Does Credit Reporting Lead to a Decline in Relationship Lending? Evidence from Information Sharing Technology

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MIT

2018

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March 2018

The online appendix is available at the end of this manuscript.

Abstract

I examine how credit reporting affects where firms access credit and how lenders contract with them. I use within firm-time and lender-time tests that exploit lenders joining a credit bureau and sharing information in a staggered pattern. I find information sharing reduces relationship-switching costs, particularly for firms that are young, small, or have had no defaults. After sharing, lenders transition away from relationship contracting, in two ways: contract maturities in new relationships are shorter, and lenders are less willing to provide financing to their delinquent borrowers. My results highlight the mixed effects of transparency-improving financial technologies on credit availability.

JEL Classification: D82; G21; G23; G30; G32; M41.
Keywords: Debt contracts; information sharing; information asymmetries; hard and soft information; credit bureaus; relationship lending; transactional lending; information economics; entrepreneurial finance; credit reports; credit scores, FinTech.

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* This paper was previously titled "The Economic Consequences of Borrower Information Sharing: Relationship Dynamics and Investment." I thank my dissertation committee for guidance and support: Christian Leuz (Chair), Phil Berger, Michael Minnis, and Amit Seru. I also thank Ray Ball, John Core, Joao Granja, Jose Liberti, Justin Murfin (discussant), Valeri Nikolaev, Daniel Paravisini, Haresh Sapra, Jason Sturgess, Rodrigo Verdi, Joseph Weber, Regina Wittenberg-Moerman, and workshop participants at the American Finance Association 2017 Annual Meeting, Columbia, Harvard Business School, Kellogg, MIT, New York University, Stanford, University of Chicago, Wharton, Yale, and especially an anonymous referee and Joanna Wu (editor) for helpful comments. I am grateful to PayNet for providing the data for this project. Any errors or omissions are my own. I gratefully acknowledge financial support from the Ernie Wish Fellowship, the University of Chicago Booth School of Business, and MIT.

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1. Introduction

Much of the information that lenders use to allocate credit—including preexisting debt, payment history, and collateral pledges—is shared among lenders by, for example, reporting to credit bureaus. How does this reporting affect where firms access credit and lenders' contracting strategies? The literature considers two distinct strategies. In a transactional strategy, the lender does not anticipate repeated interactions with the borrower and, as a result, seeks to at least break even on individual loans (Boot 2000; Berger and Udell 2006). By contrast, in the relationship strategy, a lender anticipates repeated dealings with the borrower and gathers information that can be used in future contracts. Relationship lenders often continue financing firms during crises or unprofitable periods, because losses can be recovered in subsequent contracts (Petersen and Rajan 1995; Bharath et al. 2011; Bolton et al. 2016). The lender's information advantage is central to this expectation: the borrower cannot easily switch lenders because outside creditors face an adverse-selection problem (Sharpe 1990; Dell'Ariccia and Marquez 2004).

Several ongoing developments motivate my study. First, recent research shows how credit scores—generated by lender-to-lender reporting—can substitute for financial statements in loan originations (Cassar et al. 2015). Second, advances in information technology have led to the expansion of information sharing in credit markets (World Bank 2005; 2016). Figure 1 shows that, since 2005, credit bureau coverage in the ten largest economies has grown by almost 20%. Third, many argue that the proliferation of credit scores has reduced lenders' incentives to collect soft information (for a discussion, see Liberti and Petersen 2017), which could reduce the provision of credit to firms experiencing temporary cash flow problems. However, empirical evidence supporting this assertion is limited, because few settings allow researchers to observe how relationships evolve with credit reporting.

In this paper, I examine a panel of quarterly credit files detailing firms' contracts and payment performance with lenders that join PayNet, a web-based bureau. PayNet was established in 2001 to serve the equipment finance sector, which funds 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 PayNet, lenders regularly originated contracts for construction, manufacturing, telecommunication, and other equipment without detailed credit histories (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 data that would aid their screening and monitoring of borrowers (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 information sharing affects credit relationships face a fundamental identification problem: separating the effects of sharing from contemporaneous shocks to the demand for credit. The structure of PayNet and the 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 current and past contract terms and repayment records. The sharing of past contracts by members provides a source of private contracts to use as controls. Additionally, most borrowers contract with multiple lenders that join at different times. This permits me to implement a within firm-time estimator to account for observable and unobservable firm-specific shocks that could otherwise contaminate my tests. 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 begin by studying 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 show that 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.

These initial tests support the idea that information sharing helps firms match with new lenders, but could also reflect selection bias. Specifically, lenders may decide to share in order to reduce delinquency rates (Padilla and Pagano 2000; Doblas-Madrid and Minetti 2013) or lower screening costs, particularly for unfamiliar applicants (Pagano and Jappelli 1993; Liberti et al. 2017). In less competitive credit markets, such gains need not be fully shared with borrowers. This raises concerns that if selection into information sharing is correlated with relationship turnover, then my findings may not stem from the greater availability of borrower information.

My main tests tackle such concerns about voluntary participation and directly link my findings to information availability, in several ways. First, I add lender-time fixed effects by exploiting within-borrower, across-relationship variation in contract sizes that is plausibly unrelated to selection into the bureau. Using lender-quarter fixed effects allows me to hold constant the lender's business model and decision to share information, and identify off of information-specific bureau and credit file characteristics outside the lender's control. Second, to reinforce that my findings reflect information availability, I study how my results vary with borrower opacity and default history. Third, I repeat my tests after omitting lenders undergoing business model changes before sharing that may be correlated with relationship turnover.

Contract sizes matter for information sharing. Lenders prefer knowing whether an applicant has previously serviced a similar liability (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). Consider a firm applying for a $100,000 loan with a new lender, Lender C. In the past, the firm has borrowed $30,000 from Lender A and $100,000 from Lender B. All else equal, the application is more likely to be approved if the firm has a "thick file"—a record of servicing the $100,000 loan from Lender B, as opposed to a "thin file"—a record of servicing only the $30,000 loan with Lender A. Staggered sharing by lenders, combined with rich variation in contract sizes across lenders to the same borrower, supports a quasi-natural experiment for examining the consequences of information sharing. According to the arguments above, the sharing of the borrower's largest contract allows that firm to shop around on both its shared *and* (smaller) private contract. On the other hand, the sharing of the borrower's smallest contract is less likely to trigger the termination of their larger contract.

My main results show that contract size differences moderate the effects of information sharing in a manner consistent with these predictions. When the firm's smaller relationship is shared (e.g., Lender A above shares), then this relationship is 6.1% more likely to end over the next two years than the firm's other relationship (with Lender B) remaining private. This finding is economically significant considering the stickiness of relationships in my setting. The two-year unconditional probability of relationship exit is 29%, and only one of six contracts is executed between borrowers and lenders contracting together for the first time. By comparison, sharing by the lender of the larger contract—Lender B—affects the survival of both relationships. This finding suggests information sharing by one lender creates an externality: firms use their shared track record to shop around on similar or smaller contracts with other creditors. I am not aware of other research documenting this externality.

Theory suggests any effects of information sharing will depend on the firm and its information environment. Sharing, for example, should most affect firms that are least likely to have financial statements or press coverage, since opacity can impede switching lenders (Petersen and Rajan 1994). I perform cross-sectional tests on my main results and find the effect of information sharing on relationship turnover is strongest for young, small firms. Information sharing likewise may impede firms with payment problems from switching, because outside lenders will not know what caused these problems. Using credit histories in my dataset, I show information sharing leads only borrowers with perfect records or minor delinquencies to leave their lenders. Last, I show the relationship turnover I document earlier increases with the number of bureau members.

In my next tests, I study whether, by reducing switching costs, information sharing compels lenders to transition away from relationship contracting. Relationship lenders may offer longer maturity contracts with less frequent payments, to provide flexibility to the borrower and allow time to gather borrower-specific information and earn rents on it (Chan et al. 1986; Mian 2006; Srinivasan 2014). I show that, after sharing information, the new relationships the lender establishes involve shorter maturity contracts with higher payment frequency.

Then, I examine whether joining the bureau changes lenders' willingness to originate new contracts with delinquent borrowers. Such renewals can be crucial to the survival of small firms, considering how frequently this segment encounters transitory cash shortfalls. Eighteen percent of sample firms experience at least one delinquency of over 90 days; 46% of the time the firm receives a new contract after the delinquency, and 27% of the time the firm never misses a single payment again for at least three years. 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 one-fifth of the pre-period average. I repeat my tests on a subsample of lenders maintaining similar portfolio exposures around their entry to the bureau, and in a subsample of firms with one member lender. Because my results survive, the decline in renewals is not likely explained by other business model changes or the coordination problem modeled in Hertzberg et al. (2011). Instead, my results are consistent with information sharing reducing the profits available from relationship lending.

