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

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Abstract

I use the introduction of an equipment finance credit bureau to examine the effects of lenders sharing borrower information on relationship dynamics and investment. My within-borrower-time tests exploit the fact that firms have ongoing relationships with multiple lenders that join the bureau in a staggered pattern. I find that the exchange of payment history and contract information reduces the switching costs associated with firms ending existing relationships and forming new ones with bureau members. Consistent with theoretical predictions, firms with a lengthy track record of borrowing without a serious delinquency drive this effect. Finally, I show that a reduction in switching costs has important implications for lenders' willingness to invest in relationships. Contract maturities for new relationships are shorter, and lenders are less likely to provide additional financing to a borrower following delinquencies. I conduct additional tests to rule out selection by lenders into the bureau as an alternative explanation for my findings. Collectively, my results provide the first contract-level evidence on the effects of information sharing on relationship lending and investment.

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1. Introduction

A significant portion of the information that lenders use to allocate credit and monitor commercial borrowers—including preexisting debt, payment history, and collateral pledges—has been shared among lenders. What effects does the exchange of such information have on the survival of existing lending relationships, the formation of new ones, and lenders' willingness to invest in relationships? Theoretical literature suggests that information sharing mechanisms lower switching costs for firms by reducing the information advantage of existing over outside lenders, and in turn diminish the incentive for lenders to invest in relationships (Petersen and Rajan 1995). Yet, despite the pervasiveness of borrower information sharing in modern credit markets and an extensive literature on relationship lending, there is scant contract-level evidence addressing these questions. The primary barrier has been the lack of settings where information exchange between lenders is observable.

To address this gap, I examine a panel of 19,878 firms' quarterly credit files detailing their contracting activity and payment performance with lenders that join the PayNet bureau in a staggered pattern. The bureau was established in 2001 to serve the equipment finance sector, which, unlike the consumer finance market, did not yet have a widely adopted credit-reporting system. Prior to joining, lenders in this setting regularly originated contracts without knowing how the firm had performed on comparable contracts with other lenders (Ware 2002). Hence, lenders were willing to share previously proprietary borrower information (a requirement of members) in order to gain access to more comprehensive, accurate, verified, and timely information that would help with acquiring new clients and monitoring existing ones. Eight of the top 10 lenders in this sector are members, and the repository contains over $1.2 trillion in contracts from banks, captives, and finance companies. Borrowers in this market range from small private firms to large public companies, and seek capital for computer, manufacturing, medical, mining, and telecommunication equipment. Delinquencies are common but not observable to non-members; 60% of contracts experience at least one late payment and 9% fall over 90 days behind.

Tests examining how information sharing affects credit relationships face a fundamental identification challenge: separating the effects of information sharing from contemporaneous shocks to a firm's demand for credit, such as changes in the investment opportunity set or financial constraints. The PayNet database and US equipment finance market offer several key advantages for addressing this challenge. Lenders enter the bureau at various points over more than a decade, and must fully contribute both existing and past contract terms and borrower payment records. Crucial to my identification strategy, the majority of borrowers in my sample contract with multiple lenders that join in different periods. Together, these features allow me to use borrower-time fixed effects that absorb shocks to credit demand to compare changes in the *same* firm's credit relationship with a lender that shares information relative to a lender that does not. Because my identification strategy exploits differences in the timing of lenders' entry to the bureau rather than a loan-size or risk-rating participation threshold (as in Hertzberg et al. 2011), I am able to document the effect of information sharing on firms of various sizes and credit histories. This advantage does not come at the expense of economic relevance: equipment expenditures make up 72% of private fixed non-residential investment in the United States (BEA 2013), and the majority of these expenditures are financed with loans and leases (IHS 2013). Furthermore, the Fair Credit Reporting Act (FCRA) does not apply to commercial loans; therefore, the borrowers in my sample have no say over whether or when a lender shares their credit files.

My findings are threefold. First, a firm is more likely to end its relationship with a lender that joins the bureau, relative to its contemporaneous relationship with another lender that had not yet joined the bureau. The incremental probability of relationship exit after one year is 3.4%, and grows to 16.3% after four years. This effect is economically significant given that the likelihood of exit after one (four) year(s) for relationships kept private is 14% (47%), and that 83% of sample contracts are initiated with a lender with whom the borrower has previously interacted. These findings are robust to restricting the sample to lenders that did not expand their equipment offerings during the year after joining the bureau, mitigating concerns that my results are simply capturing a broader strategic shift in lenders' approach to client interactions. Complementing these initial results, I show that borrowers are significantly more likely to start a new relationship after their credit file is available in the PayNet system, and that bureau members with access to credit files make up the majority of counterparties in these new pairs. All of this evidence is consistent with a decline in switching costs.

Second, I reinforce my initial results by demonstrating that the change in switching costs varies according to characteristics of the borrower's track record in concordance with theoretical research. Jaffee and Russell (1976) and Stiglitz and Weiss (1981) show lenders prefer to ration credit instead of charge a high interest rate to the riskiest class of borrowers. Diamond (1989) argues that the length of the borrower's track record is also relevant to their switching costs because it allows the lender to form a more precise assessment of an unfamiliar firm's quality. These theories suggest information sharing should reduce the switching costs of relationship turnover solely for those with an extensive, clean payment history. I test this prediction by classifying borrowers as having a clean (perfect record), bad (major default or delinquency), and mixed (minor delinquency) payment performance over the past three years, and measure the duration of their borrowing record at the time their lender joins PayNet. Consistent with theory, I find that information sharing leads only firms with a clean or mixed recent payment history to exit the relationship. Similarly, those with a long track record are significantly more likely to exit, whereas there is no incremental likelihood of exit for those with a short history. Payment performance and track record length have an interactive effect: having a bad (clean) history makes exit less (more) likely as the borrower's track record increases in length. Parallel to these findings, I show new relationship starts are positively associated with the quality and length of the firm's record.

Third, I show that by reducing switching costs, information sharing alters lenders' relationship investment decisions. Models of relationship lending emphasize the intertemporal nature of loan contracting that makes lenders willing to subsidize losses early in the relationship with the hope of earning rents when the firm's profits improve (Chan et al. 1986; Petersen and Rajan 1995). An increase in competition brought about by lower switching costs can reduce lenders' willingness to invest in relationships (Boot 2000). I show that after a borrower is part of the PayNet bureau, the new relationships it establishes involve shorter maturity contracts with a lower likelihood of involving guarantors, indicating a transition away from relationship lending and toward more transactional lending. Next, I examine delinquencies, which expose lenders to losses and monitoring costs, and examine whether joining the bureau changes their willingness to originate new contracts with a borrower following these events. Controlling for relationship (borrower-lender pair) fixed effects, I find that once lenders are bureau members, they are less likely to renew financing for firms that experience a delinquency. This finding suggests that by reducing switching costs for borrowers with the strongest recent payment performance, information sharing reduces lenders' willingness to make costly renewal investments on the basis of earning rents later, consistent with prior work on competition and relationship lending (Petersen and Rajan 1995).

I make four contributions to the literature. First, my paper offers empirical evidence on the effects of information sharing arrangements on relationship lending. Borrower information sharing systems are central to modern credit markets—both equipment-focused and otherwise—and have existed for over two centuries, but have proven difficult to study empirically because these systems are not typically observable to researchers. Several cross-country studies find credit bureaus can increase aggregate lending and reduce delinquencies (e.g., Jappelli and Pagano 2002; Djankov et al. 2007). However, these studies leave unresolved how any change in credit is distributed across existing and new lending relationships, and how the content and length of the credit files being shared influences this distribution. I also extend this literature by examining how information sharing alters the incentives of lenders to invest in relationships.

Second, existing evidence on the role of the borrower's information environment in contracting and relationship formation predominantly focuses on the borrower-to-lender reporting channel (Armstrong et al. 2010), leaving many important questions about the lender-to-lender channel unanswered. This is notable because a sizable segment of commercial borrowers does not even provide financial statements to its lender at the application stage or on an ongoing basis (Allee and Yohn 2009; Minnis and Sutherland 2014). In these cases, credit scoring can substitute for various aspects of borrowers' reporting in helping lenders assess creditworthiness (Cassar et al. 2014). Even for borrowers with sophisticated reporting systems, lenders typically prefer collecting certain information (e.g., payment history on past loans) from credit bureaus or other lenders because of credibility issues with firms' own disclosures.

Third, I extend the literature concerned with the public good aspect of firm information. Although theoretical studies have identified channels through which one firm's disclosure can have financial or real effects on other market participants, Leuz and Wysocki (2008) note that there is a "paucity of evidence on market-wide . . . and social consequences of reporting." The limited empirical work has examined how equity market disclosures have spillover effects on estimation risk, liquidity, capital investment, or product markets.[1] Less understood is how a lender's release of a borrower's track record impacts the establishment of the borrower's other lending relationships, despite the widespread use of payment history and preexisting debt information in loan contracting and monitoring.

