The Economic Consequences of Borrower Information Sharing: Relationship Dynamics and Investment*

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Abstract

I use the introduction of a US commercial credit bureau to examine how credit relationships are affected by information sharing. My within firm- and lender-time tests exploit the fact that firms have ongoing relationships with multiple lenders that join the bureau in a staggered pattern. I find information sharing reduces relationship-switching costs, particularly for firms that are young, small, or have had no defaults. Information sharing shortens contract maturities in new relationships, and reduces lenders' willingness to provide additional financing to their delinquent borrowers. My results highlight the mixed effects of transparency-improving financial technologies on credit access.

JEL Classification: D82; G21; G23; G30; G32; M41.
Keywords: Debt contracts; information sharing; information asymmetries; transparency; credit bureaus; relationship lending; transactional lending; information economics; entrepreneurial finance; credit scores.

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1. Introduction

Information asymmetries can help sustain credit relationships. Credit relationships develop through a lender learning more than its competitors about its own borrowers (Sharpe 1990). This information advantage makes it difficult for firms to switch lenders, and influences how lenders approach credit relationships. For example, lenders may gather firm-specific information (Chan et al. 1986), or continue financing delinquent borrowers, even at a loss (Petersen and Rajan 1995). Longer contracts and lasting relationships permit the lender to earn rents from their information advantage, because firm-specific knowledge can be reused, and delinquent borrowers often recover and become profitable clients. Transparency can heighten competition and threaten relationship lending—firms "might be tempted to switch to other banks… and (lenders) may respond by reducing their relationship-specific investments" (Boot 2000). Yet, much of the information that lenders use to allocate credit—including preexisting debt, payment history, and collateral pledges—is voluntarily shared among lenders, e.g., by reporting to credit bureaus.

What effects does this form of reporting have on credit relationships and lenders' willingness to provide credit to their delinquent borrowers? Evidence addressing these questions is limited, despite recent research showing credit scores—generated by lender-to-lender reporting—can substitute for financial statements in the loan origination process (Cassar et al. 2015). To answer these questions, I examine a panel of quarterly credit files detailing firms' contracts and payment performance with lenders that join the PayNet bureau in a staggered pattern. PayNet was established in 2001 to serve the equipment finance sector, which funds nearly three-quarters of the private fixed nonresidential investment in the US (BEA 2016; IHS 2016). Unlike the consumer finance market, equipment finance had not yet embraced credit reporting. Before joining PayNet, lenders regularly originated contracts for construction, manufacturing, telecommunication, and other equipment without detailed credit history information (Ware 2002). Hence, when PayNet appeared, lenders were willing to share previously proprietary information (a requirement for membership) to gain access to more comprehensive, verified, and timely information that would aid their screening and monitoring of firms (Doblas-Madrid and Minetti 2013). Eight of the 10 largest equipment finance lenders have joined PayNet, and the bureau contains over $1.4 trillion in contracts.

Tests examining how voluntary information sharing affects credit relationships face a fundamental identification problem: separating the effects of sharing from contemporaneous shocks to firms' demand for credit or shifts in lenders' business models. The structure of PayNet and US equipment finance market help address this problem. Firms have no say over whether or when their credit file is shared (Doblas-Madrid and Minetti 2013). Lenders enter the bureau at various points over more than a decade and must contribute both existing *and past* contract terms and firm payment records, enabling me to observe contracts *before* they were revealed in the bureau. Additionally, most firms contract with multiple lenders that join in different periods. This permits me to implement a within firm-time estimator to account for observable and unobservable firm-specific shocks that could otherwise contaminate tests of information sharing. This approach, detailed in section 4.1, follows contemporary banking research that identifies the consequences of a supply-side development (in my case, lender information sharing) by using the firm's ongoing credit relationships with *other* lenders as a counterfactual to control for demand effects.

I study firms with at least two lenders that have yet to join PayNet. When one lender joins and shares its credit files, I compare the likelihood that the firm ends its relationship with this lender in the subsequent two years with the likelihood that it ends its relationship with another lender that did not yet join PayNet. I begin by showing the pair with a shared credit file is 6.9% more likely to stop contracting together in the two years after the credit file is revealed. This finding is economically significant considering the two-year unconditional probability of relationship exit is 29%, and that the typical contract is originated seven years into a relationship.

While these initial tests support the idea that information sharing helps firms match with new lenders, they could also reflect selection bias. Related research rationalizes voluntary information sharing by linking sharing to lower delinquency rates (Padilla and Pagano 2000; Doblas-Madrid and Minetti 2013) and lower screening costs, particularly for applicants from unfamiliar markets (Pagano and Jappelli 1993; Liberti et al. 2016). If the pursuit of these benefits is correlated with relationship turnover, then my findings may not stem from the greater availability of borrower information. To address this concern, I add lender-time fixed effects to my tests by exploiting within-firm, across-relationship variation in contract sizes.

Contract sizes matter for information sharing because lenders prefer knowing whether a new applicant has serviced a similar liability in the past (Ware 2002). Indeed, when firms switch lenders, their new contract tends to resemble, in size and other terms, their old one (Ioannidou and Ongena 2010). To illustrate, consider a firm applying for a $100,000 loan with a new lender. All else equal, the loan is more likely to be approved if the firm's credit file shows a record of servicing a prior $100,000 loan than if the file only details payments on a $30,000 loan. The prevalence of multiple relationship firms in my sample, combined with differences in contract sizes across shared and private contracts, support a quasi-natural experiment for examining the consequences of information sharing. According to the arguments above, the sharing of the firm's largest contract allows the firm to shop around on both its shared *and* (smaller) private contract. On the other hand, the sharing of a small contract is less likely to trigger the termination of the firm's larger contract.

I find that contract size differences moderate the effects of information sharing in a manner consistent with my predictions. When a shared contract is smaller than the firm's private contract, the exit rate for the former is much larger. However, when the private contract is smaller or of comparable size to the shared contract, I find no difference in relationship survival across the two relationships when just one credit file is shared. This latter finding suggests information sharing by one lender creates an externality: firms can use their shared track record as a proxy in shopping around on similar (or smaller) contracts with other parties. I am not aware of other research documenting this externality. Reinforcing these results, I show that borrowers are significantly more likely to start a new relationship after their credit file is available in the PayNet system, and bureau members, who have access to shared credit files, comprise the majority of counterparties in these new pairs.

Next, I show the consequences of information sharing depend on the age, size, and track record of the firm. Information sharing should have the largest effect on the firms that are least likely to have financial statements or press coverage, given that opacity can make it difficult to switch lenders (Petersen and Rajan 1994). I find the effect of information sharing on relationship turnover is strongest for young, small firms. I then explore the role of the firm's credit history. Jaffee and Russell (1976) and Stiglitz and Weiss (1981) show lenders prefer to ration credit instead of charging high interest rates to the riskiest borrowers. These theories suggest information sharing should reduce the switching costs primarily for borrowers without histories of major payment problems. Using credit histories in my dataset, I show information sharing leads only firms with perfect records or minor delinquencies to exit the relationship.

Finally, I study whether, by reducing switching costs, information sharing alters lenders' approach to contracting. Prior research associates a relationship-focused approach with longer maturity contracts and continued financing for firms during a crisis or unprofitable period (Petersen and Rajan 1995; Boot 2000; Mian 2006; Bharath et al. 2011; Bolton et al. 2016). I show that, after a borrower's credit file is first available in the bureau, the new relationships it establishes involve shorter maturity contracts with higher payment frequency, indicating a transition away from relationship lending and toward transactional lending. Next, I examine delinquencies, which expose lenders to losses and monitoring costs, and test whether joining the bureau changes their willingness to originate new contracts with a firm following these events. Controlling for relationship (firm-lender pair) fixed effects, I find that, once lenders are bureau members, the likelihood of contract renewal following delinquency declines by more than 25% of the pre-period average. These results are consistent with information sharing reducing the profits available from relationship lending.

However, these results are also consistent with information sharing provoking a coordination problem among lenders with differing information sets about the same firm's riskiness (Hertzberg et al. 2011). Such a problem would also render new contracts less appealing. To help disentangle these explanations, I partition my sample according to whether information sharing reveals disagreement among lenders to the same firm. While I find a significant reduction in post-delinquency financing when disagreement occurs, consistent with Hertzberg et al., I also find the same evidence when no disagreement occurs or when the firm only has one lender. Thus, although coordination could contribute to the decline in originations after delinquencies, it does not appear to be the sole impetus behind the shift.

I make two contributions to the literature. First, I document how information sharing influences the formation and survival of credit relationships. Researchers widely argue that information frictions impede the flow of credit to private firms. However, the work on how these frictions are resolved predominantly focuses on firm-to-lender reporting (Armstrong et al. 2010; Christensen et al. 2016), leaving unanswered how and for whom lender-to-lender reporting facilitates credit. This gap is notable because many firms do not provide financial statements or tax returns to their lender (Allee and Yohn 2009; Minnis and Sutherland 2016) and that credit scores can substitute for financial reporting (Cassar et al. 2015).