I contribute to a broad literature debating the consequences of greater transparency in credit markets. Prior work has emphasized how transparency can reduce intermediation costs and information frictions that prevent lending. By contrast, my study provides evidence supporting Gehrig and Stenbacka's (2007) model of how transparency can reduce lenders' incentives to develop relationships with firms. Thus a consequence of the recent expansion in information sharing might be that delinquent borrowers—many of whom ultimately recover—will have more difficulty getting credit. In this way, my paper is also relevant to the literature examining how credit availability for some borrowers can worsen with bank competition (Petersen and Rajan 1995; Black and Strahan 2002; Rice and Strahan 2010; Srinivasan 2014).

I also add to the growing literature on how information asymmetry problems are addressed in the small commercial lending market. Researchers 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 the growing role of lender-to-lender reporting unaddressed. This gap is notable because many firms do not provide financial statements to their lenders (Allee and Yohn 2009;

Cassar et al. 2015; Minnis and Sutherland 2017), and that the spread of information sharing technologies may reduce requests for financial reports by banks. Supporting this, my results indicate that the small firms least likely to have audited financial statements are able to form new lending relationships once their credit file is shared.

While I focus on commercial lending, reporting technologies have also emerged in insurance and labor markets to permit principals to exchange the track records of agents.[1] 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 effects of principals sharing agents' records.

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

2. Theoretical framework and prior literature

Information sharing arises when lenders cannot efficiently screen and monitor with only firsthand knowledge of borrowers (Pagano and Jappelli 1993). A firm's credit history is

[1] For example, 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.

informative about its ability to service new contracts. Absent information sharing, lenders lack such a history for new credit applicants. Applicants may furnish evidence of a clean history (e.g., cancelled checks from payments on a prior loan), but the lender does not know whether less favorable information about other loans has been withheld. Efforts to verify a firm's self-reported credit history with a rival lender may be stymied by conflicts of interest (Padilla and Pagano 1997). Moreover, many private firms do not undergo costly audits attesting to the completeness of reported liabilities (Blackwell et al. 1998; Allee and Yohn 2009; Minnis 2011; Cassar et al. 2015; Lisowsky and Minnis 2016; Minnis and Sutherland 2017).

A lender's competitive environment influences their decision to share information. One potential cost of sharing is that making borrower contract and performance information available to rivals reduces borrower retention rates. This cost is increasing in the rents the lender earns from their existing relationships (Liberti et al. 2017), and can make relationship strategies less viable. A corresponding benefit of sharing is that gaining access to a rich set of information from other lenders reduces screening and monitoring costs (Hauswald and Marquez 2003), and facilitates transactional lending strategies. Thus, sharing not only reduces redundant information gathering efforts among lenders, but also allows lenders to compete more effectively by, for example, mitigating adverse-selection problems associated with establishing new relationships (Sharpe 1990; Liberti et al. 2017). By making payment performance widely known, sharing can also discipline borrower behavior and preclude hold-up problems, reducing the risk of lending (Jappelli and Pagano 2000; Padilla and Pagano 2000; Doblas-Madrid and Minetti 2013; Bennardo et al. 2015). Information sharing is common because such benefits, as well as those related to screening and monitoring efficiencies, are not competed away in an imperfectly competitive market.

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 in developing countries also detect increases in borrowing (Brown et al. 2009; Peria and Singh 2014). In the US, Liberti et al. (2017) find that firms increase borrowing once their credit file is first available in a bureau.

Many firms repeatedly borrow from the same lender and count on that relationship as a source of credit in bad times (Bharath et al. 2011; Lo 2014; Bolton et al. 2016; Cohen et al. 2016; Darmouni 2016). Although theory connects relationship lending strategies to information asymmetries between creditors (Gehrig and Stenbacka 2007), there is limited evidence on how information sharing affects credit relationships. Few settings allow researchers to observe how relationships evolve with information sharing. 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 a sample of predominantly opaque firms around the introduction of a credit bureau and observe which lenders provide them credit and the terms they receive. 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 afterward. Lenders publicly file Uniform Commercial Code-1 (UCC) financing statements to establish their legal right to reclaim collateral if the firm defaults on the loan or lease.[2] Loans and leases differ in other respects, including the expertise and services provided by the lender (Contino 1996; Murfin and Pratt 2015) and their tax, bankruptcy, and financial reporting treatment (FASB 2016).

The US equipment finance market, like the broader commercial credit market, is highly concentrated. The 10 largest lenders accounted 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

[2] Although lenders retain the legal title to leased assets after contract origination, they regularly make UCC filings for leases to prevent recharacterization in default (Contino 1996; Amato 2003; Murfin and Pratt 2015).

In 2001, PayNet, a commercial data provider, launched a bureau that would allow equipment financiers to obtain firm information via the internet for a nominal fee.[3] The bureau's launch and growth was spurred by several developments. First, advances in information technology beginning in the 1990s drastically reduced the cost of collecting, verifying, and sharing credit files in a timely, reliable manner (Jackson 2000). Second, a string of mergers and acquisitions in the financial sector in the 1990s and 2000s increased the market share of the largest lenders (ELFA 2004, 2011; Berger and Udell 2006). Lender size can be correlated with reliance on hard information (such as credit reports and scores) in underwriting (Berger et al. 2005). Third, equipment investment and financing volumes rose steadily from 2002 to 2008, as the US economy enjoyed sustained growth and low interest rates. In these conditions, the availability of credit reports and scores can facilitate expansion—either by de novo captives or incumbent lenders entering new territories.

The bureau operates on the principle of reciprocity: lenders may only participate by agreeing to share all past, present, and future credit files. Several features of PayNet's implementation and data collection process prevent misreporting.[4] First, before a lender can participate, PayNet establishes direct access into its accounting systems. Lenders must undertake the efforts and investments necessary for its IT systems to reach compatibility with PayNet's secure interface (Jackson 2001), and undergo extensive audits and testing to ensure their IT systems support complete and accurate information sharing (Doblas-Madrid and Minetti 2013). According to PayNet, the required improvements and testing take anywhere from six weeks to one year.

[3] Current pricing information is confidential; however, an industry magazine article from 2000 states members could access a firm's credit file for as little as $5 (Jackson 2000).
[4] Section A of the online appendix provides additional detail about these features.

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, help verify the completeness of shared information. Third, upon joining PayNet, lenders sign an agreement giving PayNet the right to bar them from the database and pursue damages in the event of misreporting.

These bureau features inhibit the manipulation or withholding of information.[5] Nevertheless, the researcher cannot know whether misreporting occurs or its extent. One possibility is that, if a lender chooses to misreport and manages to evade detection, it is most likely to withhold information about clients inclined to switch. Such a scenario would make it more difficult for me to detect an effect of information sharing on relationship turnover.

Members are prohibited from using the bureau for direct marketing or mining client lists, and lenders are anonymous in PayNet credit files (Jackson 2000). Anonymity prevents lenders from constructing a profile of one another's client base or terms offered, which reduces the proprietary cost concerns about participating. Lenders typically access the system when receiving a credit application from a new borrower or when considering a contract renewal. 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

[5] For example, PayNet's data collection and credit score estimation processes help prevent the form of misreporting documented in the Argentinean registry (Giannetti et al. 2017). In that setting, the registry simply *redistributes* credit scores *reported* by lenders, without any means of accessing or auditing lenders' accounting systems.

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 update indebtedness and contract performance information on a weekly basis. Second, the bureau provided contract-level information that was more relevant, detailed, and verified than competing sources. 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 larger, long-term credit applications (Jackson 2001; Doblas-Madrid and Minetti 2013).

In the US, lenders are not legally required to obtain permission from commercial borrowers before reporting their information to a credit bureau.[6] As a result, in my setting, information sharing is exogenous to the borrowers. Although multiple industry publications covered PayNet's launch and conversations with PayNet indicate many lenders notify borrowers of their joining to comply with privacy agreements, my tests do not require borrowers to even be aware of PayNet's

[6] By comparison, under the Fair Credit Reporting Act, US *consumers* are afforded some rights surrounding the reporting of their credit information (OCC 1996). For example, consumers must be notified when their information is reported to a credit bureau, have the right to correct incomplete or inaccurate information, and can deny prospective creditors and employers access to their reports.

existence. Rather, I assume that those who shop around are affected when potential lenders can more easily screen them with information available in the bureau.[7]

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 contract history with PayNet lenders allows me to study credit relationships with a precision unachievable 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 any one of their lenders joins the bureau to ensure a usable sample for my tests.[8] 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. For example, 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

[7] Guides on equipment finance contracting advise borrowers to shop around for credit (Contino 1996). And, 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 contracts.