Lastly, while I focus on the commercial lending setting, there are others where principals exchange information about agents to mitigate adverse-selection and information asymmetry problems. Insurance companies, employers, and landlords regularly share information about their policyholders, employees, and tenants. Similarly, review repositories such as Yelp and Angie's List reduce search costs for uninformed patrons, and discipline businesses that provide poor service. However, because information sharing is typically not observable in these markets, there is little evidence on how this reporting technology works or what role the agent's track record plays in contracting. Moreover, in employment, rental, and insurance markets, individuals typically only have one ongoing relationship, precluding the within-agent-time period specification that I am able to implement to address endogeneity concerns. By documenting how information sharing reduces switching costs for agents,

[1] See Foster (1981), Bushee and Leuz (2005), Sadka (2006), Beatty et al. (2013), and related theoretical work and discussions including Dye (1990), Admati and Pfleiderer (2000), Lambert et al. (2007), and Beyer et al. (2010).

conditional on the quality and length of their record, I offer evidence that is relevant to these other settings.

2. Motivation and theoretical framework

2.1 Relationship lending

A large literature investigates the role of reporting in mitigating information asymmetries between borrowers and lenders (see Armstrong et al. [2010] for a review). Contracting with a bank as opposed to public bondholders permits the borrower to reveal private information about its creditworthiness that it would prefer not to disclose to a broader audience (Boot 2000). In turn, the lender gains knowledge that helps it screen and monitor better than outside lenders, and uses this information in repeated transactions with the borrower (Petersen and Rajan 1994). This information advantage carries two important implications for how borrowers and lenders bargain over credit contracts. First, borrowers face switching costs when attempting to establish new relationships (Sharpe 1990; Klemperer 1995). Second, the existence of switching costs compels lenders to compete not over individual contracts, but over the entire future stream of contracts a borrower will execute in their lifetime. As a result, lenders often invest in relationships by subsidizing the firm when it is young or distressed, with the expectation that it can subsequently earn rents when the firm's profitability improves (Petersen and Rajan 1995; Boot 2000).

The switching costs associated with contracting with an unfamiliar lender for the first time can depend on the content and length of the borrower's payment history. Why an outside lender would be any less likely to transact with a borrower carrying the stigma of a poor payment history when it can price this risk may not be immediately clear. However, charging a high interest rate to risky borrowers can invite adverse-selection and moral-hazard problems, making credit rationing optimal (Jaffee and Russell 1976; Stiglitz and Weiss 1981). Moreover, the relationship lender often collects soft information in investigating the causes of delinquencies; this information is not known or easily communicated to outsiders (Rajan 1992). Even for firms with a perfect payment record, outside lenders can have difficulty deciphering creditworthiness if the borrowing history is short, because bad, risky investments can take time to become evident (Diamond 1989). Related, as a firm acquires a longer track record of paying on time, the value of its reputation increases and moral-hazard problems dissipate. Consequently, the switching costs associated with leaving an existing lender for a new one are decreasing in the quality and length of the firm's credit history, all else equal.

Borrowers face credibility problems in conveying their creditworthiness to potential lenders (Jensen and Meckling 1976; Watts 1977). Although a borrower may furnish evidence of a clean payment history with one lender, knowing whether it has withheld less favorable information about other relationships is difficult. Efforts to directly verify a firm's payment history with a rival lender can be fraught with conflict-of-interest problems (Padilla and Pagano 1997). Additionally, while financial statements provide relevant information about creditworthiness, private firms often decline to produce audited financial statements for their lender when doing so is costly (Allee and Yohn 2009; Garmaise and Natividad 2014; Minnis and Lisowsky 2014; Minnis and Sutherland 2014). In such cases, credit scores—developed by lenders exchanging information with each other through an intermediary—can substitute for sophisticated financial reporting in reducing information asymmetries between borrowers and lenders (Cassar et al. 2014). It is this reporting channel that I am interested in exploring.

2.2 Theoretical evidence on information sharing

Today, lenders regularly exchange information about borrowers' outstanding leverage, performance on prior contracts, and collateral pledges, and have done so for at least two centuries. Consistent with historical accounts of early credit-reporting mechanisms developed by nineteenth-century merchants (see Madison 1974), theoretical work shows that information sharing mechanisms endogenously arise when credit cannot be efficiently allocated using only firsthand knowledge about borrowers. For instance, in Pagano and Jappelli (1993), lenders begin sharing information with one another when the heterogeneous pool of borrowers becomes mobile and they increasingly experience immigrants approaching them for credit. Technology that aggregates and distributes information more efficiently than decentralized, spatially segmented sources also supports such exchange. Once in place, the information sharing system increases credit access by reducing processing costs for lenders and precluding hold-up problems (Jappelli and Pagano 2000). Competition between lenders is heightened (Dell'Ariccia and Marquez 2006), particularly for creditworthy borrowers with long track records (Gehrig and Stenbecka 2007).

Although each lender would prefer that others disclose proprietary information about their relationships and keep information about their own borrowers private, most modern credit bureaus operate on the principle of reciprocity (Pagano and Jappelli 1993). Hence, the primary drawback of sharing information is that the potential rents from relationship lending are put at risk (Mian 2012), which could threaten the viability of the relationship lending channel (Boot and Thakor 2000; Ongena and Smith 2000).

At the same time, lenders benefit from information sharing in multiple ways, a notion supported by the continued use and voluntary adoption of lender-to-lender reporting systems. First and foremost, such systems reduce the processing costs and redundant efforts associated with financial intermediation (Diamond 1984; Boyd and Prescott 1986), while providing relevant, verified information about borrowers. This information helps lenders overcome adverse-selection problems commonly encountered when forming new relationships, particularly in new segments (Sharpe 1990; Winton 1999; Acharya et al. 2006). Second, information sharing can reduce the risk of current and future contracts by disciplining the borrowers' behavior in making their payment performance known to a group of potential lenders (Klein 1992; Padilla and Pagano 2000; Bennardo et al. 2013). This effect is analogous to how the existence of outside employment opportunities can discipline a manager's behavior under an existing employer when a signal of their behavior is observable (Fama 1980). Third, borrowers' investment incentives can be distorted when a lender exploits their information advantage over competing lenders (Rajan 1992); information sharing can help the parties avoid such hold-up problems.

In sum, information sharing reduces switching costs for borrowers on average; however, this effect should be concentrated in borrowers with a long track record of meeting their obligations. Lenders that choose to join a bureau benefit from gaining new clients, and from better information about and a disciplinary device for existing borrowers.

2.3 Empirical evidence on information sharing

Empirical evidence on information sharing mechanisms can be classified into two categories. One line of research examines how the aggregate level of lending and defaults is associated with information sharing mechanisms and their interaction with the institutional environment. As of 2012, 87 countries had private credit bureaus, while 104 maintained public credit registries operated by state agencies (Bruhn et al. 2013). Several studies (e.g., Djankov et al. 2007; Jappelli and Pagano 2002) find these information sharing systems are positively related to aggregate credit and negatively related to default rates. The establishment of public collateral registries in developing countries has led to improved access to bank finance (Peria and Singh 2014), particularly for small borrowers (Love et al. 2013).

A second stream of literature uses contract-level details to examine the microeconomic effects of information sharing on lending. Although information sharing mechanisms have operated for centuries in the lending, insurance, employment, and product markets, producing micro-level evidence has been difficult because the exchange of information is typically not observable to researchers. In one of the few exceptions, Hertzberg et al. (2011) exploit changes in loan-size and risk-rating participation thresholds in the Argentinean public credit registry to examine the impact on leverage and defaults. They find that lenders preemptively reduce financing prior to their private information about a borrower being revealed to other lenders holding a more positive view of the borrower. The rush to reduce exposure to the borrower when a state of disagreement is revealed is analogous to a bank run and leads to an increase in defaults. Musto (2004) examines the expiration of limits on how long bankruptcies can be reported on consumers' credit files, and finds the withdrawal of adverse information leads to excessive debt and default. Brown et al. (2009) examine the establishment of information sharing systems in post-Soviet transition countries, and find improved credit access for firms with an opaque information environment. Several studies have examined how the payment history information shared through a credit repository has incremental explanatory power beyond other credit information in predicting default (Kallberg and Udell 2003; Powell et al. 2004; Dierkes et al. 2013). Doblas-Madrid and Minetti (2013) use an earlier, more limited version of the PayNet dataset and show that borrower delinquencies decline after a lender joins the bureau, and that this effect is strongest for small firms and those with low credit ratings. Because Doblas-Madrid and Minetti's sample is comprised of random contracts rather than credit files containing the entire set of a borrower's contracts, an analysis of relationship dynamics was precluded.