Second, my paper shows that changes in borrower transparency can affect how lenders approach credit relationships. Researchers have long debated the effects of bank competition on credit access, focusing on branching restrictions and bank concentration (Petersen and Rajan 1995; Black and Strahan 2002; Rice and Strahan 2010; Srinivasan 2014). To my knowledge, my study is the first to offer empirical evidence on how information sharing—a distinct but pervasive feature of modern credit markets—diminishes a lender's information advantage over its rivals and reduces its willingness to foster relationships with firms. These findings are particularly relevant in light of advances in technology that facilitate information sharing in credit markets, and recent evidence demonstrating how credit access can hinge on lending relationships (Berger and Udell 2006; Bharath et al. 2011; Bolton et al. 2016; Darmouni 2016).

While I focus on commercial lending, reporting technologies have emerged in other settings to permit principals to exchange the track records of agents. Insurance companies regularly report policyholder claims to central repositories, and employers rely on formal (e.g., LinkedIn, background checks) and informal (word-of-mouth) information sharing channels when evaluating job applicants. Although prior research examines the ways in which one firm's reporting affects other market participants (Foster 1981; Admati and Pfleiderer 2000; Bushee and Leuz 2005; Badertscher et al. 2013; Beatty et al. 2013), there is little work documenting the externalities caused by principals sharing agents' records.

I qualify an important aspect of my results. Because joining PayNet is voluntary, my findings are most relevant to voluntary information sharing arrangements, which have reached near universal coverage of individuals in most developed nations (World Bank 2016).[1] Although PayNet members finance roughly three-quarters of the US equipment market (Monitor 2015), many lenders decline to participate, and their decisions are not random. The advantage of my setting is that it allows me to account for firm- and lender-time effects in estimating the treatment effect on the treated. This feature makes it unlikely that firm-level shocks or straightforward lender business-model shifts account for my collection of findings.

2. Theoretical framework and prior literature

Theoretical work shows information sharing arises when credit cannot be efficiently allocated using only firsthand knowledge of borrowers (Pagano and Jappelli 1993). For example, although a borrower may provide a clean payment record for one contract, a lender (absent information sharing) cannot know whether the borrower has withheld unfavorable information about other contracts. Many private firms do not undergo costly audits which

[1] The 2016 World Bank Doing Business Survey reports, by country, the percent of individuals with credit files from credit bureaus (voluntary arrangements) and credit registries (mandatory arrangements). Studying the ten largest economies by GDP, I find the average coverage ratio from bureaus is 70%, compared to 22% for registries. In six of the ten countries, bureaus have 100% coverage of individuals. The survey does not provide statistics on credit file coverage for commercial firms.

provide such assurance, leaving lenders to rely on a host of alternative information sources including credit scores, tax returns, and soft information (Blackwell et al. 1998; Allee and Yohn 2009; Cassar et al. 2015; Lisowsky and Minnis 2015; Minnis and Sutherland 2016).

Sharing information puts the expected rents from relationship lending at risk. Nevertheless, sharing arrangements benefit lenders by reducing the monitoring costs of intermediation (Hauswald and Marquez 2003), precluding hold-up problems (Jappelli and Pagano 2000), and mitigating adverse-selection problems associated with establishing new relationships (Sharpe 1990; Liberti et al. 2016). By making payment performance widely known, information sharing can also discipline borrower behavior, thereby reducing the risk of current and future contracts (Padilla and Pagano 2000). Empirical work has found support for this prediction (Bennardo et al. 2015) and shown the effects are concentrated among opaque firms (Doblas-Madrid and Minetti 2013).

As of 2016, at least 126 countries had private credit bureaus, while 105 maintained public registries (World Bank 2016). Cross-country studies find that these systems are positively associated with aggregate credit and negatively associated with aggregate default rates (Jappelli and Pagano 2002; Djankov et al. 2007). Firm-level analyses surrounding the adoption or reform of information sharing systems in developing countries also find improvements in credit access (Brown et al. 2009; Peria and Singh 2014).

Relationship lending is a key mechanism through which firms access credit. Although theory connects relationship lending to information asymmetries, evidence on the effects of information sharing on credit relationships has been limited. Few settings allow researchers to observe information sharing at the relationship level. And, separating the supply and demand effects of information sharing is inherently challenging, as its introduction is frequently paired with other reforms (Djankov et al. 2007; Brown et al. 2009; Peria and Singh 2014). My setting allows me to track the relationships and contract terms for a sample of predominantly opaque firms before and after their credit file is shared. Because lenders join in a staggered pattern and I control for time effects, it is unlikely that a common shock to credit market conditions, macroeconomic policy, or information technology biases my results.

3. Setting and data

3.1 The equipment finance sector

I examine information sharing in the equipment finance market, a sector that funds investments in agricultural, computer, construction, industrial, medical, transportation, and other equipment. In 2014, the final year of my sample, US private investments in equipment and software totaled approximately $1.4 trillion; nearly three quarters of firms fund these expenditures with external financing (BEA 2016; IHS 2016). Originating lenders retain the majority of contracts: in 2010, securitization volume was under $8 billion (Goukasian and Miller 2012).

Equipment finance contracts can be broadly categorized as loans or leases. In both types of contracts, lenders rely upon monitoring and legal mechanisms to limit their losses in the event of default. Monitoring mechanisms include the gathering of information about the firm's borrowing history and ability to pay before granting credit, and the observation of the firm's behavior and performance after. Lenders publicly file UCC financing statements to establish their legal right to reclaim collateral if the firm defaults on the loan or lease.[2] Loans and leases

[2] Although lenders retain the legal title to leased assets after contract origination, they regularly make UCC filings for leases as a precaution (Contino 1996).

differ in other respects, including the expertise and services provided by the lender (Contino 1996; Murfin and Pratt 2015) as well as their tax, bankruptcy, and financial reporting treatment (FASB 2016).

The US equipment finance market, like the broader commercial and industrial credit market, is highly concentrated. The ten largest lenders account for 66.4% of the market share of net assets over the past decade (Monitor 2015). This group of large lenders consists of banks (including Bank of America and Wells Fargo), captives (IBM, John Deere, and Volvo), and nonbank finance companies (GE Capital). Banks and nonbank finance companies dominate the several hundred lenders servicing the remaining one-third of the market.

3.2 The PayNet credit bureau

In 2001, PayNet, a commercial data repository, launched a bureau that would allow equipment financiers to obtain firm information via the internet for a nominal fee.[3] The bureau operates on the principle of reciprocity: lenders may only participate by agreeing to share all past, present, and future credit files with other members.

Two features of PayNet's implementation and data collection process prevent misreporting. First, before a lender can participate, PayNet establishes direct access into their accounting systems. Lenders must undertake the efforts and investments to necessary for its IT systems to reach compatibility with PayNet's secure interface (Jackson 2001), and undergo extensive audit and testing exercises to ensure its IT systems can support complete and accurate information sharing (Doblas-Madrid and Minetti 2013). According to PayNet, the required IT infrastructure improvements and testing exercises take anywhere from six weeks to one year.

[3] Although current pricing information is confidential, an industry magazine article from 2000 states members could access a firm's credit file for as little as $5 by members (Jackson 2000).

Second, PayNet collects contract term and delinquency information via its direct access to lenders' accounting systems. PayNet employs a large team of analysts and algorithms to check this information for accuracy and completeness, upon initial collection and on an ongoing basis. Data shared by a lender is triangulated with the lenders' past data, information contributed contemporaneously by peers with similar exposures, macroeconomic and trade data from sources other than the lender, and public filings. UCC statement filings in particular provide a convenient resource to verify the completeness of shared information. US Secretaries of State maintain websites that permit the public to search, at no cost, the set of UCC statements for a given firm or lender, and view descriptions and serial numbers for assets securing individual contracts. The websites are regularly updated with new statements, and preserve those filed 25 or more years ago, helping PayNet confirm that the lender has provided contract information from both new and inactive clients. Lenders not filing UCC statements in order to hide contracts from PayNet risk losing their collateral to another creditor in the event of default.

After inspecting the lender's data, PayNet then enters the contract term and payment status information into its proprietary estimation model to generate credit scores and other statistics presented on its credit reports. PayNet credit reports also contain a variety of identifying information (e.g., address, industry, and tax ID) and filing information, if any, from bankruptcies, tax liens, and UCC statements.

Together, these bureau features work to inhibit the ability and incentive for lenders to manipulate or withhold information.[4] Additionally, upon joining PayNet lenders sign an agreement giving PayNet the right to permanently ban them from the database and pursue

[4] For example, PayNet's data collection and credit score estimation processes help prevent the form of misreporting documented in the Argentinean credit bureau (Giannetti et al. 2016). In that setting, the bureau simply *redistributes* credit scores *reported* by lenders, without any means of accessing lenders' accounting systems.

damages in the event of misreporting. Nevertheless, it is very difficult for the researcher to know whether misreporting occurs or its extent. One possibility is that, if a lender chooses to misreport and manages to circumvent PayNet's detection systems, they are most likely to withhold information about the clients most inclined to switch. Such a scenario would make it more difficult for me to detect an effect of information sharing on relationship turnover.