[8] This skews the average relationship length reported in my descriptive statistics upwards, and works against me finding relationship switches in my tests.

information.[9] I denote all such contracts private contracts. 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.[10]

Each credit file in my sample includes limited biographical information (including industry, state, and age) and a detailed contract history (including the amount, maturity, frequency, lender identifier, and payment history for each contract) updated quarterly. Figure A1 in the online appendix provides an illustrative credit file. 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 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 contracts vary from under $1,000 to the hundreds of millions of dollars.[11] Like other 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 reduce members' proprietary cost concerns. There is considerable heterogeneity in the payment performance of borrowers. For 40% of the contracts, borrowers always pay on time; for 23% (10%), the worst delinquency is less

[9] All "private" contracts in my study come from members sharing pre-entry credit files. PayNet does not collect contract information from lenders that have never joined, and I do not have any observations from such lenders.
[10] My results are robust to eliminating lenders contributing below the median share of inactive contracts upon joining.
[11] Contract amounts for leases are recorded as the sum of required payments.

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. The average firm is 10 years old and has 13 ongoing contracts.[12] 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. Panel B presents descriptive statistics for the lenders' portfolio of contracts contained in my sample. On average, lenders have 567 open contracts. Both the borrower and lender size figures are lower bounds, given they measure only contracts observed in my random sample of PayNet's database. Table 3, Panel A 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. Over the next year (two years), the unconditional probability of a relationship ending is 29% (52%). That said, I also find many long lasting relationships, which helps explain a seven year average.

4. Information sharing and relationship switches

4.1 Research design

Credit relationships are shaped by both supply and demand. Lenders, for their part, choose their underwriting policies and how much credit to provide as a function of their condition and organizational features. Firms' borrowing, in turn, is determined by their financing needs and information environment. Therefore identifying the consequences of any particular development

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

(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; Schiantarelli 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 not affected. Because the restrictions resulted from exogenous nuclear tests 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.

Motivated by this line of work, my main tests use the following linear probability specification:

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

The unit of observation is firm-lender-quarter. My dependent variable is an indicator for whether firm j no longer has *any* open contracts with lender i two years after sharing occurs at time t, which I call *Exit Relationship*. This variable collapses all of the relationship's contracts into a single indicator for whether *any* remain open for the firm-lender pair after two years following time t.[13]

Shared is measured only in firm-quarters where one of the firm's lenders joins PayNet. *Shared* is an indicator equal to 1 for all firm-lender pairs in which the lender joined the bureau in quarter t and 0 for the firm's other active relationships in quarter t, so long as the lenders in these

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[13] To illustrate, consider a lender joining in 2003 Q3. I code relationship exit as one in 2003 Q3 if the relationship terminates at *any point* in the next eight quarters, ending in 2005 Q2. That is, *no observations are recorded* for the relationship between 2003 Q4 and 2005 Q2. If the relationship survives the eight-quarter period, then relationship exit is coded as zero at 2003 Q3. This collapsing reduces the 264,999 contracts reported in Table 1 into the 26,503 firm-lender-quarter observations studied in Tables 4 and 5.

other relationships do not also join during the next two years.[14] Lender join dates are defined as the first quarter that a lender queries a credit record. Table 3, Panel B shows that *Shared* equals one in 39% of the observations in my sample. *Thin File*, measured at the firm-quarter level, considers the total dollar amount of contracts in each relationship, and which lender is sharing information. Specifically, *Thin File* is an indicator for whether the firm's credit file is only being supplemented by the sharing of smaller liabilities, leaving other liabilities that are at least twice as large off of the credit file because the lender for these liabilities is not yet a PayNet member. Studying the *Shared* credit files in my sample, I find 32% (43%) are *Thick* (*Thin*) because these files contain more than twice (less than half) as much credit as the firm's private contracts.

To illustrate the measurement of *Shared* and *Thin File*, consider the earlier example of a firm with two loans outstanding, one for $30,000 with Lender A and a second for $100,000 with Lender B.[15] If Lender A joins first, *Shared* equals 1 (0) for the relationship with Lender A (B), and *Thin File* (measured at the firm-quarter level) equals 1. Conversely, Lender B joining first provides the firm with a file detailing payments on a $100,000 loan. If Lender B joins first, *Shared* equals 0 (1) for the relationship with Lender A (B), and *Thin File* equals 0.

Figure 2 maps this illustration into my research design. Firm 2 (F_2) is the firm described in the paragraph above; F_1, F_3, and F_4 refer to firms with their own relationships with Lender A or B (L_A and L_B). When L_A joins at the beginning of the third quarter of 2003, I compare the likelihood

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[14] I examine both the first and subsequent *Shared* events for a given borrower, for two reasons. First, this avoids concentrating my sample in the early years of the bureau. Second, subsequent *Shared* events are often meaningful for the firm because of the frequency of contract size differences in my sample. Nevertheless, in Table B1 of the online appendix, I find my results are the same when I restrict my sample to the first event or to firms with only two relationships.

[15] In cases where a lender provides more than one contract to a given borrower, I aggregate the contract amounts to measure the total credit in the relationship. Thus, my measurement of *Thin File* in the illustration above would be the identical if Lender B instead provided the firm with a $40,000 contract for computers and $60,000 for manufacturing equipment. In cases where the borrower has multiple private relationships, I calculate average total credit across these relationships when measuring *Thin File* and *Thick File*.

of the shared F_2/L_A relationship ending over the next two years to the likelihood of the private F_2/L_B relationship ending in the same period.

According to my predictions, the incremental relationship termination probability for F_2/L_A over F_2/L_B, will depend on *Thin File*. If the total outstanding contracts is smaller for F_2/L_A (e.g., \$30,000), *Thin File* will equal 1 and information sharing should have a larger effect on F_2/L_A ending. On the other hand, if the total outstanding contracts is larger for F_2/L_A (e.g., \$100,000), *Thin File* equals 0 and Lender A's sharing should increase the probability of both F_2/L_A and F_2/L_B ending. Therefore, I predict β_1 to be positive. Alternatively, if a borrower can switch lenders regardless of the contracts shown on their credit file (either because contract size differences do not matter, or because alternative information sources such as tax returns can substitute for credit file information), then β_1 will equal zero.

The comparison of two relationships of the same firm at the same time comes from the inclusion of firm-quarter fixed effects, α_{jt}. This requires limiting my sample to firm-quarters where the firm has more than one ongoing credit relationship. The firm-quarter fixed effect helps me control for firm-specific credit demand shocks related to the firm's performance, risk, and competitive environment. I also include lender-quarter fixed effects, α_{it}. One difference between my setting and that of Khwaja and Mian (2008) is that my lender-level treatment variable (*Shared*) is not exogenously imposed but is instead driven by a lender choosing to share information. Therefore, to account for lender-level developments influencing the decision to join (e.g., changes in a lender's financial condition or approach to credit relationships), I conduct my analysis within lender-quarter.[16] Thus, even if a lender joins the bureau intending to change its business model,

[16] The lender-time dummies also account for differences in lender business models (e.g., bank, captive, or nonbank finance company). Although I do not observe lender identities, my main results remain after eliminating lenders resembling captives—those lending in multiple states against few collateral types.

my specification allows me to directly tie that lender's relationship turnover to features of the information being shared through the *Thin File* variable.

I also include indicators for whether the relationship is for leases, loans, or both. 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. Clustering instead by firm strengthens the significance of my results.

To summarize, I study changes in relationship status by exploiting the staggered entry of lenders to PayNet. Estimating my tests within firm-quarter makes it unlikely that firm-level developments at the time a lender joins 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 the firm's relationships—that plausibly moderates the effects of information sharing. Exploiting contract sizes in this way is appealing because when firms switch lenders, their new contract tends to resemble, in size and other terms, their old one (Ioannidou and Ongena 2010). In fact, PayNet was formed because firms 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).[17]

4.2 Information sharing, relationship survival, and outstanding credit

[17] Relying on contract size differences for identification raises questions about whether my tests will simply pick up a lender's desire to drop small clients, rather than information availability. There are several reasons this is very unlikely to happen. First, because my research design employs lender-quarter fixed effects and exploits contract size differences *across* the firm's relationships, my results cannot simply reflect an individual lender's desire to drop small contracts or small clients. Second, I repeat my tests excluding contracts under $100,000 and borrowers with less than $500,000 of credit, and find my results survive. Third, lenders have far less costly ways of abandoning small clients than sharing information. For example, they can allow existing contracts to mature and not renew them, offer less competitive terms, or exercise control rights when payments are missed. And, theory suggests that, if anything, information sharing makes small clients *more* desirable to lenders, by providing hard information on this opaque segment (Stein 2002).

As an initial step before estimating equation (1), I model relationship exits without lender-quarter fixed effects. Doing so allows me to estimate the average effect of information sharing on credit relationships by studying *Shared*, which gets absorbed by the lender-quarter indicators in equation (1). This initial estimation also allows me to use my *Thin File* variable to see whether and how the effects of information sharing depend on contract size features.