Although this line of contract-level research has advanced our understanding of information sharing, many questions remain unanswered for several reasons. First, microeconomic research has not kept up with the aforementioned theoretical models and cross-country studies in documenting the channels through which information sharing can increase credit availability. As a result, it is not clear how any increase in credit is allocated across new versus existing lenders, or whether the borrower's track record influences this allocation. Second, I am not aware of any archival study that explores how entering an information sharing arrangement alters the lender's incentives to contract with different types of borrowers, and in particular make relationship-specific investments. Third, the majority of contract-level evidence on information sharing is from developing market settings, where creditor protection is weak and recovery rates are low. Whether and how information sharing plays a role in asset-based credit markets where lenders' recovery efforts in default are more successful is unclear. Lastly, opponents of policies that expand the scope of credit-reporting have argued that information sharing leads to a premature stigmatization of those with poor credit histories, and prevents them from establishing new lending relationships (US House 2013). Empirical evidence that can inform this debate is currently lacking.

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, and transportation equipment. In 2013, private expenditures on equipment and software totaled approximately $1.2 trillion, representing 72% of private fixed non-residential investment (BEA 2013). Furthermore, nearly three quarters of US firms use some form of financing from banks, non-bank captives, and finance companies when acquiring equipment (IHS 2013).[2]

Contracts can be broadly categorized as loans or leases, which both banks and non-bank institutions offer. Loans and leases differ in their tax, bankruptcy, and financial reporting treatment, and in the technical expertise and services provided by the lender (Contino 1996). Nevertheless, I examine both contract types, given that in both cases, lenders screen potential borrowers' creditworthiness, interact with them over multiple transactions, and use information gathered to set contract terms.[3] Though asset redeployability can reduce the credit risk associated with leasing, lessors make extensive use of credit histories and financial statements, and occasionally visit the borrower's premises to perform maintenance work and verify the existence of leased assets (Contino 1996).[4] Moreover, a number of lenders in my dataset exclusively engage in leasing (i.e., they do not offer loan contracts), indicating creditworthiness is an important concern in originating contracts.

3.2 The PayNet credit bureau

[2] Securitization plays only a minor role in this market. In 2010, securitization volume was under $8 billion, representing approximately 1% of the total equipment finance volume in the US (Goukasian and Miller 2012).

[3] Later, I include contract-type fixed effects when analyzing contract terms.

[4] Contino (1996) notes that "although specific credit criteria can vary from lessor to lessor, certain basic areas will always be of review interest in the lessor's approval process…: existing banking relationship(s)…, good personal credit: personal credit reports that contain no derogatory information must be forthcoming."

In 2001, PayNet, a non-bank repository, launched a bureau that would allow equipment financiers to obtain borrower information via the internet for a nominal fee.[5] The bureau operates on the principle of reciprocity: lenders may only participate by agreeing to share all past, present, and future credit files with other members. PayNet employs algorithms and analysts to verify the accuracy and completeness of information being contributed to the bureau, and punishes members that violate its participation policies by locking them out of the system. Lenders' identities in the credit files are kept anonymous, and members are prohibited from using the bureau for direct marketing or mining client lists (Jackson 2000), dampening proprietary cost concerns about participating. When discussing Wells Fargo's involvement with PayNet, Senior Vice President and Credit Manager Curt Zoerhof commented, "PayNet does make a lot of sense. Our credit department is reluctant to call other lessors for a reference. If you have an anonymous system, that's helpful" (Jackson 2000). In fact, according to an industry publication (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.[6]

Over 250 lenders are members, including eight of the 10 largest competitors in the equipment finance market. Joining involves making expenditures to achieve compatibility with the PayNet platform, and improved members' ability to assess potential borrowers' creditworthiness in two key ways. First, by linking directly into lenders' information systems,

[5] While current pricing information is confidential, an industry magazine article from 2000 states that a firm's credit file could be accessed for as little as $5 by members (Jackson 2000).
[6] Credit-reporting systems emerged in consumer before commercial markets because contracts in the former tend to be smaller and more boilerplate, decreasing the proprietary costs of information sharing and increasing the usefulness of credit scoring (Mester 1997).

PayNet could compile and update indebtedness and contract performance information on a weekly basis. Second, the bureau provided borrower information that was more relevant, detailed, and verified than competing sources. Asking for references was problematic for the reasons mentioned above. Other credit reports (e.g., Experian) typically contained only utility bills and other smaller short-term payment histories that were consolidated at the firm level, offering a noisy signal of creditworthiness for more substantial, long-term credit applications (Jackson 2001; Doblas-Madrid and Minetti 2013). By comparison, PayNet reports provide a contract-level history of the firm's equipment financing activity (including terms and payment performance).[7] Discussions with PayNet and its members confirm that the primary benefit of joining is access to more relevant, verified, and timely information about borrowers. Appendix A provides an excerpt from an illustrative credit report.

The PayNet database and US equipment finance market offer several notable advantages for studying how information sharing affects relationship lending. First, lenders enter the bureau in a staggered pattern and are required to share both existing and past contract information. Combined with the fact that many borrowers in my sample have multiple lending relationships with lenders joining in different periods, this feature supports a quasi-natural experiment that allows me to control for both macroeconomic factors and shocks to the borrowers' demand for credit. Second, unlike in the consumer market, the FCRA does not regulate commercial lenders' sharing of information, and borrowers have virtually no say over whether or how their information is released (OCC 1996). Although the bureau's launch was prominently featured in industry publications, and conversations with

[7] PayNet does not regularly collect and distribute information on activities outside the equipment finance market, such as commercial mortgages. Although this limits the extent to which I can measure the creditworthiness of a given firm, it does not preclude me from examining the effects of information sharing because the credit files that lenders in my study are exchanging do not contain the non-equipment financing activity either.

PayNet indicate many lenders notify borrowers of their joining to comply with their privacy agreements, my tests do not even require borrowers to be aware of its existence. Rather, my assumption is that those who shop around when current contracts mature are impacted when potential lenders can more easily screen them with information available in the bureau.[8]

Nevertheless, the PayNet dataset has limitations. I do not observe lender or borrower identities, which precludes certain analyses of which lenders decide to become members.[9] My difference-in-difference design comparing contracting across lenders that join in separate periods controls for time-invariant characteristics (e.g., heavy reliance on credit scoring in underwriting) driving entry decisions; I run separate tests to address other concerns. First, to assess whether lenders join to thwart a recent spike in delinquencies, I replicate the exogeneity tests of Doblas-Madrid and Minetti (2013) and find a similar absence of an upward trend in delinquencies leading up to the join date. This finding suggests that deterioration in portfolio quality does not drive the entry decision. Second, in robustness tests, I examine how my results vary with lender characteristics. Larger lenders were more likely to join earlier, though new members have continued to enter in a relatively stable pattern over the years, with the 2009-2013 period averaging 19 per year. That larger lenders join early is not surprising given that a credit bureau is a natural monopoly, and PayNet had an incentive to "tip" the credit-reporting market by winning over the largest lenders shortly after launch.

[8] Equipment finance contracting guides advise borrowers to shop around for financing (Contino 1996). Moreover, using the 2003 Federal Reserve Survey of Small Business Finances, I note that during the last three years, the typical firm with an equipment loan applied for credit 1.6 times, *excluding* renewals of existing loans.

[9] That said, I document heterogeneity in size, geographic exposure, and industry focus of the lenders in my sample. Related, industry publications have indicated Citi, De Lage Landon, Farm Credit Leasing Services Corporation of Minnesota, and Wells Fargo are members (Jackson 2000, 2001; Ware 2002).

Lastly, I also note that joining the bureau requires the lender to ensure its IT systems are compatible with the PayNet platform, a nontrivial prerequisite.[10] Doblas-Madrid and Minetti (2013) discuss how "a certain percentage of the industry's players have custom (IT) systems, which requires a unique (technological) solution." Not surprisingly, the time spent making necessary upgrades to existing IT systems varies considerably across members, creating uncertainty around lender entry dates and representing an additional benefit of exploiting differences in timing in my tests. Despite these arguments, I interpret my results with caution and encourage empirical research that can examine selection into credit bureaus with more information about lenders.

3.3 Descriptive statistics

My initial sample contains the credit files for 20,000 randomly chosen firms in PayNet's database. Each file includes limited biographical information (including industry, state, and age) and a detailed contract history (including the terms, lender identifier, and payment performance on each contract) updated quarterly. From this initial sample, I exclude observations missing contract amount or maturity information. I then omit all observations from lenders without a sufficient contract history for my tests.[11] Table 1, Panel A reports that my final sample contains 442,742 contracts between 19,878 borrowers and 61 lenders.