Lenders' identities in PayNet credit files are kept anonymous, and members are prohibited from using the bureau for direct marketing or mining client lists (Jackson 2000), dampening proprietary cost concerns about participating. Lenders typically access the system after receiving a credit application from a new borrower, or when considering renewing an existing borrower's contract. When discussing Wells Fargo's involvement with PayNet, Curt Zoerhof, a senior vice president and credit manager, commented: "PayNet does make a lot of sense. Our credit department is reluctant to call other lessors for a reference. If you have an anonymous system, that's helpful" (Jackson 2000). An industry publication likewise wrote the following passage (Ware 2002).

> Until this year (2002), however, commercial credit bureaus in America have only been able to provide lenders with trade-type credit information … many, if not most, lenders believe comparable longer-term capital financing history is so critical to making prudent decisions that they have their staff manually telephone other institutions to get credit references—just as they would have almost a hundred years ago—even though this process can take days, adds significantly to overhead, and can result in the original lender "swiping the deal" from the lender requesting the reference.

Since 2001, eight of the 10 largest competitors in the equipment finance market have joined PayNet as well as many smaller lenders. Joining improved members' ability to assess potential borrowers' creditworthiness in two key ways. First, by linking directly into lenders' accounting systems, PayNet could compile and frequently update indebtedness and contract performance information. Second, the bureau provided contract-level information that was more relevant, detailed, and verified than competing sources. Asking competitors for references was problematic; other credit reports (e.g., Experian) typically contained only short-term payment histories that were consolidated at the firm level, offering a noisy signal of creditworthiness for more substantial, long-term credit applications (Jackson 2001; Doblas-Madrid and Minetti 2013). Appendix A provides an excerpt from an illustrative credit report.

Unlike in the consumer market, the Fair Credit Reporting Act does not regulate commercial lenders' sharing of information. As a result, in my setting, information sharing is exogenous to the borrowers because they have no say over whether, when, or how their information is released (OCC 1996). Although multiple industry publications covered the bureau's launch and conversations with PayNet indicate many lenders notify borrowers of their joining to comply with their privacy agreements, my tests do not require borrowers to even be aware of its existence. Rather, my assumption is that those who shop around when current contracts mature are affected when potential lenders can more easily screen them with information available in the bureau.[5]

3.3 Descriptive statistics

My initial sample contains the quarterly credit files for 20,000 random firms in PayNet's database, detailing 531,451 contracts. There are two main differences between my dataset and that of Doblas-Madrid and Minetti (2013). First, whereas they access a random sample of 28,000 *contracts* between 15 lenders and almost 4,000 firms, my dataset contains the *entire contract history* between 20,000 randomly chosen firms and PayNet lenders. Having firms' full

[5] Guides on equipment finance contracting advise borrowers to shop around for financing (Contino 1996). Moreover, according to the 2003 Federal Reserve Survey of Small Business Finances, the typical firm with an equipment loan applied for credit 1.6 times during the previous three years, *excluding* renewals of existing contracts.

contract history with PayNet lenders allows me to study credit relationships with a degree of precision that could not be achieved using a random sample of contracts. The firms in my dataset were chosen randomly from the set of firms that have open contracts at least two years before and two years after one of their lenders joins the bureau to ensure a usable sample for my tests. Second, Doblas-Madrid and Minetti observe employee count, revenue, and credit rating data that was not made available to me.

Furthermore, both datasets differ from what bureau members observe. Although lenders can observe the firm's name, address, and tax ID on credit files, this information is withheld from both samples for confidentiality purposes. Also, because of the backfilling requirement, both datasets contain the history of lenders' contracts with sample firms at a point *before* the lenders join the bureau. Stated differently, if a lender joins the bureau in 2004, I can observe its contracts in, say, 2002, even though members as of 2002 did not, because the lender provided the older contract information. Moreover, this older contract information is not limited to active clients. Of the contracts contributed by the typical lender upon joining, 38.1% are with firms no longer borrowing from them.[6]

Each credit file in my sample includes limited biographical information (including industry, state, and age) and a detailed contract history (including the terms, lender identifier, and payment history on each contract) updated quarterly. From my initial sample, I apply three filters for my main tests. First, I exclude 28,479 contracts missing amount or maturity information. Second, because my main tests employ an event window spanning two years before to two years after lenders join the bureau, I exclude 30,983 contracts from lenders that

[6] My results are robust to eliminating lenders contributing below the median share of inactive contracts upon joining.

do not have contracts from 1999 (two years before the launch of PayNet) to 2014 (the last year in my dataset) to maintain a constant sample of lenders. Third, I eliminate 206,990 contracts that mature before or originate after my event window. Table 1, Panel A reports that my final sample contains 246,999 contracts.

Panel B provides descriptive statistics for contract terms and payment performance. Loans make up 17% of the deals, whereas the remaining 83% are leases. The average (median) contract amount is $130,045 ($25,740), though contract sizes vary considerably from under $1,000 to the hundreds of millions of dollars. Like other credit bureaus (e.g., consumer bureaus such as Equifax) and many commercial repositories examined in related work (see Hertzberg et al. 2011), PayNet does not report the interest rate on contracts, to avoid antitrust scrutiny and dampen members' proprietary cost concerns. There is considerable heterogeneity in the payment performance of borrowers that is ultimately revealed to other members. For 40% of the contracts, borrowers always pay on time; for 23% (10%), the worst delinquency is less than 30 days (more than 90 days). Panel C shows that, on a dollar-weighted basis, the plurality of contracts is for trucks and construction and mining equipment.

Table 2, Panel A, presents descriptive statistics for borrowers. Because I cannot observe firms' financial statements and lenders often do not provide borrowers' sales figures to the bureau, I measure borrower size as the dollar sum of open contracts, equal to $1.5 million ($259,289) for the average (median) firm during the sample period. The average firm is 10 years old and has 13 open contracts.[7] Although I do not observe zip codes or MSAs, I note sample borrowers occupy all 50 states, plus the District of Columbia, Guam, and the Virgin

[7] Firms carry multiple contracts for two reasons. First, firms acquire and replace assets over time according to their investment needs and technological advances in asset features. Second, lenders often specialize by asset type. As a result, firms using multiple types of assets (e.g., computers and forklifts) often contract with multiple lenders.

Islands. Panel B presents descriptive statistics for the lenders' portfolio of contracts contained in my sample. On average, lenders have 567 open contracts; this figure obviously understates the magnitude of their activities, because I only observe their interactions with the 4,416 borrowers in my main tests. Table 3 shows that relationships are important in this setting: at origination, the borrower in an average contract has had a seven-year relationship with its lender. The unconditional probability of a relationship ending over the next year (two years) is 29% (52%).

4. Empirical tests and results

4.1 Research design

Credit relationships are shaped by both supply and demand forces. For example, lenders choose their underwriting policies and how much credit to provide as a function of their condition and strategy; firms' credit access is determined by their financing needs and information environment. Therefore, identifying the consequences of any particular development (e.g., information sharing) requires the researcher to hold constant contemporaneous developments related to the other supply and demand forces. The banking literature has recently made methodological advances toward this ideal by examining firms with more than one credit relationship and implementing a within firm-time estimator (Khwaja and Mian 2008; Lin and Paravisini 2011; Jimenez and Ongena 2012; Scianarelli et al. 2016). To illustrate, Khwaja and Mian study the effects of bank liquidity shocks on lending by comparing, *for the same firm*, the change in borrowing across two sets of banks: those affected by withdrawal restrictions, and those unaffected. Because the withdrawal restrictions resulted from exogenous nuclear testing events in Pakistan, and changes in demand for credit are accounted for by the within firm-time estimator, the authors claim to identify the consequences of liquidity shocks on lending.

My identification strategy is motivated by Khwaja and Mian (2008) but differs in two respects. First, my lender-level treatment variable is not exogenously imposed but is instead driven by a lender deciding to enter the bureau and completing the implementation and testing procedures necessary to become a member. Although this treatment is exogenous to firms and my tests examine information sharing from the firm's perspective, lender selection could enter my results. Therefore to account for lender-level developments influencing their decision to join (e.g., changes in their financial condition or approach to credit relationships), I include lender-time fixed effects.

Second, to provide the necessary variation for my within borrower-time/within lender-time tests, I exploit the fact that firms have open contracts of different sizes across their shared and private relationships. Because lenders prefer making application decisions with a comparable contract history (Ware 2002; Ioannidou and Ongena 2010), precisely what information gets revealed on a firm's credit file matters for its ability to switch lenders. Consider the earlier illustration of a firm with two loans outstanding, one for $30,000 with Lender A and a second for $100,000 with Lender B. Lender A joining first causes the firm's credit file to detail only payments on a $30,000 loan, and their thin file does little to help the firm's efforts to refinance or renew its $100,000 loan with an unfamiliar lender. Conversely, Lender B joining first endows the firm with a credit history detailing payments on a $100,000 loan. This latter scenario helps the firm apply for either a $100,000 or $30,000 loan with an unfamiliar lender. The bureau's existence warrants an identification strategy relying on contract size differences: PayNet was formed because borrowers could not easily convey their creditworthiness for one type of contract using payment history information about another, particularly when the contract size of the latter was smaller (Jackson 2000, 2001; Ware 2002). My sample contains meaningful contract size differences across shared and private contracts: for 31% of the treated firm-quarters in my sample, private contracts are more than two times as large as the contracts being revealed.