Column 1 shows that, without conditioning on contract size differences, firms are 6.9% more likely to exit relationships shared in the bureau than their private relationships during the two years after sharing occurs. Next, in column 2 I add an interaction for *Thin File*. The coefficient on *Shared * Thin File* is positive and significant as predicted. In other words, sharing of a smaller contract is more likely to lead to the end of that relationship than the firm's larger (private) relationship. On the other hand, *Shared* is insignificant. This suggests that a borrower's private contracts with one lender are affected when the borrower's similar sized or larger contracts are shared by a different lender: the borrower can use their credit history to switch out of both private and shared contracts at comparable rates. Together, these findings establish that contract size differences largely determine the effects of information sharing on relationship survival, and that sharing can cause negative externalities for creditors with smaller or similar contracts to a common borrower.

The estimation for my main and cross-sectional tests use equation (1) to address the possibility that lender business model changes unrelated to information sharing drive my results. Column 3 shows that, consistent with my predictions, the coefficient for β_1 is positive and significant. The 6.1% coefficient is economically significant considering the unconditional two-year relationship termination probability is 29%. The slight attenuation in *Shared * Thin File* from columns 2 to 3 indicates that not accounting for endogeneity in voluntary information sharing settings could lead to a modest upward bias in the results. Column 4 studies the change in credit for the relationship and offers further support: over the four-year window, the average shared relationship sees an 8.1% decline in credit, compared to the firm's other (larger) relationship.[18]

I then perform three specification checks of my column 3 result. I continue to use equation (1) but arrive at similar inferences if I omit lender-quarter fixed effects. First, I consider a more holistic measure of contract differences across relationships. I create an indicator, *Dissimilar,* equal to 1 if (1) the relationships are for different collateral types, or (2) the shared contracts are leases, whereas the other contracts are loans.[19] Panel B, Column 1, finds a positive coefficient on *Shared * Dissimilar*, parallel to my earlier result showing that contract size differences moderate the effects of sharing on relationship survival. Second, 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 drives relationship turnover, then a sufficient base of members may be needed before I find results. In column 2, 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.[20] 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 borrower has more opportunity to shop around. 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,

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[18] The change in log credit is measured at time t as the difference between average log credit in the two-year post-sharing period and the two-year pre-sharing period. I Winsorize the change at −100% and +100% to prevent the logarithmic approximation from skewing my results.
[19] Like *Thin File*, the lease/loan component of *Dissimilar* carries an asymmetric prediction for differences across relationships. Because leases generally require a smaller down payment than loans and are offered to riskier firms, the sharing of a lease contract credit history should be more useful for shopping around on leases than loans.
[20] In Table B2 of the online appendix, I show inferences are similar if I measure the number of members or contracts in the bureau, instead of an indicator for larger membership base.

column 3, shows an 8.1% coefficient for *Shared * Thin File*. This result is larger, though not statistically different from, the two-year window result.

To provide additional assurance that my results are driven by information sharing rather than other business model changes, I repeat my main tests excluding lenders with an increase in relationship turnover, or an increase in geographic or collateral market exposure in the year before joining. Table B3 shows my main results are unaffected by these sample restrictions. Therefore, it does not appear that my results can be explained by lender strategy changes predating information sharing.

To uncover the sources of my main results, I now perform cross-sectional tests that examine whether the effects of information sharing depend on the characteristics of the firm and the content of its payment record. 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 they are most opaque to potential lenders before their file is shared. Table 5 provides support for this prediction. Column 1 repeats the original result from Table 4, Panel A column 3 to ease comparison. In column 2, I find that the effects of information sharing are driven entirely by the youngest quartile of firms (age 7.7 years or younger). Similarly, column 3 shows the smallest set of firms (less than $91,000 of contracts) experience relationship turnover at roughly triple the rate of larger firms.

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 made a late payment over the past three years. Those having defaulted (recorded in PayNet's system as a bankruptcy, legal action, repossession, collection, or write-off) or falling 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 at least one payment coming between one and 90 days late. If the firm has a different record across its lenders, I classify it according to the record being revealed in the bureau. Using this specification, 39% (12%, 49%) of firm-lender-quarter observations in my tests are assigned a clean (bad, mixed) record.

Column 4 of Table 5 shows my main results are strongest for firms with perfect records or only modest delinquencies over the past three years. By comparison, firms with bad records are no more likely to exit their shared than their other relationships, consistent with my predictions. One implication of these findings is that information sharing could worsen hold-up problems for these less creditworthy borrowers, if their current lender anticipates the borrower's difficulty switching lenders with a bad record (Rajan 1992).

Taken together, my cross sectional results offer support for the theoretical predictions in Gehrig and Stenbacka (2007). Information sharing reduces switching costs, particularly for creditworthy firms. The effects also vary according to opacity, initiating relationship turnover for young, small firms.

4.3 Information sharing and new relationships

I now explore how information sharing accelerates the formation of new relationships, using the following linear probability specification:

$$Y_{jt} = \beta_1 * Post\ File_{jt} + \alpha_j + \epsilon_{jt}\ . \qquad (2)$$

The dependent variable is an indicator for whether firm j establishes any new credit relationship during time t. *Post File* is an indicator for the period after the borrower's credit file first appears in PayNet. The unit of observation is firm-*Post File*, as I collapse my sample into two-year pre and post observations for each firm, spanning the creation of the firm's credit file. I include firm fixed effects α_j, 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 File*, and my dependent variable contains measurement error because I cannot observe new relationships with lenders that never join PayNet. Likewise, I cannot include lender-time and firm-time effects, α_{it} and α_{jt}. Accordingly, the results are meant to complement rather than be directly comparable with those in Tables 4 and 5.

Column 1 of Table 6 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 three ways. First, I introduce an interaction between *Post File* and *Membership* in column 2 and find new pairs are only being formed once the bureau has 12 participating lenders. Second, I study new firm-lender matches and find nearly two-thirds of firms' new relationships in the two-year *Post File* window are with participating lenders. Third, in column 3 I introduce an interaction for *Thick File*, equal to one if the firm's file is being created with contracts more than twice as large as the firm's private contracts. I find new relationship formation only for firms with their largest liabilities shown on their credit file.

Columns 4–6 of Table 6 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 begin new relationships than old ones. On the other hand, column 5 shows that whether a firm contracts with a new lender depends on its size: only small firms are initiating new relationships. Finally, I find a positive effect for firms with perfect payment histories, compared to no effect for firms that have experienced any form of payment problem (*Post File* + *Post File* * *Clean Record* is positive and significant at the 1% level). These results complement my prior findings: when there is a sufficient base of bureau members, information sharing leads to both the termination of relationships and the formation of new ones.

5. Information sharing and relationship contracting

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? My final tests examine this question, in two ways. First, a lender may contract differently with new borrowers once it must share these borrowers' credit files. A lender pursuing a relationship strategy may offer longer maturity contracts with fewer payments. This arrangement provides flexibility to the borrower and allows time for the lender to gather and use firm-specific information (Chan et al. 1986; Mian 2006; Srinivasan 2014). Longer maturity contracts also push the renewal date into the future, giving the borrower less opportunity to switch lenders. Thus a relationship focus can shelter the lender from the competition that accompanies information sharing (Boot and Thakor 2000). Alternatively, the pursuit of a transactional strategy may produce shorter contracts with more frequent payments. This can constrain borrower-lender conflicts of interest (Myers 1977; Barclay and Smith 1995; Costello and Wittenberg-Moerman 2010) without requiring intensive information collection.

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

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

The dependent variable Y_{ijt} equals the natural log of maturity, payment frequency, or 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 originating after the lender has joined PayNet. 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. Indicators for lease and loan relationships are included. The tests also include firm-quarter fixed effects α_{jt}; 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 (first difference) and for the period after versus before the lender is sharing information (second difference). Unlike (1), these tests include lender (but not lender-quarter) fixed effects, α_i, because I am seeking changes in lender contracting that accompany information sharing.

Prior to conducting my analysis on the full sample, I study how contract terms evolve *before* the lender shares information. To do so, I estimate (3), but replace *Post* with *Placebo Post*, equal to one during various quarters before the lender joins PayNet. This allows me to detect changes in lender behavior unrelated to information sharing that could contaminate my results. For example, if the *New Relationship * Placebo Post* interaction is significantly negative (positive) for maturity (payment frequency), then lenders would appear to be pursuing a transactional strategy before joining PayNet. Table B4 presents the results. I do not find lenders gravitating toward shorter maturity, higher payment frequency contracts before information sharing. The interaction term of interest is never negative (positive) for maturity (frequency) in any of the six pre-entry quarters. This provides confidence that my estimation of (3) will yield reliable estimates of the effects of information sharing on contracting.