Panel B provides descriptive statistics for contract terms and payment performance. Loans comprise 17% of the deals, whereas the remaining 83% are leases. The average (median) contract amount is $123,148 ($28,081), though contract sizes vary considerably from under $1,000 to the hundreds of millions of dollars. Seventeen percent of the contracts

[10] A 2005 KPMG survey of 600 organizations (33% of them in the financial services sector) found that 49% experienced at least one IT project failure (not completed on time, on budget, or to specification) in the prior year; 57% report at least one failure in the 2002-2003 survey.

[11] Appendix C provides additional details about the joining process and sample selection criteria.

have a personal or corporate guarantor (or both).[12] Like other credit bureaus (e.g., consumer bureaus such as Equifax) and many commercial bureaus examined in related work (see Hertzberg et al. [2011]), PayNet does not report the interest rate on contracts, in order to avoid antitrust scrutiny and mitigate members' proprietary cost concerns. There is considerable heterogeneity in the payment performance of borrowers that ultimately gets revealed to other members. For 40% of the contracts, borrowers always pay on time; for 25% (9%), the worst delinquency is less than 30 days (more than 90 days). Panel C shows that on a dollar-weighted basis, the plurality of contracts are for trucks. Contract start dates span 1980 to 2014.

Table 2, Panel A presents descriptive statistics for borrowers. Because firms' financial statements are not observable to me, 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 $1.4 million ($129,170) for the average (median) firm during the sample period. The typical firm is 11 years old, and has eight years of borrowing history and six open contracts. Sixty percent of borrowers have been late at least once on an open contract, and 7% have been in arrears by over 90 days. Panel B shows that business equipment providers represent the most common industry group. Although I do not observe zip codes or MSAs, I note that sample borrowers occupy all 50 states, plus the District of Columbia, Guam, and the Virgin Islands. Panel C presents descriptive statistics for the lenders' portfolio of contracts contained in my sample. On average, lenders have 1,438 open contracts; this figure obviously understates the magnitude of their activities, because I only observe their interactions with the 19,878 borrowers in the sample.

Table 3 shows that relationships are important in this setting: at origination, the borrower in an average contract has had a six-year relationship with its lender, and in only

[12] Approximately 10% of the contracts are missing information about the existence of a guarantor.

17% of the deals is the borrower interacting with the lender for the first time. During the sample period, borrowers (lenders) have an average of 1.6 (379) ongoing contracting relationships. The unconditional probability of a relationship ending over the next year (two, three, and four years) is 15% (30%, 42%, and 53%).

4. Empirical tests and results

4.1 Research design

My main specification employs the following within-borrower-quarter estimator to examine how information sharing affects relationship survival:

$$Y_{ijt} = \beta_1^{FE} * Join_i + \lambda_{jt}^{borrower-quarter} + \varepsilon_{ijt} \quad (1),$$

The unit of observation is borrower-lender-quarter.[13] The dependent variable is an indicator for whether borrower j exits the relationship with lender i after various periods.[14] Consistent with prior literature (Ioannidou and Ongena 2010), I examine relationship terminations and new relationships separately because firms can replace an existing lender, let outstanding contracts with an existing lender wind down before doing so, or keep existing relationships alive while adding new ones, and I refer to all of these decisions as "switching." *Join* is an indicator equal to 1 for the borrower-lender pairs in which the lender joined the bureau that quarter, and 0 for borrowers' other open pairs.[15] Lender join dates are defined as the first date

[13] Collapsing instead at the borrower-lender-contract type-quarter level and including contract-type fixed effects increases the number of observations and slightly strengthens my results.

[14] I classify a relationship exit as the failure to maintain non-zero credit for a given number of consecutive quarters. However, my results are similar if I allow a one-quarter buffer for delays in renewal (e.g., a relationship in which the only contract matures in Q1 but a new one starts in Q3 is not classified as having an exit).

[15] I omit pairs in which the join dates occur in the event window. For example, assume a borrower has credit with lender A (joined Q1 2002), B (Q3 2003), and C (Q3 2008). When testing relationship survival one (four) years after A joins, B would (would not) be used as a control, because the window does not (does) overlap with B's entry to the bureau. C would be used as a control in both the one- and four-year tests. Hence, my sample size varies with the event window. For later entry dates, I use relationships with early lenders as controls (provided there is no overlap in the event window), assuming any effect of information sharing dissipates over time. This

that a lender queries a credit record in the PayNet system. Finally, parallel to Khwaja and Mian (2008) and Lin and Paravisini (2011), I include borrower-quarter fixed effects. 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.[16]

Intuitively, this specification is analogous to an event study, where I compare the long-term survival for relationships whose past and current contract terms and payment history have been collected, reviewed, and revealed by PayNet, relative the firm's other current relationship(s) that are kept private throughout the event window. The likelihood of the former ending is higher because outside lenders should be more willing to contract with a firm when they can observe how they have performed on similar contracts in the past, and the current contract terms are visible and have been verified by the bureau. The primary advantage of this specification is that the borrower-quarter fixed effect absorbs demand-side shocks unrelated to information sharing, such as changes in the investment opportunity set or cash constraints that could impact the decision to continue or exit a lending relationship. The identifying assumption is that any shock to the borrower's demand for credit is the same across its lenders. The drawback of this approach is that in some cases, the borrower could use its credit history to replace both relationships detailed in its credit file and relationships kept private (but are observable to me because lenders backfill contracts upon joining PayNet). While, I note this "treatment spillover" makes finding any effect of information sharing more difficult, I run robustness tests using controls instead of a borrower-quarter fixed effect and find my inferences are similar.

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increases my sample size and power of my tests but does not change my inferences. In fact, consistent with my predictions, I find the largest effect for the first time a borrower has its relationship shared in the bureau.

[16] Clustering instead by lender strengthens the significance of my results.

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

$$\Delta Y_{ijt} = \beta_1^{FE} * Join_i + \lambda_{jt}^{borrower-quarter} + \varepsilon_{ijt} \quad (2),$$

When measuring the change in log credit, I collapse the pre and post periods into equal length four- or eight-quarter period averages (excluding the join quarter) to address concerns about serial correlation and facilitate comparison between borrowers with early and late join dates. I Winsorize the change at -100% and +100% to prevent the logarithmic approximation from skewing my results, though my inferences are unchanged if I instead use the Winsorized raw percent change in credit.[17]

4.2 Information sharing and relationship survival

Table 4, Panel A presents my main results. Columns 1-4 use (1) to explore the likelihood that the borrower and lender continue their relationship over various horizons. Column 1 shows the likelihood of exit in the next year is 3.4% higher for relationships revealed in the bureau, which is a sizable effect considering that the probability for untreated relationships is 14%. Because the typical borrower has multiple open contracts with its lender and abruptly refinancing each is likely costly, I expect the effect of the lender joining the bureau on relationship survival to manifest over time as old contracts mature and borrowers explore their options in the credit market. The results in columns 2-4 support this notion. The incremental likelihood of relationship exit for pairs in which the lender has joined the bureau is 8.3%, 12.2%, and 16.3% after two, three, and four years, respectively; each estimate is statistically significant and an economically material margin above the unconditional

[17] When the change in credit is large (e.g., a decrease from $1M to $300,000), the log change drastically exceeds the actual percent change (-120% using logs vs. 70% in actual percent). In instances where outstanding balance on the contract is missing, I interpolate the balance using the original amount and contract term.

probability of exit. Column 5 uses (2) to compare the change in likelihood of prepayment for relationships that were revealed in the bureau relative to ones that remain private. I find an incremental increase in the probability of repayment with the lender that joins the bureau, though the difference is not statistically significant. This finding could reflect the preference of firms to wait until ongoing contracts expire before contracting with a new lender, rather than abruptly prepaying and possibly incurring prepayment penalties.

My next set of tests uses (2) to examine changes in credit around lenders' entry to the bureau. Over the two- (four-) year window, the unconditional average change in credit is -21% (-19%), as borrowers pay down outstanding balances, and either renew, exit the relationship, or cease to survive. Columns 6 and 7 show a decrease in outstanding credit for relationships shared in the bureau, relative to others remaining private during the same period, but the drop is not significant. In sum, Table 4 indicates that information sharing expedites the dissolution of lending relationships, an effect that strengthens as time passes. However, the average credit outstanding does not differ, suggesting that although information sharing leads some relationships to end, others survive and actually increase in depth.

