of Eq. (4) to study borrower credit, relationships, collateral exposures, and delinquency status. The dependent variables in columns (1)–(3) are the log credit outstanding, number of lending relationships, and unique collateral types that quarter (*Log Borrower Credit*, *Log Relationships*, *Log Collateral Types*), respectively. The dependent variable in column (4) is an indicator for whether the borrower is delinquent on any contract that quarter (*Delinquent*). *Shared* is an indicator equal to one for quarters after the borrower's credit file is first shared in the bureau. *Good Record* is an indicator equal to one for borrowers without a delinquency worse than 30 days (Panel A) or 90 days (Panel B) during the three-year period before their credit file is first shared in the bureau. The sample is limited to the three years before and after the borrower's credit file is first shared. The unit of observation is borrower-quarter. Reported below the coefficients are *t*-statistics calculated with standard errors clustered at the borrower level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

Panel A: Good Record is No Delinquency>30 Days in Three Years before Credit File Shared

	(1) Log Borrower Credit	(2) Log Relationships	(3) Log Collateral Types	(4) Delinquent
Shared	-0.097***	0.031***	0.015**	-0.082***
	[-5.95]	[4.33]	[2.24]	[-11.96]
Shared + Shared x Good Record	0.183***	0.031***	0.022***	0.082***
	[9.81]	[3.90]	[2.95]	[12.56]
Adj R-Sq.	0.86	0.75	0.73	0.37
N	281,914	281,914	281,914	281,914
Shared + Shared x Good Record p-value	0.000	0.000	0.000	0.961
Borrower FEs	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes

Panel B: Good Record is No Delinquency>90 Days in Three Years before Credit File Shared

	(1) Log Borrower Credit	(2) Log Relationships	(3) Log Collateral Types	(4) Delinquent
Shared	-0.172***	0.004	-0.007	-0.095***
	[-6.13]	[0.34]	[-0.66]	[-9.39]
Shared x Good Record	0.228***	0.054***	0.041***	0.079***
	[7.77]	[4.62]	[3.69]	[7.97]
Adj R-Sq.	0.86	0.75	0.73	0.37
N	281,914	281,914	281,914	281,914
Shared + Shared x Good Record p-value	0.000	0.000	0.000	0.001
Borrower FEs	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes

Table 10: Information Sharing and Intensive Margin Effects

This table modifies our Table 9 analyses of borrower credit and delinquency status to introduce a lender dimension to the data and include borrower-lender relationship fixed effects. The dependent variable in column (1) is the log credit outstanding that quarter (*Log Borrower Credit)*. The dependent variable in column (2) is an indicator for whether the borrower is delinquent on any contract that quarter (*Delinquent*). *Shared* is an indicator equal to one for quarters after the borrower's credit file is first shared in the bureau. *Good Record* is an indicator equal to one for borrowers without a delinquency worse than 30 days during the three-year period before their credit file is first shared in the bureau. The sample is limited to the three years before and after the borrower's credit file is first shared. The unit of observation is borrower-lender-quarter. Reported below the coefficients are *t*-statistics calculated with standard errors clustered at the borrower level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Log Borrower Credit	(2) Delinquent
Shared	-0.044***	-0.035***
	[-4.53]	[-4.44]
Shared x Good Record	0.044***	0.033***
	[3.52]	[4.47]
Adj R-Sq.	0.91	0.47
N	547,617	547,617
Borrower x Lender FEs	Yes	Yes
Industry x Quarter FEs	Yes	Yes

Table 11: Borrower Credit Exposures and Bureau Membership

This table uses Eq. (5) to model borrower credit access as a function of bureau membership. The dependent variable in columns (1) and (2) is the borrower's log credit (*Log Borrower Credit*). The dependent variable in columns (3) and (4) is the borrower's log number of lending relationships (*Log Relationships*). *Shared* is an indicator equal to one for quarters after the borrower's credit file is first shared in the bureau. *Member Count* is the number of bureau members in that market that quarter. The unit of observation is borrower–collateral type-quarter. Reported below the coefficients are *t*-statistics calculated with standard errors clustered at the borrower level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1)	(2)	(3)	(4)
	Log Borrower Credit		Log Relationships	
Shared x Log Member Count	0.079**	0.050***	0.050***	0.017**
	[2.56]	[4.56]	[4.56]	[2.10]
Adj R-Sq.	0.91	0.77	0.77	0.88
N	265,225	265,225	265,225	265,225
Borrower x Quarter FEs	Yes	Yes	Yes	Yes
Collateral x Quarter FEs	Yes	Yes	Yes	Yes
Borrower x Collateral FEs	Yes	Yes	Yes	Yes
Borrower x Collateral Trends	No	Yes	No	Yes

Online Appendix to:

How Voluntary Information Sharing Systems Form: Evidence from a U.S. Commercial Credit Bureau

May 2021

This online appendix tabulates additional analyses not reported in the paper.

Table A1: Random Sampling

This table repeats our main analyses on a sample of 10,000 randomly chosen borrowers. The variables and specifications are otherwise the same as in the original tables.

Table 2: Time to Bureau Adoption

	(1)	(2)
	Time to Adoption	
Home Market Switch Rate	-0.193**	-0.210***
	[-2.45]	[-2.95]
New Market Switch Rate		0.204***
		[2.66]
Log Portfolio Credit	-0.667***	-0.673***
	[-5.37]	[-5.39]
Lender Market Share	0.355***	0.393***
	[3.12]	[3.56]
Regional Specialist	0.291	0.249
	[1.61]	[1.40]
Collateral Specialist	0.740***	0.758***
	[3.98]	[4.17]
N	1,621	1,621
Year FE	Yes	Yes

Table 8: Borrower Credit Exposures

	(1)	(2)	(3)	(4)
	Log Borrower Credit	Log Relationships	Log Collateral Types	Delinquent
Shared	0.025*	0.060***	0.035***	-0.024***
	[1.79]	[9.49]	[6.09]	[-3.48]
Adj R-Sq.	0.86	0.76	0.73	0.37
N	141,607	141,607	141,607	141,607
Borrower FEs	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes

Table 9: Borrower Credit Exposures by Credit Record

	(1) Log Borrower Credit	(2) Log Relationships	(3) Log Collateral Types	(4) Delinquent
Shared	-0.085***	0.045***	0.024**	-0.079***
	[-3.72]	[4.40]	[2.52]	[-8.18]
Shared x Good Record	0.155***	0.021*	0.02	0.077***
	[5.78]	[1.92]	[1.59]	[8.31]
Adj R-Sq.	0.86	0.76	0.73	0.37
N	141,607	141,607	141,607	141,607
Shared + Shared x Good Record p-value	0.000	0.000	0.000	0.796
Borrower FEs	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes

Table 11: Borrower Credit Exposures and Bureau Membership

	(1)	(2)	(3)	(4)
	Log Borrower Credit		Log Relationships	
Shared x Log Member Count	0.152***	0.037**	0.064**	0.023*
	[3.54]	[2.33]	[2.51]	[1.87]
Adj R-Sq.	0.91	0.77	0.95	0.85
N	131,253	131,253	131,253	131,253
Borrower x Quarter FEs	Yes	Yes	Yes	Yes
Collateral x Quarter FEs	Yes	Yes	Yes	Yes
Borrower x Collateral FEs	Yes	Yes	Yes	Yes
Borrower x Collateral Trends	No	Yes	No	Yes