Figure 1 illustrates the research design for my main tests. Firm 2 (F2) has a relationship with both Lender 1 and 2 (L1 and L2). When L1 joins at the beginning of 2003 Q3, I compare the likelihood that the relationships F2/L1 and F2/L2 end over the subsequent two years. According to my predictions surrounding contract size differences, if the contract size is larger for F2/L1 (e.g., $100,000), then information sharing about this relationship should increase the probability of both F2/L1 and F2/L2 ending. On the other hand, if the contract size is smaller for F2/L1 (e.g., $30,000), then information sharing should have a larger effect on F2/LI ending. To implement my tests, I employ the following linear probability model:

$$Y_{ijt} = \alpha_{it} + \alpha_{jt} + \alpha_{ijt}^{type} + \beta_1 * Shared_{it} * Thin\ File_{jt} + \epsilon_{ijt}. \quad (1)$$

Intuitively, this specification is analogous to an event study, where the "treatment" event is a lender joining the bureau. My analysis compares the long-term survival for relationships whose contract terms and payment history have been collected, reviewed, and revealed by PayNet, relative to the firm's other current relationship(s) that are kept private throughout the event window. The dependent variable is an indicator for whether firm j no longer has *any* open contracts with lender i after two years, which I call relationship exit. This indicator is measured only once for each active relationship during the quarter a treatment occurs (the indicator is not repeated each quarter of the two years). The unit of observation is firm-lender-quarter; when the relationship spans multiple contracts I collapse the contracts into a single indicator for whether any remain open for the firm-lender pair after two years.

Following my discussion above about how shifts in lenders' business models or firm-specific credit demand shocks can influence the decision to continue or exit a credit relationship, I include lender-quarter and firm-quarter fixed effects. Therefore my analysis is limited to firm-quarters where the firm has more than one ongoing credit relationship.[8] I include indicators (*Type)* for whether the relationship is for leases, loans, or both. *Shared* is an indicator equal to 1 for all firm-lender pairs in which the lender joined the bureau that quarter and 0 for firm's other active pair(s), so long as the lenders in these other pairs do not also join during the event window. Lender join dates are defined as the first date that a lender queries a credit record in the PayNet system.[9] *Thin File*, measured at the firm-quarter level, is an indicator for whether the firm's credit file is only being supplemented by the sharing of smaller contracts, leaving other contracts that are at least twice as large off of the credit file because the lender for these contracts is not yet a PayNet member. To account for potential cross-sectional correlation within the set of borrowers whose lender joins in the same quarter, I cluster standard errors at the quarter-year level.[10]

In my second set of tests, I alter the dependent variable in equation (1) to measure the change in log credit for the pair at time t as follows:

$$\Delta Y_{ijt} = \alpha_{it} + \alpha_{jt} + \alpha_{ijt}^{type} + \beta_1 * Shared_{it} * Thin\,File_{jt} + \epsilon_{ijt}\,. \quad (2)$$

[8] Restricting my analysis to firms with exactly two relationships does not affect my inferences.
[9] I examine both the first and subsequent *Shared* events for a given firm but find my main results are strongest when I restrict my sample to the first event.
[10] Clustering instead by firm strengthens the significance of my results.

As in (1), my tests compare outcomes across existing relationships only; hence β_1 can be positive, negative, or zero. When measuring the change in log credit, I collapse the pre and post periods into equal length two-year averages to address concerns about serial correlation. I Winsorize the change at −100% and +100% to prevent the logarithmic approximation from skewing my results.

To summarize, I study changes in relationship status and credit by exploiting the staggered entry of lenders to PayNet, and comparing changes across lenders to the same firm. Estimating my tests within firm-quarter makes it unlikely that firm-level developments at the time a lender joins, such as changes in their demand for credit or financial reporting environment, could explain my results. To account for lender selection into the bureau, I add lender-quarter fixed effects. This requires identifying off of a separate source of variation—differences in contract sizes across shared and private relationships—that plausibly moderates the effects of information sharing.

4.2 Information sharing, relationship survival, and outstanding credit

Table 4, Panel A, presents my main results. As an initial step, I omit lender-quarter fixed effects, which allows me to study a main effect for *Shared*. Column 1 shows that, without conditioning on contract differences, firms are 6.9% more likely to exit relationships shared in the bureau during the two years after sharing occurs. Column 2 finds an insignificant 3.5% decline in credit during the same period. Counterfactually shifting the *Shared* date back by two years and repeating these tests produces no effect for *Shared* (not tabulated for brevity).

Next, I add an interaction for *Thin File* but continue to omit lender-quarter fixed effects, which allows me to include a main effect for *Shared* to examine how much of the average effect documented in columns 1 and 2 comes from contract size disparities. Column 3 shows the coefficient on *Shared* is insignificant, whereas the interaction *Shared * Thin File* is positive and significant as predicted. This establishes that contract size differences influence the incremental effect of information sharing on shared over private contracts. Stated differently, when the shared and private contracts are of comparable size, the lender can use the shared contract as a proxy when attempting to exit the *private* contract and is ultimately no more likely to exit one than the other. Likewise, column 4 shows a significantly negative coefficient on *Shared * Thin File* for the change in credit, while the coefficient on Shared is insignificant.

In my subsequent tests, I add lender-quarter fixed effects and use equation (1) to address the possibility that lender business model changes drive my results. Using equation (1) in column 5, I find shared relationships that are distinct from private ones are 7.0% more likely to end over the next two years. This finding is economically significant considering the unconditional termination probability is 29%. Column 6 offers consistent evidence: over the four-year window, the average shared relationship sees a 6.3% decline in credit, compared to the firm's private credit relationship. The slight attenuation in *Shared * Thin File* from columns 3 and 4 to 5 and 6 indicates that not accounting for lender business-model shifts in voluntary information sharing settings could lead to an upward bias in the results.

I then perform several specification checks of my column 5 result. First, I consider a more holistic measure of contract differences across shared and private relationships. I create an indicator, *Dissimilar*, equal to 1 if (1) the shared and private relationships are for different collateral types, (2) the shared contracts are leases, whereas the private contracts are loans, or 3) *Thin File* equals 1.[11] Panel B, Column 1, finds a significantly positive coefficient on *Shared*

[11] Like *Thin File*, the contract type component of *Dissimilar* carries an asymmetric prediction for differences across shared and private relationships. Because leases generally require a smaller down payment than loans and are

* *Dissimilar*, parallel to my earlier result showing that contract size differences moderate the effects of information sharing on relationship survival. Second, I examine instances where the firm's shared contracts are more than twice as large as its private contracts—the opposite scenario as what my *Thin File* variable measures. Column 2 interacts a new variable for these instances, *Thick File*, with Shared, and finds a significantly negative coefficient. This provides supplemental evidence of how the sharing of one contract can create externalities for others, particularly when these other contracts are much smaller.

Third, I study whether the relationship turnover I document is sensitive to the number of lenders in the bureau. If the availability of borrower credit files is driving the relationship turnover, then it may take a sufficient base of members before I find any results. In column 3, I introduce *Membership*, an indicator for whether the quarter has at least a dozen lenders in the bureau at the *Shared* date. I find the effects of information sharing are concentrated in periods with more members.[12] Last, I extend my event window from two to four years to examine whether the effects of information sharing on relationship termination strengthen over time as old contracts mature and the firm has more opportunity to shop around with its credit file in the bureau. Because I require treated firms to also have a relationship with a lender that does not join during the event window, my sample size is smaller than in my original tests using a shorter window. Panel B, column 1, shows that, after four years, the shared relationship is 7.7% more likely to have ended than the firm's private dissimilar relationship. This result is slightly larger but not statistically different than the two-year window result.

offered to riskier firms, the sharing of a lease contract credit history should be more useful for shopping around on leases than loans.

[12] My inferences are similar if I measure the number of members instead of an indicator for larger membership base.

To further reinforce my main results, I now perform cross-sectional tests using equation (1) that examine whether the effects of information sharing depend on the characteristics of the firm and the content of their payment record as predicted by theory. First, I assign firms to quartiles according to their age and size, measured by their total contracts outstanding. The effects of information sharing are predicted to be strongest for younger, smaller borrowers because these firms are most opaque to outside lenders before their file is shared. Table 5 provides support for this prediction. Column 1 repeats the original result to facilitate comparison; in column 2, I find that the effect of information sharing is stronger for the youngest quartile of firms (age 7.7 years or younger) than the rest of the sample. Similarly, column 3 shows the smallest set of firms (less than $91,000 of contracts) experience relationship turnover at a nearly 90% greater rate than larger firms (p-value <0.01).