Panel B presents a robustness analysis of my initial results. I focus on my exit tests analyzing the two years after lenders' bureau entry, but my inferences are similar if I examine other horizons. Column 1 repeats the original result to facilitate comparison; column 2 replicates (1) without borrower-quarter fixed effects to examine how failing to adequately control for demand-side factors would have affected my results.[18] I find the magnitude of the coefficients on my exit test without fixed effects is approximately 5% *smaller*. This difference, combined with the fact my original result is likely downward biased because of the

[18] Here, I include borrower and lender fixed effects, plus controls for the borrower's (lender's) current average days delinquent on open contracts and an indicator for whether the borrower has had a serious delinquency in the last three years (percentage of the contract portfolio with serious and non-serious delinquencies).

treatment-effect spillover, indicates a *negative* cross-sectional correlation between information sharing and demand-side shocks affecting the propensity to exit the relationship. In other words, this finding suggests that lenders do not join the bureau at a given point because their borrowers are more likely to leave the relationship anyway.

Next, I examine whether my results are sensitive to lenders' selection into the bureau. One concern is that my results could reflect lenders making a deliberate shift in strategy toward transactional lending and away from relationship lending, rather than just the availability of borrower information in the bureau. In this interpretation, lenders first decide to alter their approach to client interactions, for example, out of a desire to enter new markets, and joining PayNet happens after they have made this decision. Though the information provided by PayNet would facilitate such a transition, other concurrent changes to the lender's operations that I do not observe could also play a role.[19] Although my staggered design and uncertainty around lenders' actual entry dates helps mitigate this concern, I proceed to assess my results in two robustness tests. First, in column 3, I restrict my sample to lenders that have *not* increased their offerings (defined as the number of equipment types in which they contract) over the first year after joining the bureau. Second, I examine the market from the borrower's perspective, and in column 4, only include firms that exclusively contract for one type of equipment in the dataset. In both cases, I find my results are similar—the incremental exit probability after two years (8.2% and 9.4% in columns 3 and 4, respectively)—is statistically significant and indistinguishable from the original result (8.3%). Moreover, I note that my subsequent cross-sectional tests based on the borrower's track record are consistent with the possibility that borrower information provided by the bureau

[19] Specifically, I expect information sharing to be instrumental in transitioning away from relationship lending by providing the lender with "hard" information in the form of credit scores and credit histories.

explains my results. Though I cannot rule out that lenders shifting their strategy might contribute to my results, such shifting does not appear to be the sole force.

In columns 5 and 6, I explore whether my results differ for relationships with larger lenders (proxied by having an above-median number of contracts in the system).[20] Considering that smaller lenders tend to be more specialized and are often better positioned to collect soft information about borrowers than larger peers (Berger et al. 2005), I expect them to have an advantage with respect to retaining clients. Because the majority of larger lenders joined prior to 2006, this test simultaneously examines the difference between large and small and early and late entrants. Columns 5 and 6 confirm my prediction, and show that large lenders (which underwrote over 90% of the sample contracts) drive the incremental likelihood of exit.[21] Lastly, to address concerns that borrowers matched to lenders knowing whether or when they would join the bureau, I restrict my sample in column 7 to pairs that first did business together in 1999 or earlier (given that PayNet was announced in 2000 and launched in 2001), and I find similar results.

I now perform cross-sectional tests to examine how the effect of information sharing on relationship survival depends on the borrower's payment record. I split my sample into three groups: borrowers revealed to have a clean, bad, and mixed credit record. Those with a clean record are current on all outstanding contracts and have not been late on any payment with the lender over the past three years. Those experiencing a default event (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 considered

[20] In untabulated robustness tests, I also find my results are robust to excluding borrowers above the 90th (below the 10th) size percentile from my sample, and to including contract-type fixed effects. Furthermore, I analyze the change in relationship survival around placebo dates for lenders' entry to the bureau, and find no effect.

[21] I also compare specialized versus unspecialized lenders (based on the median number of equipment types and three-digit SIC industry exposure) and do not find a significant difference in results.

to have a bad track record. The history of remaining borrowers is considered mixed, given the lack of a default event but the experience of at least one payment falling between one and 90 days late. I apply this classification scheme at the pair level (so a borrower could have a clean record with one lender and a mixed or bad record with another) and update it every quarter. According to this specification, 36% (12%, 52%) of borrower-lender-quarter observations are assigned a clean (bad, mixed) record.

Columns 1 and 3 of Table 5, Panel A reveal that borrowers with a clean or mixed record are most likely to exit the relationship within two years of their lender joining the bureau (for brevity, I tabulate these cross-sectional tests for only the two-year post-join period), and the difference is an economically and statistically significant 9%. On the other hand, bad-record borrowers are no more likely to exit.[22] Column 2 shows that information sharing increases the amount of credit from the joining lender for clean record firms by 8% (though the change is not statistically significant), whereas for mixed- and bad-record firms, there is a significant decrease in credit from the joining lender. These results suggest the effects of information sharing vary according to credit quality, initiating relationship turnover for those with perfect or mixed records. However, even accounting for the greater propensity of exit among those with perfect records, their relationship with the joining lender on average *deepens* in terms of outstanding credit.

Next, I examine whether the *length* of the borrower's track record alters the effect of information sharing on relationship survival and credit outstanding, on its own and in conjunction with the *quality* of the track record. I classify firms with less than two years of credit history at the time their lender joins the bureau as having a short track record, and all

[22] Employing an interactive specification reveals the incremental likelihood of exit for clean and mixed firms is statistically significant.

others as having a long track record (my inferences are similar if I use partitions of one or three years). Table 5, Panel B presents the results. Columns 1 and 2 show that those with a lengthy borrowing history are significantly more likely to leave and receive less credit from the joining lender. The incremental likelihood of exit for these firms is an economically large 11.5%, nearly 40% above the unconditional mean. By contrast, those with a short track record are weakly less likely to exit, and instead deepen the relationship via an increase in credit.

I then supplement (1) and (2) with interactions between *Join*, credit quality category indicators, and the natural logarithm of the track record length; mixed credit quality firms are the holdout category and all main effect and interaction terms not shown are subsumed by the borrower-quarter fixed effect. Columns 5 and 6 show that the length of a borrower's track record interacts with the content of the record in a manner consistent with my predictions. Those with a bad payment record become less likely to exit as their track record gets longer; a one standard deviation increase in track record length reduces the probability of exit for these firms by an economically and statistically meaningful 5.6%. On the other hand, a long track record *helps* those with a perfect payment record leave, with an incremental probability of exit of 5.7% for a one-standard-deviation in track record length. Column 6 examines the change in credit and tells a parallel story. An extensive track record increases (decreases) poor- (clean-) payment history firms' reliance on the lender for credit.

4.3 Information sharing and new relationships

So far, my results suggest that information sharing reduces switching costs by accelerating the termination of existing relationships, particularly for borrowers with a clean, lengthy track record. To bolster this evidence, I now explore how information sharing facilitates the formation of new relationships. Table 6 examines whether the borrower is more likely to contract for the first time with a lender after the former's information appears in the bureau relative to before. I run borrower fixed-effect regressions, comparing the likelihood of starting a new relationship in the window before versus after the borrower's credit file is first available in the system.[23] In addition to not being able to employ borrower-*quarter* fixed effects, another drawback of these tests relative to my exit tests is that I only observe new relationships with lenders that ultimately become members of PayNet, which creates measurement error for my dependent variable.[24]

Column 1 (2) reveals a statistically significant incremental likelihood of contracting with a new lender in the one- (two-) year period after the borrower's information is first made available. The 3.1% (4.9%) increase is an economically material margin above the unconditional likelihood of 13% (22%) of starting a new relationship in the pre period. Consistent with the bureau playing an important role in facilitating new matches, 65% of borrowers' new relationships in the two-year period after their credit file is available are with lenders that are PayNet members at the time. I also find that of the firms starting new relationships in the two year period after their file is available, 54% have left an existing lender while the rest maintain their existing relationship(s), indicating a variety of responses by firms to having their credit file shared.

Columns 3-7 test whether the content and length of a borrower's track record influences whether information sharing helps them form new relationships. I find a significantly positive effect for firms with a perfect payment history, and no statistical effect for those carrying a mixed or poor record (though for the latter, the coefficient magnitude is

[23] To facilitate comparison with my prior tests, I continue to restrict my sample to multiple relationship borrowers (in this case, those with more than one relationship at the beginning of the event window).

[24] I am not able to apply (1) for these tests because whereas (1) allows me to use the borrower's other current private relationships as a control when studying the survival of the relationship being revealed, no analogous control exists for examining whether a new relationship is formed.

surprisingly high). Similarly, Columns 6 and 7 show that borrowers with a long track record are most likely to establish a new relationship, whereas those with a track record of less than two years are no more likely to do so. While I am constrained in only observing new relationships with lenders that ultimately joined PayNet (and that meet my sample selection criteria), these results nicely complement my prior findings: information sharing leads to both the termination of existing relationships and the formation of new ones, and those with a long track record without serious delinquencies drive this effect.