I now estimate (3) on the full sample. Table 7 shows that, on average, in new relationships, the firm's contracts are shorter and smaller. For relationships begun after the lender shares information, terms differ in two ways. First, contract maturity shortens by 2.8%. Given the median maturity is 48 months, this represents 1.3 fewer months of contract length for a typical firm. Second, payment frequency increases by 1.3%. 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. Column 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 are shorter and require more frequent 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 are an early signal that borrowers will default; offering additional credit intensifies lenders' exposure to these risky firms. Poorly performing loans also often require more scrutiny and even visits to borrowers' premises, reducing the human and financial resources that can be used elsewhere (Doblas-Madrid and Minetti 2013). Moreover, for banks, delinquencies increase regulatory costs by attracting attention from examiners. Lastly, missed payments and loan losses reduce cash flows and can create liquidity problems. Although late payments impose costs on lenders, contract renewals occur regularly because borrowers' performance often improves—today's young, delinquent firms often mature into tomorrow's stalwarts. Such renewals are an investment in the relationship, because any losses incurred on the renewal cannot be recovered if the borrower subsequently leaves.

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

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

The dependent variable, *Renewal after Delinquency*, is an indicator for whether the lender initiated a new contract with the firm at any point in the three years following a given type of delinquency. I conduct my analysis separately for each delinquency type, to control for changes in borrower payment behavior that can accompany information sharing (Doblas-Madrid and Minetti 2013). Following the convention in the equipment finance market and the categorization used on PayNet's credit reports, I break delinquencies into default events/payments over 90 days late ("bad delinquencies"), and payments late by 30 days or less, 31–60 days, 61–90 days (all "non-bad delinquencies"). *Post* is an indicator for renewal decisions occurring after the lender has joined the bureau.[21] 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. Similar to (3), (4) does not include lender x quarter fixed effects because I am seeking changes in lender behavior across the pre and post sharing periods. To address concerns about serial correlation in renewal decisions within a lending relationship, I cluster my standard errors at the firm-lender pair level and perform my tests on a collapsed sample (though my results are not sensitive to this choice). The unit of observation is firm-lender-post, and the sample is restricted to the three years following the respective delinquency type. Because

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

different types of delinquency occur with different frequency, my sample size varies by delinquency type.

Table 8 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 bad (non-bad) delinquency; in 46% (49%) of the relationships, the parties subsequently begin a new contract. At first glance, lenders providing financing to delinquent firms may appear to be throwing good money after bad. However, this perspective does not consider how regularly firms dramatically recover from even the most adverse payment problems. Notably, for those 9,918 relationships with a bad delinquency, 27% of the firms subsequently go three years without missing a single payment, while another 29% only experience non-bad delinquencies.

Table 9, Panel A, presents the results of estimating (4). Column 1 shows a statistically significant 3.4% reduction in the likelihood of renewal after the mildest payment problems once the lender has joined the bureau. This reduction equals one-tenth of the pre-period mean renewal rate of 36.7%. Columns 2–4 find statistically significant declines in renewal following more severe delinquencies. What's more, the drop in renewals is sharpest for firms experiencing the worst payment problems. Firms defaulting or falling more than 90 days behind on payments experience a 5.6% decline in renewals after their lender joins the bureau, representing one-fifth of the pre-period mean renewal rate.

Next, I verify that the shift in renewal decisions I find arises from information sharing rather than other business model changes predating information sharing. I repeat my tests on three different samples of lenders. The first sample is limited to lenders not experiencing an increase in relationship turnover the year before sharing information. The last two samples are restricted to lenders competing in the same geographic and collateral markets, respectively, during the year before sharing information. For brevity and to control for delinquency type, I focus on renewals after delinquencies of 30 days or less.[22] Panel B of Table 9 shows a significant decline in renewal in the post period across all three samples.

Overall, these findings complement my contract-term analysis in documenting a second way information sharing compels creditors to shift away from relationship lending: fewer contract renewals occur following missed payments. Together, these results indicate that some firms, particularly those depending on new financing to endure temporary cash flow problems, are harmed by greater transparency.

5.3 Information sharing, contract renewals, and coordination problems

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, as my results are also in line with lenders worrying 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 other creditors lack, information sharing can spur a run and reduce the firm's ability to borrow.

Table 10 presents analyses attempting to disentangle these competing explanations. I use my credit record categories from Table 5 (clean, bad, and mixed) to define *Disagreement* as happening when one lender reveals that its credit record for the firm differs from that of other lenders to the same firm. Revisiting the earlier example, if Firm 2 had a mixed record with Lender A and a bad record with Lender B, then Lender B joining reveals disagreement. Columns 1 and 2 analyze disagreement among lenders and support the Hertzberg et al. hypothesis: new originations

[22] A borrower's effort to avoid missed payments may change with information sharing (Doblas-Madrid and Minetti 2013). Because such changes are most likely to affect serious delinquencies, I focus on the mildest delinquency category. Nevertheless, I find my results hold within all four delinquency categories.

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* explanation for 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.[23] Single-relationship firms are those that have only one lender in my sample at the time this lender joins. The coordination problem modeled by Hertzberg et al. is not predicted to emerge in either of the two samples. 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 bad and moderate delinquencies. Likewise, columns 5 and 6 show a material drop in post-delinquency financing for single-relationship firms. My results suggest coordination alone does not explain the reduction in post-delinquency financing.

6. Conclusion

I examine how information sharing affects where firms access credit and whether lenders choose relationship or transactional contracting. 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 firms' credit files detailing their contracting and payment history with lenders that join PayNet in a staggered pattern over more than a decade. This setting allows me to examine changes in relationship status while accounting for firm-time 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

[23] 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.

covers is opaque and repeatedly contracts with the same lender, providing a suitable setting for studying information sharing and relationship lending.

I find sharing significantly reduces switching costs for borrowers, enabling them to exit longstanding relationships and form new ones with other members of the bureau. However, this effect is not uniform. Because lenders want to know if a new applicant has serviced a similar loan in the past, whether the applicant's largest past contract appears on their credit file moderates the effects of sharing. Consistent with theory, young, small firms are most likely to abandon their lender once their credit file is shared. I also show borrowers without serious delinquencies are most likely to contract with new lenders, while those with poor credit histories are most likely to stay with their lenders.

Finally, I demonstrate that lower switching costs for borrowers have two important implications for how lenders contract once they have committed to sharing information. In short, lending becomes more transactional. For contracts with new borrowers, maturities are shorter and payment frequency increases. Lenders are less likely to originate new contracts with borrowers that run into payment trouble, and the decline is largest for borrowers experiencing the most severe delinquencies. My findings reflect information availability rather than pre-sharing business model changes, because my results survive omitting lenders expanding their geographic reach or collateral market offerings before joining.

My paper offers evidence of the mixed effects of information sharing on credit availability. On one hand, I highlight how it makes opaque firms with clean payment histories less dependent on their existing lenders. On the other hand, sharing jeopardizes the profits 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 the literature examining the effects of transparency-improving technologies and regulations in credit markets (Powell et al. 2004; Mian 2012; Breuer et al. 2017; Ertan et al. 2017; Balakrishnan and Ertan 2017).

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Appendix A: Variables Definitions

Dependent Variables	
Exit Relationship after 2 (4) years	An indicator equal to 1 for if the borrower no longer has *any* open contracts with the lender after two (four) years, and 0 otherwise. To avoid serial correlation bias, I collapse the two (four) year period into one observation for each relationship. Therefore, this variable is only recorded once, in the first quarter of the two (four) year period, and not repeated in subsequent quarters.
Δ Log Credit 4-year window	The change in log credit in the relationship from the two-year pre period to the two-year post period. For leases, the credit amount is the sum of lease payments during the contract. I collapse the pre and post periods into equal length two-year averages, and Winsorize the change at −100% and +100%. The change in credit is only recorded once, in the first quarter of the two year post period, and not repeated in subsequent quarters.
Has New Relationship	An indicator equal to 1 if the borrower began a new relationship during the four years around when it first has a credit file in the bureau, and 0 otherwise.
Renewal after Delinquency	An indicator equal to 1 if the lender initiated a new contract with the borrower at any point in the three years following a given type of delinquency. I consider bad delinquencies (default event or more than 90 days late) and non-bad delinquencies (late, but only by 90 or fewer days).
Other 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). 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.
Thin File	An indicator equal to 1 when shared relationships are for less than half the amount of total credit than the same borrower's other relationships, and 0 otherwise. When a relationship has multiple ongoing contracts (e.g., one contract for $20,000 and another for $10,000), I calculate the total ($30,000) before defining Thin File. In cases where the borrower has multiple private relationships, I use the average total credit across these relationships. Thin File is measured at the firm-quarter level.
Thick File	An indicator equal to 1 when shared relationships are for more than twice the amount of total credit than the same borrower's other relationships, and 0 otherwise. When a relationship has multiple ongoing contracts (e.g., one contract for $20,000 and another for $10,000), I calculate the total ($30,000) before defining Thick File. In

	cases where the borrower has multiple private relationships, I use the average total credit across these relationships. Thick File is measured at the firm-quarter level.
Dissimilar	An indicator measuring how much the borrower's lending relationships differ from one another. The indicator equals 1 if the relationships involve different collateral types, or the shared contract is for a lease while the other 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.
New Relationship	An indicator equal to 1 for borrower-lender pairs originating a contract for the first time that quarter, and 0 for the borrower'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 File	An indicator equal to 1 for the period after the firm's credit file first appears in the bureau, and 0 otherwise.
Post	An indicator equal to 1 for the period after the lender has joined the bureau, and 0 otherwise.
Disagreement	Disagreement occurs when sharing by one lender reveals that the firm has a different credit record (clean, bad, or mixed) than with its other lender(s). An example of a Disagreement scenario would be if the firm has a 120 day delinquency with its sharing lender, but no delinquencies with its other lender.
Single Relationship	Firms with just one lender in my sample at the time this lender joins PayNet.