Next, I split my sample into three groups: firms revealed to have a clean, bad, or mixed credit record at the time their file is added to the bureau. Those with a clean record are current on all outstanding contracts and have not been late on any payment with the lender over the past three years. Those having defaulted (recorded in PayNet's system as a bankruptcy, legal action, repossession, collection, or write-off) or fallen more than 90 days behind on a payment at any point during the last three years are coded as having a bad record. The history of remaining borrowers is considered mixed, given the lack of a default but the experience of at least one payment falling between one and 90 days late. If the firm has a different track record across its lenders, I classify it according to the record being revealed in the bureau. According to this specification, 39% (12%, 49%) of firm-lender-quarter observations in my tests are assigned a clean (bad, mixed) record.

Column 4 shows my main results are strongest for firms with a perfect record or only modest delinquencies over the past three years. By comparison, firms with a bad payment record are no more likely to exit their shared than their private relationships, consistent with my predictions. Taken together, my cross-sectional tests in Table 5 show the effects of information sharing vary according to opacity and credit quality, initiating relationship turnover for young, small firms and those without major blemishes on their record.

4.3 Information sharing and new relationships

So far, my results suggest information sharing reduces switching costs by accelerating the termination of existing relationships, particularly for young or small firms and those with clean records. To bolster this evidence, I now explore how information sharing facilitates the formation of new relationships. Table 6 compares the likelihood of a firm establishing a new relationship in the two years before versus after their credit files are available in the bureau. I collapse the pre and post periods into single observations for each firm (so the unit of observation is firm-post). I include firm fixed effects, which, given the collapsed design, absorb any time effect associated with the period the file first enters the bureau, and cluster standard errors according to the quarter in which the firm's credit file is first available.

Similar to my prior tests, this test exploits the fact that I can observe all of the firm's credit relationships with PayNet members, even those that join the bureau long after the relationship began. However, unlike my prior tests, I cannot apply equation (1), because the unit of observation is firm-post, and my dependent variable contains measurement error because I cannot observe new relationships with lenders that never join PayNet. Accordingly, the results are not directly comparable with those in Tables 4 and 5.

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Column 1 reveals a statistically significant incremental likelihood of contracting with a new lender in the two years after the borrower's information is first made available. The 5.8% increase is economically significant, considering only 25% of firms begin a new relationship in the pre period. Next, I attribute this new relationship formation to the bureau in two ways. First, I introduce an interaction between *Post* and *Membership* in column 2, and find new pairs are only being formed once the bureau has reached an ample base of participating lenders. Second, I study new firm-lender matches and find nearly two-thirds of firms' new relationships in the two-year *Post* window are with participating lenders.

Columns 3–5 test whether firm age, size, and credit history influence the effect of information sharing on new relationships. On one hand, I do not find young firms are any more likely to establish new relationships than old firms. On the other hand, column 4 shows that whether a firm starts a contract with a new lender depends on firm size: only small firms are initiating new relationships. Finally, I find a positive and significant effect for firms with perfect payment histories, compared to no effect for firms that have experienced any form of payment problem (*Post* + *Post* * *Clean Record* is positive and significant at the 1% level). These results complement my prior findings: information sharing leads to both the termination of existing relationships and the formation of new ones, and bureau membership explains this behavior.

5. Information sharing and relationship lending

5.1 Information sharing and the terms of credit

Are lenders less willing to foster credit relationships once they agree to share the terms on which they provide financing and their borrowers' payment records? The literature presents conflicting perspectives on this question. To summarize, relationships could either become less profitable because borrowers are more capable of fleeing (Petersen and Rajan 1995; Gehrig and Stenbacka 2007), or more profitable because they allow lenders to differentiate themselves (Boot and Thakor 2000).

My final tests examine how lenders' relationship focus is influenced by information sharing, in two ways. First, a lender may contract differently with a new firm when this firm's credit file is available to others. Reducing maturity can constrain borrower-lender conflicts of interest (Myers 1977; Barclay and Smith 1995; Costello and Wittenberg-Moerman 2010); alternatively, the lender can engage in costly monitoring (Diamond 1991). The value of information the lender accumulates through monitoring increases with the likelihood that it will contract with the borrower again (Chan et al. 1986). Also, there are fewer opportunities for the lender to gather and use firm-specific information when contract maturity is shorter, all else equal (Mian 2006). Together, these arguments suggest lenders could rely more on the payment schedule (maturity and frequency) when contracting with new firms whose files are available to others.

My tests apply the following difference-in-differences specification:

$$Y_{ijt} = \alpha_{jt} + \alpha_{ijt}^{type} + \beta_1 * New\ Relationship_{ijt} + \beta_2 * New\ Relationship_{ijt} * Post_{jt} + \epsilon_{ijt}. \quad (3)$$

The dependent variable is equal to the natural log of maturity, payment frequency, or average contract size. If more than one contract is outstanding for the firm-lender pair, I take the dollar-weighted terms of the contracts. *New Relationship* is an indicator equal to 1 for pairs contracting together for the first time, while *Post* is an indicator equal to 1 for contracts originated after the firm's information is first available in the PayNet system. I restrict the sample to firm-quarters in which the firm started a new relationship and include the contract terms for both the current and new relationships (where the contract terms are not missing). The unit of observation is firm-lender-contract type-quarter. The tests include firm-quarter and contract-type fixed effects; hence I am comparing the terms of the new contract(s) at initiation to those for the existing contract(s) with other lenders at the same point in time (first difference) and for the period after versus before the firms' credit record was in the system (second difference). Unlike (1), these tests omit lender-quarter fixed effects because I am seeking changes in lender contracting that accompany information sharing.

Table 7 shows that, on average, in new relationships, the firm's contracts are smaller. For relationships initiated after the firm's information has been shared in the bureau, terms differ in two ways. Contract maturity shortens by an economically and statistically significant 5.1%, while payment frequency increases by 2.1%. These results are noteworthy given the boilerplate nature of such terms in equipment financing: contract maturity is linked to the life of the asset, and payment frequency has limited variation in my sample. Columns 3 shows the typical contract size is no different. In sum, although deciphering the welfare implications of these changes in terms is difficult, I note the *mix* of terms supports a transition away from relationship lending and toward transactional lending. Contracts have shorter terms and require more regular payments.

5.2 Information sharing and contract renewals after delinquencies

The second aspect of relationship lending I examine is the provision of credit to firms experiencing payment problems. Originations in these cases represent costly actions to the lender for multiple reasons. Missed payments present an early warning signal that borrowers will default on their obligations altogether; offering additional credit intensifies lenders' exposure to these risky firms. Poorly performing loans also often require more careful scrutiny and visits to borrowers' premises, reducing the human and financial resources that can be deployed elsewhere (Doblas-Madrid and Minetti 2013). Moreover, for banks, delinquent firms increase regulatory costs by attracting closer attention from examiners. Lastly, missed payments and loan losses reduce cash flows and can provoke liquidity problems. Although late payments impose costs on lenders, contract renewals occur regularly because borrowers' performance often improves—the young, delinquent firms of today often grow into mature, stable firms.

I examine contract renewal decisions using the following linear probability specification:

$$Y_{ijt} = \beta_1 * Post\ Join_{it} + \alpha_{ij} + \epsilon_{ijt}\ . \tag{4}$$

The dependent variable takes two forms. The first is an indicator for whether the lender initiated a new contract with the firm at any point in the three years after a serious delinquency, defined as a default event or a payment more than 90 days late. I also employ a second variable for whether the pair initiates a new contract in the three years following a non-serious delinquency, defined as any contract falling between one and 90 days behind but not experiencing a default. Conditioning on delinquency severity helps me control for changes in borrower payment behavior that can accompany information sharing (Doblas-Madrid and Minetti 2013). If I further classify non-serious delinquencies according to whether they are 30 days or less, 31 to 60 days, or 61 to 90 days I find similar results within each group. *Post Join* is an indicator for renewal decisions occurring after the lender has joined the bureau.[13] I include relationship (firm-lender pair) fixed effects, which control for time-invariant firm and lender characteristics, the forces behind the matching of the pair, and whether the relationship is for leases, loans, or both.

[13] I omit observations after the second quarter of 2011, given that I do not observe the full three-year post period for these observations.

To address concerns about serial correlation in renewal decisions within a lending relationship, I cluster my standard errors at the relationship level and run additional tests using a collapsed sample. The unit of observation is firm-lender-quarter, and the sample is restricted to the three years following the respective delinquency type. Unlike my main tests, the specification does not require only studying firms with multiple lenders.

Table 8, Panel A, presents descriptive statistics for renewal decisions and the evolution of firms' records after a delinquency. I find 9,918 (43,372) relationships have experienced a serious (non-serious) delinquency; in 4,593 (21,169) instances, the parties subsequently originate a new contract. Firms' payment performance often improves following even the most adverse events: for those experiencing a serious delinquency, the firm later goes three consecutive years without missing a single payment in 2,635 cases and with only non-serious delinquencies in another 2,891 cases.

Table 8, Panel B, presents the results. Column 1 shows a statistically significant 8.7% reduction (representing 31% of the pre-period mean) in the likelihood of renewal after a serious delinquency occurring once the lender has joined the bureau. Column 2 shows a similarly significant reduction (26% of the sample mean) in renewal following less serious delinquencies after the lender is sharing information. In columns 3 and 4, I collapse the observations for each lender into single pre- and post-join periods, retaining singletons, to mitigate concerns about serial correlation overstating the significance of my prior results. I continue to find an economically meaningful effect of information sharing on renewal decisions. Overall, these findings complement my contract-term analysis in documenting a second channel through which information sharing influences lenders' relationship investment decisions: fewer contract renewals occur following missed payments.