4.4 Changes in relationship dynamics for single-relationship borrowers

One limitation of (1) and (2) is that by including borrower-quarter fixed effects, I require firms to have at least two active lending relationships in the period surrounding the join date. This requirement imposes only modest restrictions on my sample size (of the 19,878 borrowers in my initial sample, approximately one third exclusively contract with a single lender in the dataset), but requires the development of another estimation approach if single-relationship firms are to be studied separately. Information sharing could play a different economic role for such firms, given the increased reliance on an individual lender for credit. I apply the following cross-sectional test for single-relationship borrowers:

$$Y_{ij} = \beta_1^{OLS} * Join\,Cohort_i + \chi * Borrower\,Controls_j + \phi * Lender\,Controls_i + \varepsilon_{ij} \quad (3),$$

Here, I restrict the sample to the subset of single-relationship firms with contracts beginning between 1997 and 1999, and ending in 2003. *Join Cohort* is an indicator for those whose lender joined prior to 2003, and control firms are limited to those whose lender joined in 2005 or later. This test exploits the fact that this subset of borrowers did not know in 1997 to 1999 that the bureau would exist, let alone whether or when their lender would participate. All of these borrowers would have to originate contracts again in 2003, some after having their information shared in the bureau and others not. The dependent variable is an indicator for whether after 2003, the borrower has exited the relationship (or in later tests, begun a new one). Borrower controls include size, age, one-digit industry, and indicators for whether they are currently delinquent on a contract and whether they have experienced a serious delinquency in the last three years. Lender controls include size (proxied by the log of total current outstanding contracts in the sample), and the portfolio's current average delinquency and serious delinquency rates over the past three years. In these tests, I cluster standard errors at the lender level to account for correlation between observations within the same lender. One limitation of these tests is the measurement error associated with identifying single-relationship borrowers in my sample. Because I only observe contracts with lenders who joined the PayNet bureau at some point, I could misclassify borrowers as having one lending relationship when in fact they have others with non-bureau members. Also, my sample contains just fewer than 1,100 firms with the prerequisite characteristics (single relationship, and have a contract starting in the late 1990s that ends in 2003) for testing (3). Given these limitations, the objective of these tests is to offer descriptive evidence.

Table 7 applies (3) to examine how information sharing affects single relationship borrowers. Columns 1 and 2 show that firms whose lender joined the bureau prior to 2003 were more likely to exit the relationship, though the difference is not close to being significant at conventional levels. Likewise, columns 3 and 4 find no change in credit from the existing lender following its entry to the credit bureau. On the other hand, columns 5 and 6 reveal that those whose lender joined the bureau are significantly more likely to commence a new relationship in subsequent periods. Within one (two) years of the 2003 renewal for this cohort, borrowers whose information has been contributed to the bureau are 8.5% (13.9%) more likely to have established a contract with a new lender, a sizable margin above the unconditional mean of 30% (44%).[25]

5. Information sharing and investments in relationship lending

5.1 Theory

Are lenders less willing to make relationship-specific investments once they agree to share the terms on which they provide financing and borrowers' payment records, both of which they previously had the discretion to keep private? On the one hand, lenders could decrease relationship investments, anticipating that borrowers have a greater opportunity to access financing from bureau members now endowed with more information about their creditworthiness. Such turnover would threaten the lender's ability to share in the borrower's future surplus and recover any losses incurred early in the relationship (Petersen and Rajan 1995; Gehrig and Stenbacka 2007). On the other hand, heightened competition could compel lenders to differentiate themselves according to relationship services (Boot and Thakor 2000). In this section, I empirically examine how information sharing impacts two aspects of relationship investment.

First, a lender may contract differently with a new borrower when this borrower's credit file is available to others. Borrower-lender conflicts of interest can be constrained by reducing maturity (Myers 1977; Flannery 1986; Barclay and Smith 1995).[26] Alternatively, the lender can engage in costly monitoring (Diamond 1991). The value of information that the lender accumulates through monitoring is increasing in the likelihood that it will contract with

[25] Given the power issues I encounter in examining single-relationship firms, I do not investigate whether these results depend on the quality and length of the borrower's track record.

[26] Complementing this evidence, Graham et al. (2008) and Costello and Wittenberg-Moerman (2010) find that in new contracts issued after a borrower's financial restatements, maturity is shorter.

the borrower again (Chan et al. 1986). Hence, holding all else constant, if information sharing reduces the likelihood of relationship survival, costly monitoring becomes a less appealing device for constraining agency problems relative to maturity. A similar logic applies to guarantor requirements. Guarantors offer additional security for credit contracts, and soft information gathered through interaction with guarantors is most valuable when the lender expects to subsequently contract with the firm. Together, these arguments suggest lenders could rely more on the payment schedule (maturity and frequency) and less on guarantors when contracting with new borrowers whose credit files are available to others.

Second, in the information sharing regime, the lender could be less likely to continue providing credit to borrowers experiencing payment problems. Such incidents represent costly investments to the lender for multiple reasons. Missed payments present an early warning signal that borrowers will default on their obligations altogether; offering additional credit intensifies lenders' exposure to these risky firms. Poorly performing loans also often require more careful scrutiny and visits to borrowers' premises, reducing the human and financial resources that can be deployed elsewhere (Doblas-Madrid and Minetti 2013). Moreover, for banks, delinquent borrowers and loan losses increase regulatory costs by attracting closer attention from examiners (OCC 2001). Lastly, missed payments and loan losses reduce cash flows and can provoke liquidity problems. While late payments impose costs on lenders, contract renewals occur regularly because borrowers' performance often improves—the young, delinquent firms of today often grow into mature, stable firms.

5.2 Information sharing and the terms of credit

In my next set of tests, I apply a difference-in-differences specification similar to (1) but modify the dependent variable to equal one of four contract terms: the (log) maturity, (log) payment frequency, whether there is a guarantor, and (log) average contract size. I add an interaction for new contracts originated after the borrower's information is available in the PayNet system. If more than one contract is outstanding for the pair, I take the dollar-weighted terms of the open contracts. The sample is restricted to borrowers who started a new relationship that quarter, and the tests include borrower-quarter and contract-type fixed effects. Hence, I am comparing the terms of the new contract(s) at initiation to those for the existing contract(s) with other lenders at the same point in time (first difference), for the period after versus before the borrowers' credit record was in the system (second difference). Table 8 shows that on average, in new relationships the borrower is more likely to provide a guaranty and get smaller contracts.

However, for relationships initiated after the borrower's information has been shared in the bureau, terms differ in several ways. Contract maturity shortens by an economically and statistically significant 6.6%. I also find an increase in payment frequency, though the increase is significant at just the 12% level. These results are notable given the boilerplate nature of such terms in equipment financing: contract maturity is typically linked to the life of the asset, and my sample contains little variation in payment frequency. Columns 3 and 4 show that the likelihood of having a guarantor decreases by almost 4% and the typical contract size rises by 12%; both effects are statistically and economically significant. Though I pool lease and loan contracts in these tests and include contract-type fixed effects, I note that my results are similar if I examine each contract type separately. In sum, while deciphering the welfare implications of these changes in terms is difficult, I note that the *mix* of terms supports a transition away from relationship lending and toward more transactional lending. Contracts are shorter term and require (weakly) more regular payments. Contract guarantees, which often involve personal interaction with the firm's stakeholders that fosters the accumulation of reusable information about the borrower, become less common.

5.3 Information sharing and contract renewals after delinquencies

I next examine contract renewal decisions using the following specification:

$$Y_{ijt} = \beta_1^{FE} * Post\ Join_i + \lambda_{ij}^{Pair} + \varepsilon_{ijt} \quad (4),$$

The dependent variable takes two forms. The first is an indicator for whether the lender initiated a new contract with the borrower at any point in the three-year period after a serious delinquency, defined as a default event or a payment more than 90 days late. I also employ a second variable for whether the pair initiates a new contract in the three-year period following a non-serious delinquency, defined as any contract falling between one and 90 days behind but not experiencing a default event. *Post Join* is an indicator for renewal decisions occurring after the lender has joined the bureau.[27] I include relationship (borrower-lender pair) fixed effects, which control for time-invariant borrower and lender characteristics and the forces behind the matching of the pair, and cluster my errors at the quarter-year level. Given that lenders choose to join the bureau and have some discretion over the timing of their entry, I interpret these tests with caution.

Panel A presents descriptive statistics for renewal decisions and the evolution of borrowers' track records after a delinquency. There are 10,291 (42,242) relationships that have experienced a serious (non-serious) delinquency; in 3,814 (20,989) instances, the parties subsequently originate a new contract. Borrowers' performance often improves following even the most adverse events: for those experiencing a serious delinquency, the firm later

[27] I omit observations from lenders joining after the second quarter of 2011, and observations with delinquencies with other lenders occurring after the second quarter of 2011, given that I do not observe the full three-year post period for these observations.

goes three consecutive years without missing a single payment in 1,644 cases and with only non-serious delinquencies in another 2,178 cases.