Figure 1: Credit Reporting Arrangements in the Largest Economies

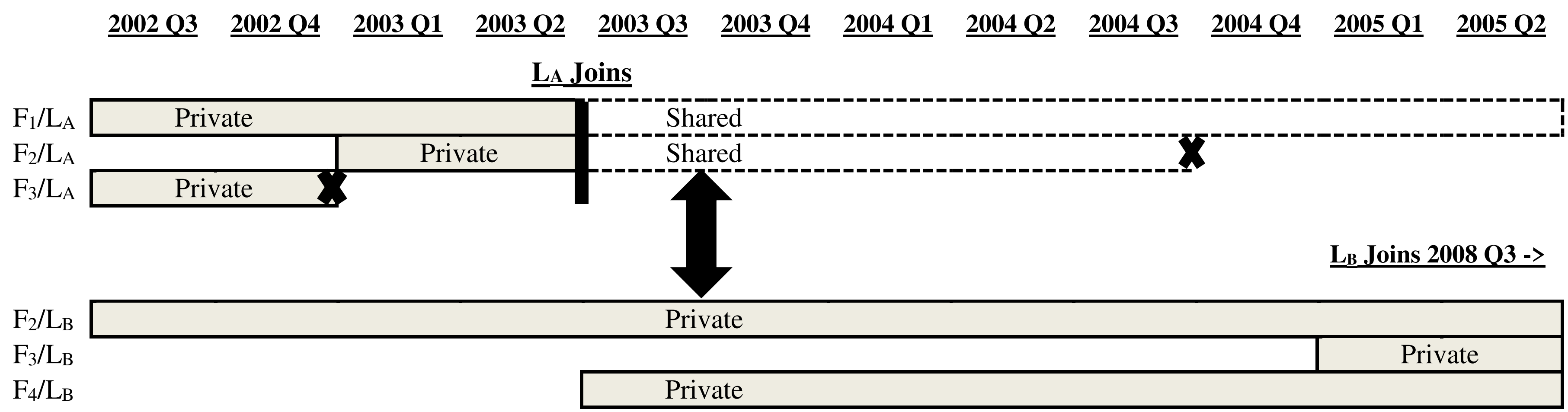
This figure summarizes the percent of adults covered by credit registries (mandatory information sharing arrangements) and credit bureaus (voluntary sharing arrangements) in the ten largest economies. The registry and bureau statistics come from the 2005 and 2016 World Bank Doing Business Surveys (World Bank 2005, 2016). GDP rankings are as of 2016.

Country	GDP Rank	Mandatory Coverage (Credit Registries)		Voluntary Coverage (Credit Bureaus)	
		2005	2016	2005	2016
US	1	0.0%	0.0%	100.0%	100.0%
China	2	0.4%	89.5%	0.0%	0.0%
Japan	3	0.0%	0.0%	61.5%	100.0%
Germany	4	0.6%	1.6%	85.6%	100.0%
UK	5	0.0%	0.0%	76.2%	100.0%
France	6	12.3%	45.1%	0.0%	0.0%
India	7	0.0%	0.0%	0.0%	22.0%
Italy	8	7.9%	27.3%	57.1%	100.0%
Brazil	9	7.8%	55.1%	42.5%	79.0%
Canada	10	0.0%	0.0%	100.0%	100.0%
Average		**2.9%**	**21.9%**	**52.3%**	**70.1%**

Figure 2: Research Design

This figure provides an illustration of my research design. Firms and lenders are labeled F and L, and a relationship is labeled F/L. An 'X' marks the end of the relationship. Lender A (L_A) joins the bureau at the beginning of 2003 Q3, and Lender B (L_B) joins at the beginning of 2008 Q3. A relationship is defined as private before the lender joins the bureau, and shared after. Both active and inactive relationships can be classified as private. 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 L_A joining event. Because I collapse the data this way, no observation is recorded for 2003 Q4 to 2005 Q2. This collapsing accounts for the transition from 264,999 contracts reported in Table 1 to 26,503 firm-lender-quarter observations studied in Tables 4 and 5.

I use this setup in two sets of tests. First, my initial tests estimate the average effect of *Shared* on *Exit Relationship after 2 years*. I compare the probability of relationship termination across the same firm's shared and private relationships during the same period. For example, when L_A joins at the beginning of 2003 Q3, my initial tests compare the probability of relationship termination between 2003 Q3 through 2005 Q2 for F_2/L_A and F_2/L_B. Second, my main tests compare the same two relationships, but interact *Thin File* with *Shared* and add lender-quarter fixed effects.



Coding of *Exit Relationship after 2 years*	2003 Q3	2003 Q4-2005 Q2
F_2/L_A	1	-
F_2/L_B	0	-
Coding of *Shared*		
F_2/L_A	1	-
F_2/L_B	0	-

Table 1: Sample Selection and Descriptive Statistics for Contracts

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

Panel C: Contract Count by Collateral 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 A for variable definitions.

Panel A: Descriptive Statistics for Firms

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
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	2.9	1.8	2.0	2.4	3.6	4,416
Firm Size (total contracts outstanding, in dollars)	1,497,634	5,465,280	90,202	259,289	846,888	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 (Panel A) and credit reports (Panel B) for observations used in my main tests.

Panel A: Descriptive Statistics for Relationships

	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

Panel B: Descriptive Statistics for Credit Reports

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
Shared	38.7%	48.7%	0.0%	0.0%	100.0%	26,503
For Shared=1						
Thin File	43.0%	49.5%	0.0%	0.0%	100.0%	10,249
Thick File	32.0%	46.6%	0.0%	0.0%	100.0%	10,249
Clean Record	38.5%	48.7%	0.0%	0.0%	100.0%	26,503
Mixed Record	49.7%	50.0%	0.0%	0.0%	100.0%	26,503
Bad Record	11.8%	32.3%	0.0%	0.0%	0.0%	26,503

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 (4) 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 first shared in the bureau that quarter. Thin File is an indicator equal to 1 for shared relationships that are for less than half the amount of credit relative to the same firm's other relationships. In Panel B, the dependent variable in columns 1–3 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 the firm's relationships involve different contract types or collateral. Membership is an indicator equal to 1 for quarters with at least 12 bureau members. See Appendix A 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) Exit Relationship after 2 years	(3) Exit Relationship after 2 years	(4) Δ Log Credit 4-year window
Shared	0.069***	0.024		
	[3.32]	[0.75]		
Shared * Thin File		0.065**	0.061**	-0.081**
		[2.49]	[2.30]	[-2.75]
Adj R2	0.077	0.078	0.190	0.124
N	26,503	26,503	26,503	26,503
Contract Type FE?	Yes	Yes	Yes	Yes
Firm x Quarter FE?	Yes	Yes	Yes	Yes
Lender x Quarter FE?	No	No	Yes	Yes

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

	(1)	(2)	(3)
	Exit Relationship after 2 years	Exit Relationship after 2 years	Exit Relationship after 4 years
Shared * Dissimilar	0.091***		
	[3.45]		
Shared * Thin File		-0.001	0.081***
		[-0.03]	[3.06]
Shared * Thin File * Membership		0.086*	
		[1.99]	
Adj R2	0.190	0.190	0.262
N	26,503	26,503	13,401
Contract Type FE?	Yes	Yes	Yes
Firm x Quarter FE?	Yes	Yes	Yes
Lender x Quarter FE?	Yes	Yes	Yes

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 3 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 A 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	0.061**	0.028	0.054**	-0.041
	[2.30]	[0.89]	[2.09]	[-1.32]
Shared * Thin File * Young		0.161***		
		[7.46]		
Shared * Thin File * Small			0.109***	
			[3.20]	
Shared * Thin File * Clean Record				0.121***
				[7.78]
Shared * Thin File * Mixed Record				0.117***
				[4.62]
Adj R2	0.190	0.195	0.190	0.191
N	26,503	26,503	26,503	26,503
Contract Type FE?	Yes	Yes	Yes	Yes
Firm x Quarter FE?	Yes	Yes	Yes	Yes
Lender x Quarter FE?	Yes	Yes	Yes	Yes