5.3 Discussion

The preceding analyses of renewal decisions offer evidence consistent with information sharing lowering informational rents and reducing relationship investments. Nevertheless, I interpret these tests with caution for two reasons. First, my results are also in line with lenders being concerned about information sharing inducing a coordination problem with other creditors to the firm (Hertzberg et al. 2011). Specifically, if a lender has negative private information about a firm that its other creditors are not aware of, information sharing can spur a run and reduce the firm's ability to borrow.

Table 9 presents analyses attempting to disentangle these competing explanations. First, columns 1 and 2 analyze cases in which information sharing reveals disagreement among lenders and offer support for the Hertzberg et al. hypothesis: new originations decline with bureau membership when lenders hold differing views of a firm's recent payment history. Next, to examine whether a coordination problem is the *only* force explaining the decline in contract renewals, I repeat my renewal analysis but first restrict the sample to instances in which the information sharing does *not* reveal a disagreement among lenders to the same firm and, second, to single-relationship firms.[14] The coordination problem modeled by Hertzberg et al. is not predicted to emerge in such cases. Columns 3 and 4 show that, when creditors share a similar view of the firm's credit history, a significant decline in renewals occurs after both serious and moderate delinquencies. Likewise, columns 5 and 6 show a material drop in post-delinquency financing for single-relationship firms. My results suggest coordination is a plausible channel for reducing post-delinquency financing but not the only channel.

[14] I measure disagreement among lenders whether or not they are bureau members at the time one joins; my results are similar if I examine only cases in which disagreement is among bureau members.

A second limitation is that firms are likely aware of their payment record being shared in this setting (Doblas-Madrid and Minetti 2013). Therefore they may take steps to avoid delinquencies, such as shifting payment problems onto other relationships that are not shared in PayNet (e.g., trade credit, commercial mortgages, or the owner's personal debts). Then, the delinquencies I observe after the lender joins could fundamentally differ from the pre-entry delinquencies. Addressing this concern is difficult without observing the firms' relationships with lenders that are not part of the bureau or without a clear sense of whether they are aware of their payment record being shared. In light of this concern, I interpret my contract renewal results with caution. Future research in settings with firm identities and universal coverage of lending relationships can better examine this possibility.

6. Conclusion

I examine how information sharing affects the survival of credit relationships, the creation of new ones, and lenders' willingness to invest in relationships. Despite the pervasiveness of lender-to-lender reporting in credit markets and a rich theoretical literature on relationship lending, evidence documenting these effects is scarce. I fill this gap using a panel of borrowers' credit files that detail their contracting activity and payment performance with lenders that join the PayNet bureau in a staggered pattern over more than a decade. This setting allows me to examine relationship and contracting dynamics while accounting for firm- and lender-time effects, because firms have distinct credit relationships with multiple lenders that must provide both ongoing and past contracts upon joining. The typical firm the bureau covers is opaque and repeatedly contracts with the same lender, providing a suitable setting to examine the effects of information sharing on relationship lending.

I find information sharing significantly reduces switching costs for firms, enabling both the exit from longstanding relationships and the formation of new relationships with other lender-members of the bureau. However, this effect is not uniform across the sample. Consistent with theory, young, small firms are most likely to abandon their current lender once their credit file is available in the bureau. I also show borrowers revealed to have records without recent serious delinquencies are most likely to be able to contract with outside lenders for the first time, whereas those with poor credit histories are most likely to stay with their existing lenders.

Finally, I demonstrate that a reduction in switching costs for borrowers has two important implications for how lenders contract once they have committed to sharing information. Lending becomes more transactional and less relationship-based: for contracts with new borrowers whose credit files are available to other members, maturities are shorter, and payment frequency increases. After they join the bureau, lenders are less likely to originate new contracts with borrowers that run into payment trouble. Coordination problems do not appear to be the primary driver of this outcome, because I find my results hold when lenders have similar information about the firm's credit risk and for single-relationship firms.

By offering contract-level evidence of the effect of information sharing on relationship dynamics and investment, my paper documents the nuanced effects of transparency-improving financial technologies on credit access. On the one hand, I highlight how credit file availability improves access to finance by enabling opaque firms with clean payment histories to form new lending relationships. On the other hand, the greater transparency jeopardizes the rents from relationship lending, shortening the maturity of new contracts and reducing lenders' propensity to extend credit to firms experiencing payment problems. These results are relevant to academics and policymakers concerned with how private firms access credit, and to the literature examining the effects of transparency-improving technologies and regulations in credit markets (Powell et al. 2004; Mian 2012; Ertan et al. 2016; Breuer et al. 2016).

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Appendix A: Illustrative Credit File

I provide an excerpt of the firm information, contract terms, and payment performance details in an illustrative credit file in my sample.

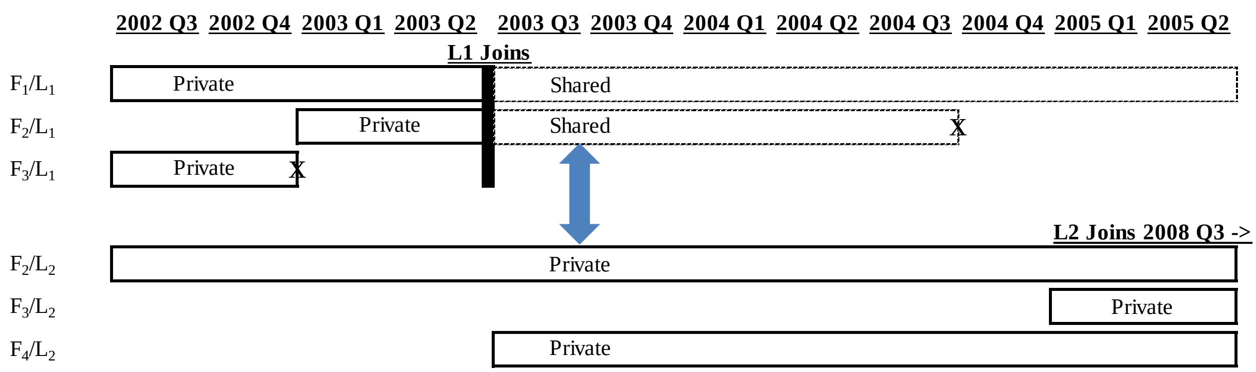
Firm ID	As of	SIC	Age	State	Contract ID	Lender ID	Asset Type	Contract Type	Guarantor	Start	Term	Amount	Balance	Avg Days Past Due	Max Days Past Due
X---04	1-Oct-06	5013	8	NV	5732952	X--25	MFG	Loan	NO	8-Jul-06	42	$64,562	$59,951	15	15
X---04	1-Jan-07	5013	8	NV	5732952	X--25	MFG	Loan	NO	8-Jul-06	42	$64,562	$55,339	11	15
X---04	1-Apr-07	5013	8	NV	5732952	X--25	MFG	Loan	NO	8-Jul-06	42	$64,562	$50,728	6	15
X---04	1-Jul-07	5013	8	NV	2059534	X--53	TRCK	Loan	NO	6-Apr-07	36	$201,128	$184,368	4	11
X---04	1-Jul-07	5013	8	NV	5732952	X--25	MFG	Loan	NO	8-Jul-06	42	$64,562	$46,116	4	15
X---04	1-Oct-07	5013	9	NV	5732952	X--25	MFG	Loan	NO	8-Jul-06	42	$64,562	$41,504	3	15
X---04	1-Oct-07	5013	9	NV	2059534	X--53	TRCK	Loan	NO	6-Apr-07	36	$201,128	$167,607	3	11
X---04	1-Oct-07	5013	9	NV	7705932	X--25	MFG	Loan	NO	14-Jun-07	60	$27,222	$25,861	0	0
X---04	1-Jan-08	5013	9	NV	2582722	X--53	COMP	Loan	NO	17-Oct-07	36	$3,267	$2,994	11	11
X---04	1-Jan-08	5013	9	NV	2059534	X--53	TRCK	Loan	NO	6-Apr-07	36	$201,128	$150,846	2	11
X---04	1-Jan-08	5013	9	NV	7705932	X--25	MFG	Loan	NO	14-Jun-07	60	$27,222	$24,460	0	0
X---04	1-Jan-08	5013	9	NV	5732952	X--25	MFG	Loan	NO	8-Jul-06	42	$64,562	$36,893	3	15