Table 9, Panel B presents the results. Column 1 shows a statistically significant 9.7% reduction (representing 34% of the sample mean) in the likelihood of renewal after a serious delinquency occurring once the lender has joined the bureau. Column 2 shows a similarly significant reduction (27% of the sample mean) in renewal following less serious delinquencies after the lender is sharing information. In columns 3 and 4, I collapse the observations for each lender into single pre- and post-join periods to mitigate concerns about serial correlation overstating the significance of my prior results. I continue to find an economically meaningful effect of information sharing on renewal decisions, though my column 4 estimates for renewals after less serious delinquencies are not statistically significant. These findings complement my contract term analysis in documenting a second channel through which information sharing affects lenders' relationship investment decisions: fewer contract renewals occur following missed payments.

6. Conclusion

In this paper, I examine how information sharing affects the survival of existing credit relationships, the creation of new ones, and the willingness of lenders to invest in relationships. Despite the pervasiveness of information sharing in credit markets and a rich theoretical literature on relationship lending, contract-level evidence documenting these relationship dynamics is virtually non-existent. I fill this gap using a panel of borrowers' credit files that detail their contracting activity and payment performance with lenders that join the PayNet equipment finance bureau in a staggered pattern over more than a decade. The primary advantage of this setting is that it allows me to examine relationship and contracting dynamics within borrower-time period, effectively controlling for firm-specific shocks to credit demand, because lenders must provide both ongoing and past contracts upon joining.

I find that information sharing significantly reduces switching costs for borrowers, enabling both the exit from longstanding relationships and the formation of new contracting relationships with other lender members of the bureau. However, this effect is not uniform across the sample of borrowers. Consistent with theory, I show that borrowers revealed to have a long track record without recent serious delinquencies are most likely to be able to contract with an outside lender for the first time, whereas those with a short, poor credit history are most likely to stay with their existing lender. Finally, I demonstrate that a reduction in switching costs for borrowers has two important implications for how lenders contract once they have committed to sharing borrower information. Lending becomes more transactional and less relationship-focused: for contracts with new borrowers whose credit file are available to other members, maturities are shorter and interaction with the firm's owners via guarantees is less likely. After they join the bureau, lenders are less willing to originate new contracts with borrowers that run into either moderate or serious payment trouble.

By offering the first contract-level evidence of the effect of information sharing on relationship dynamics and investment, my paper contributes to our understanding of the role of the borrower's information environment in relationship lending. My results are also relevant to the numerous other settings in which principals exchange information about agents—including insurance, employment, and rental markets—where the reporting of agents' track records mitigates information asymmetries that impede contracting.

References

Acharya, V. V., Hasan, I., & Saunders, A. (2006). Should banks be diversified? Evidence from individual bank loan portfolios. Journal of Business, 79(3), 1355-1412.

Admati, A. R., & Pfleiderer, P. (2000). Forcing firms to talk: Financial disclosure regulation and externalities. Review of Financial Studies, 13(3), 479-519.

Allee, K. D., & Yohn, T. L. (2009). The demand for financial statements in an unregulated environment: An examination of the production and use of financial statements by privately held small businesses. The Accounting Review, 84(1), 1-25.

Armstrong, C. S., Guay, W. R., & Weber, J. P. (2010). The role of information and financial reporting in corporate governance and debt contracting. Journal of Accounting and Economics, 50(2), 179-234.

Barclay, M. J., & Smith, C. W. (1995). The maturity structure of corporate debt. Journal of Finance, 50(2), 609-631.

Beatty, A., Liao, S., & Yu, J. J. (2013). The spillover effect of fraudulent financial reporting on peer firms' investments. Journal of Accounting and Economics.

Bennardo, A., Pagano, M., & Piccolo, S. (2013). Multiple-bank lending, creditor rights and information sharing. Working paper.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., & Stein, J. C. (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. Journal of Financial Economics, 76(2), 237-269.

Beyer, A., Cohen, D. A., Lys, T. Z., & Walther, B. R. (2010). The financial reporting environment: Review of the recent literature. Journal of Accounting and Economics, 50(2), 296-343.

Boot, A. W. (2000). Relationship banking: What do we know?. Journal of Financial Intermediation, 9(1), 7-25.

Boot, A. W., & Thakor, A. V. (2000). Can relationship banking survive competition?. Journal of Finance, 55(2), 679-713.

Boyd, J. H., & Prescott, E. C. (1986). Financial intermediary-coalitions. Journal of Economic Theory, 38(2), 211-232.

Brown, M., Jappelli, T., & Pagano, M. (2009). Information sharing and credit: Firm-level evidence from transition countries. Journal of Financial Intermediation, 18(2), 151-172.

Bruhn, Miriam, Farazi, S. & Kanz, M. (2013). Bank competition, concentration, and credit reporting. Policy Research Working Paper Series 6442, The World Bank.

Bureau of Economic Analysis, "Table 5.3.5. Private Fixed Investment by Type," http://www.econstats.com/nipa/nipa_5__3___5q.htm (accessed November 24, 2013).

Bushee, B., & Leuz, C. (2005). Economic consequences of SEC disclosure regulation: Evidence from the OTC bulletin board. Journal of Accounting and Economics, 39(2): 233-264.

Cassar, G., Ittner, C., and Cavalluzzo, K. (2014). Alternative information sources and information asymmetry reduction: Evidence from small business debt. Journal of Accounting and Economics, forthcoming.

Chan, Y. S., Greenbaum, S. I., & Thakor, A. V. (1986). Information reusability, competition and bank asset quality. Journal of Banking & Finance, 10(2), 243-253.

Contino, R. M. (1996). Handbook of equipment leasing: A deal maker's guide. American Management Association.

Costello, A. M, and Wittenberg-Moerman, R. (2011). The impact of financial reporting quality on debt contracting: Evidence from internal control weakness reports. Journal of Accounting Research, 49(1), 97-136.

Dell'Ariccia, G., & Marquez, R. (2006). Lending booms and lending standards. Journal of Finance, 61(5), 2511-2546.

Diamond, D.W. (1984). Financial intermediation and delegated monitoring. Review of Economic Studies, 51(3): 393-414.

Diamond, D. W. (1989). Reputation acquisition in debt markets. Journal of Political Economy, 828-862.

Dierkes, M., Erner, C., Langer, T., & Norden, L. (2013). Business credit information sharing and default risk of private firms. Journal of Banking & Finance, 37(8), 2867-2878.

Djankov, S., McLiesh, C., & Shleifer, A. (2007). Private credit in 129 countries. Journal of Financial Economics, 84(2), 299-329.

Doblas-Madrid, A., & Minetti, R. (2013). Sharing information in the credit market: Contract-level evidence from US firms. Journal of Financial Economics, 109(1), 198-223.

Dye, R. A. (1990). Mandatory versus voluntary disclosures: The cases of financial and real externalities. The Accounting Review, 1-24.

Fama, E. F. (1980). Agency problems and the theory of the firm. Journal of Political Economy, 288-307.

Flannery, M. J. (1986). Asymmetric information and risky debt maturity choice. Journal of Finance, 41(1), 19-37.

Foster, G. (1981). Intra-industry information transfers associated with earnings releases. Journal of Accounting and Economics, 3(3), 201-232.

Garmaise, M. J., & Natividad, G. (2014). Does more information lead to more financing? Local information shocks and bank credit. Working paper.

Gehrig, T., & Stenbacka, R. (2007). Information sharing and lending market competition with switching costs and poaching. European Economic Review, 51(1), 77-99.

Goukasian, L. & Miller, A. (2012). Equipment lease and loan securitization performance versus other asset classes. Journal of Equipment Lease Financing, 30(1).

Graham, J. R., Li, S., & Qiu, J. (2008). Corporate misreporting and bank loan contracting. Journal of Financial Economics, 89(1), 44-61.

Hertzberg, A., Liberti, J., & Paravisini, D. (2011). Public information and coordination: evidence from a credit registry expansion. Journal of Finance, 66(2), 379-412.

IHS. (2013). 2012-2013 U.S. Equipment Finance Market Study.

Ioannidou, V., & Ongena, S. (2010). “Time for a change”: loan conditions and bank behavior when firms switch banks. Journal of Finance, 65(5), 1847-1877.

Jackson, S. (2000). Lessees’ payment history now available online. Equipment Leasing Today, October, 55-61.

Jackson, S. (2001). Better credit data, better credit decisions. Equipment Leasing Today, June/July, 44-49.

Jaffee, D. M., & Russell, T. (1976). Imperfect information, uncertainty, and credit rationing. Quarterly Journal of Economics, 90(4), 651-666.