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 1–6 is an indicator for whether the firm starts a new relationship. 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 2–6 include interactions for the pool of bureau members, features of the firm's credit file, and the firm's age, size, and credit record. Post File is an indicator for the period after the firm's credit file is first available in the bureau. Membership is an indicator equal to 1 for quarters with at least 12 bureau members. Thick File is an indicator equal to 1 for firms where the shared relationships are for at least twice as much credit as the same firm's other relationships. 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 A 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) Has New Relationship	(2) Has New Relationship	(3) Has New Relationship	(4) Has New Relationship	(5) Has New Relationship	(6) Has New Relationship
Post File	0.058**	-0.010	-0.035	0.063**	-0.048***	0.056
	[2.65]	[-1.43]	[-1.50]	[2.42]	[-3.74]	[1.33]
Membership		-0.029				
		[-1.19]				
Post File * Membership		0.108***				
		[4.08]				
Post File * Thick File			0.112***			
			[10.09]			
Post File * Young				-0.016		
				[-1.01]		
Post File * Small					0.253***	
					[8.48]	
Post File * Clean Record						0.019
						[0.69]
Post File * Mixed Record						-0.040*
						[-1.71]
Adj R2	0.208	0.212	0.212	0.208	0.246	0.209
N	22,304	22,304	22,304	22,304	22,304	22,304
Firm FE?	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Collapsed	Collapsed	Collapsed	Collapsed	Collapsed	Collapsed

Table 7: Contract Terms for Firms Starting New Relationships

This table presents OLS regressions examining whether lenders agree to different contract terms in new relationships after they have joined 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-lender pairs contracting for the first time. Post is an indicator for the period after the lender has joined the bureau. See Appendix A 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	-0.053***	-0.008	-0.166***
	[-7.96]	[-1.50]	[-11.81]
New Relationship * Post	-0.028***	0.013**	0.017
	[-3.04]	[2.25]	[0.89]
Adj R2	0.804	0.784	0.684
N	132,231	127,484	132,231
Firm x Quarter FE?	Yes	Yes	Yes
Lender FE?	Yes	Yes	Yes
Contract Type FE?	Yes	Yes	Yes

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

This table presents descriptive statistics for delinquencies, and tabulates how frequently the lender originates a new contract with the firm in the three years after the delinquency. In the case of multiple delinquencies for the firm-lender pair, I count if there is *any* instance of renewal within three years of a delinquency. The bottom part of the table presents the probability of the firm's record improving, deteriorating, or not changing after the delinquency (not conditional on renewal). A bad (non-bad) delinquency is defined as a default event or a payment more than 90 days late (payment late by 90 days or less). See Appendix A for variable definitions.

	Bad Delinquency	Non-Bad Delinquency
Firm-Lender Pairs with delinquency type	9,918	43,372
% of time renewal occurs within three years after delinquency	46.3%	48.8%
% of time the firm's record with lender over next three years:		
Does not change	44.3%	39.9%
Improves to perfect	26.6%	48.8%
Improves to mixed	29.1%	--
Deteriorates to bad	--	11.3%

Table 9: Delinquencies and Contract Renewals in the Information Sharing Regime

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. The dependent variable in columns 1-4 is an indicator equal to 1 if the firm and lender initiate a new contract in the three years after the given delinquency type. Post is an indicator equal to 1 for quarters after the lender has joined the bureau. The sample in both Panels collapses all observations into a single pre- and post- period for the firm-lender pair. In Panel B, the sample is restricted to lenders not experiencing changes in their business model in the year before joining, as described at the bottom of the table. See Appendix A for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the relationship (firm-lender) level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

Panel A: Delinquencies and Contract Renewals

	(1) Renewal after <=30 day Delinquency	(2) Renewal after 31-60 day Delinquency	(3) Renewal after 61-90 day Delinquency	(4) Renewal after Bad Delinquency
Post	-0.034***	-0.043***	-0.040***	-0.056***
	[-5.18]	[-4.75]	[-3.53]	[-3.64]
Adj R2	0.382	0.403	0.428	0.493
N	35,879	23,873	12,770	9,967
Relationship FEs?	Yes	Yes	Yes	Yes

Panel B: Business Model Robustness

	(1) Renewal after <=30 day Delinquency	(2) Renewal after <=30 day Delinquency	(3) Renewal after <=30 day Delinquency
Post	-0.024*	-0.049***	-0.017**
	[-1.75]	[-5.67]	[-2.44]
Adj R2	0.478	0.349	0.396
N	9,116	20,522	30,848
Relationship FEs?	Yes	Yes	Yes
Sample	No pre-entry increase in exits	No pre-entry geographic expansion	No pre-entry collateral type expansion

Table 10: 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. 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 bad (non-bad) delinquency. Columns 1 and 2 restrict the sample to firm-lender pairs where information sharing reveals differences in the firm's credit history across lenders; "Disagreement." Columns 3 and 4 (5 and 6) restrict the sample to firm-lender pairs where information sharing does not reveal differences (single-relationship firms); "No Disagreement" ("Single Relationship"). Each test collapses all observations into a single pre- and post-join period for the pair. Post is an indicator equal to 1 for quarters after the lender has joined PayNet. See Appendix A for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the relationship (firm-lender) level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Renewal after Bad Delinquency	Renewal after Non-Bad Delinquency	Renewal after Bad Delinquency	Renewal after Non-Bad Delinquency	Renewal after Bad Delinquency	Renewal after Non-Bad Delinquency
	Disagreement	Disagreement	No Disagreement	No Disagreement	Single Relationship	Single Relationship
Post	-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
Relationship FEs?	Yes	Yes	Yes	Yes	Yes	Yes

Online Appendix to:

Does Credit Reporting Lead to a Decline in Relationship Lending? Evidence from Information Sharing Technology

March 2018

This online appendix provides descriptive detail of the PayNet data, and tabulates additional analyses.

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Section A. Data Description

PayNet was founded in Skokie, Illinois in 1999. To that point, there was no widely used credit reporting system for commercial term loans in the US. In 2001, PayNet launched a credit bureau that would allow lenders to access credit files for a fee. PayNet focuses on the equipment finance market, given this is a distinct but large segment for US lenders, and the founders had experience in this segment. The bureau operates on the principle of reciprocity: lenders could only access credit files by agreeing to fully share information about their own clients. Three policies governing participation help mitigate lenders' concerns about sharing their proprietary information. First, lenders' identities are not revealed on firms' credit files. Thus, a credit file will present a firm's credit history without identifying the individual lender providing any given contract. Second, lenders cannot mine the database by, for example, downloading a batch of credit files for every firm in a particular geographic area, collateral type, or industry. Instead, lenders use PayNet to access individual credit files upon receiving an application from a new client, monitoring an existing one, preparing for contract renewals, or targeted marketing. Third, PayNet has developed a secure interface that allows it to electronically collect lenders' information on a weekly basis.

Several features of the data collection process ensure the integrity of shared information and prevent misreporting by lenders:

1) An invasive implementation process, where PayNet establishes a direct link into the lenders' accounting system. During this process, PayNet performs an exhaustive set of tests and audits to ensure the lender is fully sharing its credit files. This process consumes as little as two months or as much as one year. Therefore, before the lender is granted entry to the bureau, they must undergo a thorough review to ensure their accounting system can be relied upon to produce truthful reports. Moreover, regardless of lenders' initial IT system infrastructure, they must take necessary steps to reach compatibility with PayNet's interface, even if doing so consumes significant resources (Jackson 2001; Doblas-Madrid and Minetti 2013).

2) PayNet then uses this direct link to access the lenders' accounting system on a recurring basis. Thus, credit files get added to the bureau through PayNet's access to the lenders' accounting system, and not through the lender providing the credit files it chooses to share on a discretionary basis via mail, for example.

3) PayNet employs a large team of analysts to check shared data for accuracy and completeness on an ongoing basis. According to discussions with PayNet, a lender's data is cross-checked against:
    a) the lender's past contributions
    b) information contributed contemporaneously from other lenders with similar exposures
    c) public records including Uniform Commercial Code-1 (UCC) filings, bankruptcy filings, and tax liens. 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

d) industry/macroeconomic data from the lender's locale

To facilitate this process, PayNet has developed algorithms to identify specific credit files or lending patterns that require further verification.

4) As in other voluntary information arrangements, lenders caught misreporting are banned from the system (Padilla and Pagano 1997; Doblas-Madrid and Minetti 2013). PayNet's member agreement grants them the right to immediately terminate a lender's participation and seek damages if they are caught misreporting.

PayNet has experienced significant growth since 2001. Today, it describes itself as "the leading provider of credit ratings on small businesses", and boasts over 23 million contracts from $1.4 trillion in obligations. As of February 2017, the typical contract in their database is for $64,109, with a term of 44 months. The bureau is the source of data for the Thomson Reuters/PayNet Small Business Lending Index and Thomson Reuters/PayNet Small Business Delinquency Index, which is regularly cited by the business media. Approximately 200 lenders were members at the time the data for this study was provided.