Appendix B: Variables Definitions

Treatment Variables	Description
Shared	An indicator equal to 1 for borrower-lender pairs in which the lender joined the bureau that quarter. For other pairs involving the same borrower but a different lender joining in a different quarter, the indicator is set equal to 0. The indicator is recorded as missing if none of the borrower's lenders join the bureau that quarter (no treatment that quarter). To prevent overlapping event windows from biasing my results, I also omit pairs in which the join dates occur in the event window being examined in the regression. The date at which the lender joined the credit bureau is defined as the date the lender first queried a credit report in the PayNet system.
New Relationship	An indicator equal to 1 for borrower-lender pairs originating a contract for the first time that quarter, and 0 for the firm's existing relationship(s). The indicator is recorded as missing if the borrower does not start a new relationship that quarter (no treatment that quarter).
Post	An indicator equal to 1 for the period after the borrower's credit file is first available in the bureau, and 0 otherwise.
Post Join	An indicator equal to 1 for the period after the lender has joined the bureau, and 0 otherwise.
Partitioning Variables	**Description**
Thin File	An indicator equal to 1 for shared relationships that are for less than half the amount of credit than the same firm's private relationships, and 0 otherwise.
Thick File	An indicator equal to 1 for shared relationships that are for more than double the amount of credit than the same firm's private relationships, and 0 otherwise.
Dissimilar	An indicator measuring how much the firm's shared and private lending relationships differ from one another. The indicator equals 1 if either Thin File equals 1, the shared and private relationships involve different collateral types, or the shared contract is for a lease while the private contracts are loans, and 0 otherwise.
Membership	An indicator equal to 1 for quarters with at least 12 bureau members, and 0 otherwise.
Clean Record	Borrowers that are current on all outstanding contracts and have not been late on any payment with the lender over the past three years.
Bad Record	Borrowers that defaulted (recorded in PayNet's system as a bankruptcy, legal action, repossession, collection, or write-off) or have fallen more than 90 days behind on a payment at any point during the last three years.
Mixed Record	Borrowers that have not defaulted but have fallen behind on a payment by between one and 90 days at any point in the last three years.

Figure 1: Research Design

This figure illustrates the research design for Table 4. Firms and lenders are labeled F and L, and a relationship is labeled F#/L#. An 'X' marks the end of the relationship. Lender 1 (L1) joins the bureau at the beginning of 2003 Q3, and Lender 2 (L2) joins at the beginning of 2008 Q3 (not illustrated for simplicity). A relationship is defined as private before the lender joins the bureau, and shared after. By including firm-quarter fixed effects, my tests compare the probability of relationship termination across the same firm's shared and private relationships during the same period. For example, when L1 joins at the beginning of 2003 Q3, my tests compare the probability of relationship termination between 2003 Q3 through 2005 Q2 for F2/L1 and F2/L2. The coding for my dependent (Exit Relationship after 2 years) and independent (Shared) variables for these two pairs is provided below the illustration. These variables are only measured once, in 2003 Q3, for the L1 joining event.



Coding for Exit Relationship after 2 years	2003 Q3
F2/L1	1
F2/L2	0
Coding for Shared	
F2/L1	1
F2/L2	0

Table 1: Sample Selection and Descriptive Statistics for Contracts

This table presents the sample selection (Panel A), descriptive statistics (Panel B), and equipment types (Panel C) for observations used in my main tests. See Appendix B for variable definitions.

Panel A: Sample Selection	*# Contracts*
Initial Observations	531,451
Eliminate contracts missing contract amounts and/or maturity information	(28,479)
Eliminate contracts from lenders with only partial sample observations	(30,983)
Eliminate contracts not spanning the event window in main tests	(206,990)
Final Sample	264,999

Panel B: Descriptive Statistics for Contracts

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
Loan Contract	16.5%	37.1%	0.0%	0.0%	0.0%	264,999
Lease Contract	83.5%	37.1%	100.0%	100.0%	100.0%	264,999
Contract Amount (dollars)	130,045	691,796	8,750	25,740	87,316	264,999
Contract Term (months)	45.7	17.0	36.0	48.0	60.0	264,999
Payment Frequency (times per year)	11.5	2.3	12.0	12.0	12.0	250,590
Contract Always Paid on Time	39.9%	49.0%	0.0%	0.0%	100.0%	264,999
Worst Delinquency for Contract: Late by <=30 days	23.0%	42.1%	0.0%	0.0%	0.0%	264,999
Worst Delinquency for Contract: Late by 31-60 days	19.3%	39.4%	0.0%	0.0%	0.0%	264,999
Worst Delinquency for Contract: Late by 61-90 days	7.9%	27.0%	0.0%	0.0%	0.0%	264,999
Worst Delinquency for Contract: Late by >90 days	9.8%	29.7%	0.0%	0.0%	0.0%	264,999
Maximum Days Past Due	31.5	70.4	0.0	9.0	32.0	442,742

Panel C: Contract Count by Equipment Type

Equipment Type	*# Contracts*	*% of Total*	*$-Weighted*
Agricultural	11,942	4.5%	3.0%
Aircraft	233	0.1%	2.4%
Automobiles	1,633	0.6%	0.3%
Boats	56	0.0%	0.5%
Buses & Motor Coaches	529	0.2%	0.4%
Construction & Mining	35,535	13.4%	20.8%
Computer	19,038	7.2%	12.0%
Copier & Fax	93,670	35.3%	5.5%
Energy	29	0.0%	0.1%
Forklift	13,698	5.2%	2.0%
Logging & Forestry	666	0.3%	0.3%
Medium/Light Duty Trucks	9,788	3.7%	2.6%
Medical	3,212	1.2%	3.5%
Manufacturing	3,399	1.3%	3.7%
Office Equipment	2,594	1.0%	0.6%
Printing & Photographic	816	0.3%	1.1%
Railroad	231	0.1%	2.1%
Real Estate	75	0.0%	0.4%
Retail	4,577	1.7%	1.9%
Telecommunications	6,845	2.6%	1.2%
Truck	45,866	17.3%	29.3%
Unknown	9,044	3.4%	5.7%
Vending	1,104	0.4%	0.2%
Waste & Refuse Handling	419	0.2%	0.4%
Total	264,999	100.0%	100.0%

Table 2: Descriptive Statistics for Firms and Lenders

This table presents descriptive statistics for firms and lenders in my main tests. All figures are derived from within-firm or lender averages of quarterly observations. Lender figures reflect only the relationships with firms in my sample. See Appendix B for variable definitions.

Panel A: Descriptive Statistics for Firms

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
Firm Size (total contracts outstanding, in dollars)	1,497,634	5,465,280	90,202	259,289	846,888	4,416
Age (years)	10.3	3.8	7.7	9.9	12.5	4,416
Number of Contracts Outstanding	12.7	56.2	3.0	4.1	8.9	4,416
Number of Types of Equipment Being Financed	11.2	8.2	6.0	9.0	13.7	4,416

Panel B: Descriptive Statistics for Lenders

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
Average Contract Amount	217,277	309,198	42,602	90,241	257,538	68
Average Number of Open Contracts	567.0	941.9	29.1	149.4	698.1	68

Table 3: Descriptive Statistics for Relationships

This table presents descriptive statistics for firm-lender relationships for observations used in my main tests.

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
Relationship Length at Contract Origination (years)	6.8	5.3	2.4	6.0	10.7	264,999
Relationship Ends within Next Two Years	28.9%	45.3%	0.0%	0.0%	100.0%	26,503
Relationship Ends within Next Four Years	52.4%	49.9%	0.0%	100.0%	100.0%	13,401

Table 4: Relationship Dynamics and Changes in Credit around Lenders' Bureau Entry

This table presents OLS regressions examining the change in relationship status and credit outstanding for relationships around the time a lender joins the bureau. In Panel A, the dependent variable in columns 1, 3, and 5 (2, 4, and 6) is an indicator for whether the borrower exits the relationship within two years of the join quarter (the change in credit during the four years surrounding the join quarter). Shared is an indicator equal to 1 for relationships shared in the bureau and 0 for the firm's private relationships. Thin File is an indicator equal to 1 for shared relationships that are for less credit than the same firm's private relationships. In Panel B, the dependent variable in columns 1–4 is an indicator for whether the borrower exits the relationship within either two or four years of the join quarter. Dissimilar is an indicator equal to 1 if Thin File equals 1, or if the firm's shared and private relationships involve different contract types or collateral. Thick File is an indicator equal to 1 for shared relationships that are for at least twice as much credit as the same firm's private relationships. Membership is an indicator equal to 1 for quarters with at least 12 bureau members. See Appendix B for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the quarter-year level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

Panel A: Relationship Dynamics and Changes in Credit

	(1) Exit Relationship after 2 years	(2) Δ Log Credit 4-year window	(3) Exit Relationship after 2 years	(4) Δ Log Credit 4-year window	(5) Exit Relationship after 2 years	(6) Δ Log Credit 4-year window
Shared	0.069***	-0.035	0.018	0.018		
	[3.32]	[-1.22]	[0.62]	[0.51]		
Shared * Thin File			0.079***	-0.082***	0.070***	-0.063**
			[3.58]	[-3.85]	[2.87]	[-2.37]
Adj R2	0.077	0.057	0.079	0.058	0.190	0.123
N	26,503	26,503	26,503	26,503	26,503	26,503
Fixed Effects	Firm-Quarter Contract Type	Firm-Quarter Contract Type	Firm-Quarter Contract Type	Firm-Quarter Contract Type	Firm-Quarter Lender-Quarter Contract Type	Firm-Quarter Lender-Quarter Contract Type
Clustering	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year

Panel B: Contract Differences, Bureau Composition, and Long-Run Exits

	(1)	(2)	(3)	(4)
	Exit Relationship after 2 years	Exit Relationship after 2 years	Exit Relationship after 2 years	Exit Relationship after 4 years
Shared * Dissimilar	0.114***			
	[3.14]			
Shared * Thick File		-0.130***		
		[-5.80]		
Shared * Thin File			0.010	0.077***
			[0.72]	[3.59]
Shared * Thin File * Membership			0.083**	
			[2.59]	
Adj R2	0.191	0.190	0.191	0.262
N	26,503	26,503	26,503	13,401
Fixed Effects	Firm-Quarter	Firm-Quarter	Firm-Quarter	Firm-Quarter
	Lender-Quarter	Lender-Quarter	Lender-Quarter	Lender-Quarter
	Contract Type	Contract Type	Contract Type	Contract Type
Clustering	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year

Table 5: Firm Opacity, Credit History, and Relationship Dynamics around Lenders' Bureau Entry

This table presents OLS regressions for cross-sectional analyses of the change in relationship status for firms after one of their lenders joined the bureau. The dependent variable in columns 1–4 is an indicator for whether the borrower exits the relationship within two years of the join quarter. Column 1 repeats the original result from Table 4, Panel A, column 5 to facilitate comparison. Columns 2–4 add interactions for the firm's age, size, and credit record. Young and Small are indicators equal to 1 for firms in the lowest quartile of age and size, respectively. Clean Record and Mixed Record are indicators equal to 1 for firms with a credit record of no or only moderate delinquencies in the past three years, respectively. See Appendix B for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the quarter-year level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	(1) Exit Relationship after 2 years	(2) Exit Relationship after 2 years	(3) Exit Relationship after 2 years	(4) Exit Relationship after 2 years
Shared * Thin File	0.070***	0.037	0.064**	-0.044
	[2.87]	[1.22]	[2.68]	[-1.42]
Shared * Thin File * Young		0.172***		
		[8.61]		
Shared * Thin File * Small			0.123***	
			[3.56]	
Shared * Thin File * Clean Record				0.138***
				[8.80]
Shared * Thin File * Mixed Record				0.128***
				[5.11]
Adj R2	0.190	0.195	0.191	0.192
N	26,503	26,503	26,503	26,503
Fixed Effects	Firm-Quarter Lender-Quarter Contract Type	Firm-Quarter Lender-Quarter Contract Type	Firm-Quarter Lender-Quarter Contract Type	Firm-Quarter Lender-Quarter Contract Type
Clustering	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year

Table 6: New Relationships After the Firm's Credit File Is Available in Bureau

This table presents OLS regressions examining the change in probability that a firm establishes a new relationship from the period before to the period after its credit file is available in the bureau. The dependent variable in columns 1–5 is an indicator for whether the firm starts a new relationship during the four-year window. All observations are collapsed into two-year pre and post periods for the firm around the time its credit file is first available in the bureau. Columns 2–5 include interactions for the pool of bureau members and the firm’s age, size, and credit record. Membership is an indicator equal to 1 for quarters with at least 12 bureau members. Young and Small are indicators equal to 1 for firms in the lowest quartile of age and size, respectively. Clean Record and Mixed Record are indicators equal to 1 for firms with a credit record of no or only moderate delinquencies in the past three years, respectively. See Appendix B for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered according to the quarter-year when the firm’s credit file is first available in the bureau. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	(1) New Relationship 4-year window	(2) New Relationship 4-year window	(3) New Relationship 4-year window	(4) New Relationship 4-year window	(5) New Relationship 4-year window
Post	0.058**	-0.010	0.063**	-0.048***	0.056
	[2.65]	[-1.43]	[2.42]	[-3.74]	[1.33]
Membership		-0.029			
		[-1.19]			
Post * Membership		0.108***			
		[4.08]			
Post * Young			-0.016		
			[-1.01]		
Post * Small				0.253***	
				[8.48]	
Post * Clean Record					0.019
					[0.69]
Post * Mixed Record					-0.040*
					[-1.71]
Adj R2	0.208	0.212	0.208	0.246	0.209
N	22,304	22,304	22,304	22,304	22,304
Fixed Effects	Firm	Firm	Firm	Firm	Firm
Clustering	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year
Sample	Collapsed	Collapsed	Collapsed	Collapsed	Collapsed

Table 7: Contract Terms for Firms Starting New Relationships

This table presents OLS regressions examining whether firms get different contract terms relative to existing contracts when they initiate a new relationship after their credit file is available in the bureau. When more than one contract is outstanding between the firm and lender, I use the dollar-weighted average terms of the contract. New Relationship is an indicator equal to 1 for firm-lenders pair contracting for the first time. Post is an indicator for the period after the firm's credit file is first available in the bureau. See Appendix B for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the quarter-year level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	(1) Log Maturity	(2) Log Payment Frequency	(3) Log Average Contract Size
New Relationship	0.002	-0.005	-0.299***
	[0.15]	[-0.66]	[-10.44]
New Relationship * Post	-0.051***	0.021**	0.015
	[-3.00]	[2.36]	[0.40]
Adj R2	0.297	0.647	0.200
N	132,231	127,484	132,231
Fixed Effects	Firm-Quarter	Firm-Quarter	Firm-Quarter
	Contract Type	Contract Type	Contract Type
Clustering	Quarter	Quarter	Quarter

Table 8: Delinquencies and Contract Renewals in the Information Sharing Regime

Panel A presents descriptive statistics for delinquencies, tabulates whether the lender originates a new contract with the firm after the delinquency, and tabulates whether the firm's record improves or deteriorates after the delinquency. A serious (non-serious) delinquency marks the firm with a bad (mixed) record for three years. Panel B presents OLS regressions of the incidence of financing after a delinquency on an indicator for the period after the lender joined the bureau and relationship (firm-lender pair) fixed effects. The dependent variable in columns 1 and 3 (2 and 4) is an indicator equal to 1 if the firm and lender initiate a new contract in the three years after a serious (non-serious) delinquency. Columns 3 and 4 collapse all observations into a single pre- and post-join period for the firm-lender pair. Post Join is an indicator equal to 1 for quarters after the lender has joined PayNet. See Appendix B for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the relationship (lender-firm) level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

Panel A: Descriptive Statistics

	Serious Delinquency	Non-Serious Delinquency
Firm-Lender Pairs with delinquency type	9,918	43,372
Renewal occurs within 3 years after delinquency	4,593	21,169
Firm subsequently improves to having perfect record with lender for 3 years	2,635	17,687
Firm subsequently improves to having mixed record with lender for 3 years	2,891	
Firm subsequently deteriorates to having serious delinquency		4,906

Panel B: Contract Renewals after Delinquencies

	(1) Renewal after Serious Delinquency	(2) Renewal after Non-Serious Delinquency	(3) Renewal after Serious Delinquency	(4) Renewal after Non-Serious Delinquency
Post Join	-0.087***	-0.089***	-0.056***	-0.041***
	[-5.76]	[-16.38]	[-3.64]	[-6.82]
Adj R2	0.723	0.542	0.493	0.372
N	33,927	217,196	9,967	41,336
Fixed Effects	Relationship	Relationship	Relationship	Relationship
Clustering	Relationship	Relationship	Relationship	Relationship
Sample	Full	Full	Collapsed	Collapsed

Table 9: Coordination and Contract Renewal

This table presents OLS regressions of the incidence of financing after a delinquency on an indicator for the period after the lender joined the bureau and relationship (firm-lender pair) fixed effects. The dependent variable in columns 1, 3, and 5 (2, 4, and 6) is an indicator equal to 1 if the firm and lender initiate a new contract in the three years after a serious (non-serious) delinquency. Columns 1 and 2 (3 and 4, 5 and 6) restrict the sample to firm-lender pairs where information sharing reveals differences in the firm's credit history across lenders (does not reveal differences, single-relationship firms). Each test collapses all observations into a single pre- and post-join period for the pair. Post Join is an indicator equal to 1 for quarters after the lender has joined PayNet. See Appendix B for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the relationship (lender-firm) level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Renewal after Serious Delinquency	Renewal after Non-Serious Delinquency	Renewal after Serious Delinquency	Renewal after Non-Serious Delinquency	Renewal after Serious Delinquency	Renewal after Non-Serious Delinquency
	Disagreement	Disagreement	No Disagreement	No Disagreement	Single Relationship	Single Relationship
Post Join	-0.059***	-0.078***	-0.053**	-0.015*	-0.067***	-0.052***
	[-2.85]	[-8.91]	[-2.28]	[-1.85]	[-2.77]	[-5.80]
Adj R2	0.575	0.474	0.373	0.289	0.405	0.342
N	3,230	10,637	6,737	30,699	4,376	19,811
Fixed Effects	Relationship	Relationship	Relationship	Relationship	Relationship	Relationship
Clustering	Relationship	Relationship	Relationship	Relationship	Relationship	Relationship
Sample	Collapsed	Collapsed	Collapsed	Collapsed	Collapsed	Collapsed