This study uses a panel of 20,000 randomly chosen firms' credit files. Each quarter, the credit files update the firms' contracts with PayNet lenders, the terms of the contracts, and the payment status (e.g., whether the firm is delinquent, and if so, how many days delinquent). Because PayNet requires lenders to share both ongoing and past contracts, and has several mechanisms for ensuring compliance, contracts are visible for firms both before and after they have a PayNet credit file. Figure A1 below presents the credit file information and shows how this information is updated over time. The identity of lenders and borrowers is withheld to preserve confidentiality; an anonymous identifier allows researchers to track the contracts for each party. PayNet credit files provided to lenders contain additional fields withheld from researchers, primarily biographical information and document numbers for UCC filings and tax liens, if any. PayNet records collateral types using its own classification scheme spanning agricultural, boating, construction, copier, energy, logging, medical, manufacturing, office, printing, retail, telephone, and waste equipment, as well as airplanes, automobiles, buses, computers, forklifts, and trucks. A very small number (<0.1%) of contracts involve real estate. Like other credit bureaus in the US (e.g., consumer bureaus), PayNet does not systematically collect and make available interest rate information.

Figure A1: 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. The dataset updates credit files each quarter, on the "As of" date.

Firm ID	As of	SIC	Age	State	Contract ID	Lender ID	Collateral 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

Section B. Supplemental Analyses

Table B1: Sample Selection Robustness

This table reports robustness analysis of the results in Table 4, Panel A, columns 3 and 4 (Panel A) and Table 5 (Panel B). The tests in Panel A are limited to the first instance a firm's lender enters the bureau (column 1 and 2), and firms with exactly two relationships (columns 3 and 4). The tests in Panel B are limited to the first instance a firm's lender enters the bureau (columns 1-3), and firms with exactly two relationships (columns 4-6). See Appendix A 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: Robustness Tests for Table 4

	(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
	First Join	First Join	Two Lenders	Two Lenders
Shared * Thin File	0.071*	-0.071*	0.054**	-0.039
	[1.94]	[-1.85]	[2.10]	[-0.88]
Adj R2	0.170	0.128	0.164	0.107
N	8,133	8,133	9,184	9,184
Contract Type FE?	Yes	Yes	Yes	Yes
Firm x Quarter FE?	Yes	Yes	Yes	Yes
Lender x Quarter FE?	Yes	Yes	Yes	Yes

Panel B: Robustness Tests for Table 5

	(1) Exit Relationship after 2 years	(2) Exit Relationship after 2 years	(3) Exit Relationship after 2 years	(4) Exit Relationship after 2 years	(5) Exit Relationship after 2 years	(6) Exit Relationship after 2 years
	First Join	First Join	First Join	Two Lenders	Two Lenders	Two Lenders
Shared * Thin File	0.014	0.054	-0.069*	-0.014	0.026	-0.051
	[0.45]	[1.58]	[-1.77]	[-0.44]	[1.14]	[-1.18]
Shared * Thin File * Young	0.171***			0.210***		
	[6.55]			[8.93]		
Shared * Thin File * Small		0.115***			0.141***	
		[2.95]			[4.04]	
Shared * Thin File * Clean Record			0.129***			0.106*
			[3.55]			[1.84]
Shared * Thin File * Mixed Record			0.169***			0.121***
			[6.10]			[3.17]
Adj R2	0.180	0.171	0.172	0.179	0.166	0.164
N	8,133	8,133	8,133	9,184	9,184	9,184
Contract Type FE?	Yes	Yes	Yes	Yes	Yes	Yes
Firm x Quarter FE?	Yes	Yes	Yes	Yes	Yes	Yes
Lender x Quarter FE?	Yes	Yes	Yes	Yes	Yes	Yes

Table B2: Bureau Membership Base Robustness

This table reports robustness analysis of the results in Table 4, Panel B, column 2. Lender Count (Contract Count) is the number of lenders (contracts) in the bureau at the Shared date. See Appendix A for variable definitions. Two-way effects for Shared * Thin File are included but not tabulated because they are not economically interpretable. 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
Shared * Thin File * Lender Count	0.003*		
	[1.91]		
Shared * Thin File * Log Lender Count		0.071***	
		[3.31]	
Shared * Thin File * Log Contract Count			0.075***
			[4.45]
Adj R2	0.190	0.191	0.191
N	26,503	26,503	26,503
Contract Type FE?	Yes	Yes	Yes
Firm x Quarter FE?	Yes	Yes	Yes
Lender x Quarter FE?	Yes	Yes	Yes

Table B3: Business Model Robustness Tests for Main Analyses

This table reports robustness analysis of the results in Table 4, Panel A, column 3. Column 1 restricts the sample to lenders not experiencing an increase in relationship exit in the year before joining the bureau. Column 2 (3) restricts the sample to lenders not expanding their geographic (collateral type) exposure in terms of number of states (collateral offerings) in the year before joining the bureau. Shared is an indicator equal to 1 for relationships first shared in the bureau that quarter. Thin File is an indicator equal to 1 for shared relationships that are for less than half the amount of credit than the same firm's other relationships. See Appendix A 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
Shared * Thin File	0.076**	0.073**	0.059*
	[2.21]	[2.06]	[1.96]
Adj R2	0.160	0.212	0.192
N	15,978	16,327	22,807
Contract Type FE?	Yes	Yes	Yes
Firm x Quarter FE?	Yes	Yes	Yes
Lender x Quarter FE?	Yes	Yes	Yes
Sample	No pre-entry increase in exits	No pre-entry geographic expansion	No pre-entry collateral type expansion

Table B4: Contracting before Information Sharing

This table reports robustness analysis of the results in Table 7. Each column reports the results of estimating (3), where I replace Post with an indicator for Placebo Post. Placebo Post is an indicator equal to one in a quarter prior to actual entry (as labeled at the top of the column), and zero for prior quarters. Because the objective of these tests is to study pre-entry contracting, observations after the Placebo Post date are not included. Therefore, the number of observations differs across the columns. Panel A (B; C) studies contract maturity (payment frequency; size). See Appendix A 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: Robustness Tests for Maturity

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Maturity	Log Maturity	Log Maturity	Log Maturity	Log Maturity	Log Maturity
	T-6 quarters	T-5 quarters	T-4 quarters	T-3 quarters	T-2 quarters	T-1 quarters
New Relationship	-0.061***	-0.064***	-0.065***	-0.067***	-0.067***	-0.065***
	[-8.54]	[-8.79]	[-8.60]	[-9.01]	[-9.65]	[-10.22]
New Relationship * Placebo Post	-0.035	-0.014	-0.044	0.018	0.044*	-0.037
	[-0.68]	[-0.32]	[-1.14]	[0.78]	[1.81]	[-0.48]
Adj R2	0.943	0.940	0.936	0.934	0.930	0.926
N	43,007	45,446	47,788	49,978	52,287	54,582
Firm x Quarter FE?	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE?	Yes	Yes	Yes	Yes	Yes	Yes
Contract Type FE?	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Robustness Tests for Payment Frequency

	(1) Log Payment Frequency	(2) Log Payment Frequency	(3) Log Payment Frequency	(4) Log Payment Frequency	(5) Log Payment Frequency	(6) Log Payment Frequency
	T-6 quarters	T-5 quarters	T-4 quarters	T-3 quarters	T-2 quarters	T-1 quarters
New Relationship	-0.002	-0.002	-0.004	-0.004	-0.004	-0.007
	[-0.36]	[-0.40]	[-0.61]	[-0.61]	[-0.68]	[-1.14]
New Relationship * Placebo Post	0.017	0.001	0.019	-0.012	-0.042**	-0.039
	[1.08]	[0.03]	[1.01]	[-0.61]	[-2.36]	[-0.87]
Adj R2	0.843	0.837	0.833	0.830	0.829	0.826
N	41,120	43,493	45,776	47,911	50,151	52,374
Firm x Quarter FE?	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE?	Yes	Yes	Yes	Yes	Yes	Yes
Contract Type FE?	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Robustness Tests for Contract Size

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Average Contract Size	Log Average Contract Size	Log Average Contract Size	Log Average Contract Size	Log Average Contract Size	Log Average Contract Size
	T-6 quarters	T-5 quarters	T-4 quarters	T-3 quarters	T-2 quarters	T-1 quarters
New Relationship	-0.132***	-0.145***	-0.144***	-0.146***	-0.145***	-0.143***
	[-6.26]	[-7.38]	[-8.09]	[-9.53]	[-9.27]	[-8.63]
New Relationship * Placebo Post	-0.216	-0.016	-0.107	-0.039	0.025	-0.216
	[-1.23]	[-0.12]	[-0.93]	[-0.47]	[0.23]	[-1.49]
Adj R2	0.762	0.755	0.750	0.745	0.740	0.735
N	43,007	45,446	47,788	49,978	52,287	54,582
Firm x Quarter FE?	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE?	Yes	Yes	Yes	Yes	Yes	Yes
Contract Type FE?	Yes	Yes	Yes	Yes	Yes	Yes