Jappelli, T., & Pagano, M. (2000). Information sharing in credit markets: a survey (Vol. 36). CSEF Working Paper.

Jappelli, T., & Pagano, M. (2002). Information sharing, lending and defaults: Cross-country evidence. Journal of Banking & Finance, 26(10), 2017-2045.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics, 3(4), 305-360.

Kallberg, J. G., & Udell, G. F. (2003). The value of private sector business credit information sharing: The US case. Journal of Banking & Finance, 27(3), 449-469.

Khwaja, A. I., & Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. American Economic Review, 1413-1442.

Klein, D. B. (1992). Promise keeping in the great society: A model of credit information sharing. Economics & Politics, 4(2), 117-136.

Klemperer, P. (1995). Competition when consumers have switching costs: An overview with applications to industrial organization, macroeconomics, and international trade. Review of Economic Studies, 62(4), 515-539.

KPMG (2005). Global IT project management survey.

Lambert, R., Leuz, C., & Verrecchia, R. E. (2007). Accounting information, disclosure, and the cost of capital. Journal of Accounting Research, 45(2), 385-420.

Leuz, C., & Wysocki, P. (2008). Economic consequences of financial reporting and disclosure regulation: A review and suggestions for future research. Working paper.

Lin, H., & Paravisini, D. (2011). Delegated monitoring of fraud: The role of noncontractual incentives. Working paper, IMF and Columbia University.

Lisowsky, P., & Minnis, M. (2013). Financial reporting choices of US private firms: Large-sample analysis of GAAP and audit use. Chicago Booth Research Paper, (14-01).

Love, I., Piera, M.S.M., & Singh, S. (2013). Collateral registries for movable assets. Working paper

Madison, J. H. (1974). The evolution of commercial credit reporting agencies in nineteenth-century America. Business History Review, 48(02), 164-186.

Mester, L. J. (1997). What's the point of credit scoring?. Business Review, 3, 3-16.

Mian, A. (2012). The case for a credit registry. In Risk topography: Systemic risk and macro modeling. University of Chicago Press.

Minnis, M., & Sutherland, A. (2014). Financial statements as monitoring mechanisms: Evidence from small commercial loans. Working paper.

Myers, S. C. (1977). Determinants of corporate borrowing. Journal of Financial Economics, 5(2), 147-175.

Musto, D. K. (2004). What happens when information leaves a market? Evidence from postbankruptcy consumers. Journal of Business, 77(4), 725-748.

Office of the Comptroller of the Currency (OCC) (1996). Fair credit reporting: Comptrollers handbook. Report No. CCE-FCR. Oct. 1996.

Office of the Comptroller of the Currency (OCC) (2001). Rating credit risk: Comptroller's handbook. Report No. A-RCR. April 2001.

Ongena, S., & Smith, D. C. (2000). What determines the number of bank relationships? Cross-country evidence. Journal of Financial Intermediation, 9(1), 26-56.

Padilla, A. J., & Pagano, M. (2000). Sharing default information as a borrower discipline device. European Economic Review, 44(10), 1951-1980.

Pagano, M., & Jappelli, T. (1993). Information sharing in credit markets. Journal of Finance, 48(5), 1693-1718.

Peria, M. S. M., & Singh, S. (2014). The impact of credit information sharing reforms on firm financing (No. 7013). The World Bank.

Petersen, M. A., & Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. The Journal of Finance, 49(1), 3-37.

Petersen, M. A., & Rajan, R. G. (1995). The effect of credit market competition on lending relationships. Quarterly Journal of Economics, 407-443.

Powell, A., Majnoni, G., Miller, M., & Mylenko, N. (2004). Improving credit information, bank regulation, and supervision: On the role and design of public credit registries (Vol. 3443). World Bank Publications.

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. Journal of Finance, 47(4), 1367-1400.

Sadka, G. (2006). The economic consequences of accounting fraud in product markets: Theory and a case from the US telecommunications industry (WorldCom). American Law and Economics Review, 8(3), 439-475.

Sharpe, S. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. Journal of Finance, 45(4), 1069-1087.

U.S. House. Subcommittee on Financial Institutions and Consumer Credit of the Committee on Financial Services. (2013). Examining the uses of consumer credit data hearing, 13 September 2012. Washington: Government Printing Office, 112-157.

Ware, T. (2002). The future of commercial credit data. Equipment Leasing Today, June/July, 22-29.

Watts, R. L. (1977). Corporate financial statements, a product of the market and political processes. Australian Journal of Management, 2(1), 53-75.

Winton, A. (1999). Don’t put all your eggs in one basket? Diversification and specialization in lending. Manuscript, University of Minnesota.

World Bank. (2013). Doing business 2014: Understanding regulations for small and medium-size enterprises. Washington, DC: World Bank Group. DOI: 10.1596/978-0-8213-9984-2.

Appendix A: Illustrative Credit File

Borrower ID	As of	SIC	Age	State	Contract ID	Lender ID	Asset Type	Contract Type	Guarantor?	Start	Term	Amount	Balance	Avg Days Past Due	Max Days Past Due
687343204	1-Oct-06	5013	8	NV	5732952	4825	MFG	Loan	YES	8-Jul-06	42	$64,562	$59,951	15	15
687343204	1-Jan-07	5013	8	NV	5732952	4825	MFG	Loan	YES	8-Jul-06	42	$64,562	$55,339	11	15
687343204	1-Apr-07	5013	8	NV	5732952	4825	MFG	Loan	YES	8-Jul-06	42	$64,562	$50,728	6	15
687343204	1-Jul-07	5013	8	NV	2059534	1053	TRCK	Loan	YES	6-Apr-07	36	$201,128	$184,368	4	11
687343204	1-Jul-07	5013	8	NV	5732952	4825	MFG	Loan	YES	8-Jul-06	42	$64,562	$46,116	4	15
687343204	1-Oct-07	5013	9	NV	5732952	4825	MFG	Loan	YES	8-Jul-06	42	$64,562	$41,504	3	15
687343204	1-Oct-07	5013	9	NV	2059534	1053	TRCK	Loan	YES	6-Apr-07	36	$201,128	$167,607	3	11
687343204	1-Oct-07	5013	9	NV	7705932	4825	MFG	Loan	YES	14-Jun-07	60	$27,222	$25,861	0	0
687343204	1-Jan-08	5013	9	NV	2582722	1053	COMP	Loan	YES	17-Oct-07	36	$3,267	$2,994	11	11
687343204	1-Jan-08	5013	9	NV	2059534	1053	TRCK	Loan	YES	6-Apr-07	36	$201,128	$150,846	2	11
687343204	1-Jan-08	5013	9	NV	7705932	4825	MFG	Loan	YES	14-Jun-07	60	$27,222	$24,460	0	0
687343204	1-Jan-08	5013	9	NV	5732952	4825	MFG	Loan	YES	8-Jul-06	42	$64,562	$36,893	3	15

I provide an excerpt of the borrower information, contract terms, and payment performance details in an illustrative credit file that is representative of the credit files in my sample. Not all fields in the dataset are presented for the purpose of brevity.

Appendix B: Variable Definitions

This appendix describes the measurement of each variable used in my study.

Treatment Variables	Description
Join	A treatment 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 a bureau that quarter (no treatment that quarter). I also omit pairs in which the join dates occur in the one- to four-year event window being examined in the regression, to prevent overlapping event windows from biasing my results. The date at which the lender joined the credit bureau is defined as the date that the lender first queried a credit report in the PayNet system.
Join Cohort	A treatment indicator used in single-relationship borrower tests equal to 1 for borrower-lender pairs in which the lender joined the bureau before January 1, 2003, and 0 for pairs in which the lender joined the bureau after January 1, 2004.
New	A treatment indicator equal to 1 for borrower-lender pairs originating a contract for the first time that quarter, and 0 for the firm's preexisting relationship(s). The indicator is recorded as missing if the borrower does not start a new relationship that quarter (no treatment that quarter).
Post	A treatment indicator equal to 1 for the period after the borrower's credit file is first available in the bureau, and 0 otherwise.
Post Join	A treatment indicator equal to 1 for the period after the lender has joined the bureau, and 0 otherwise.
Partitioning Variables	**Description**
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 have experienced a default event (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 experienced a default event, but have fallen behind on a payment by between one and 90 days at any point in the last three years.
Long Record	Borrowers with more than two years of history in their PayNet credit file.
Short Record	Borrowers with two or fewer years of history in their PayNet credit file.

Other Variables	Description
Size	The total dollar amount of all outstanding contracts at the beginning of the quarter. I employ this measure for both borrowers and lenders.
Age	The number of years that the borrower has been in business.
Relationship Length at Origination	The number of years since the start of the borrower and lender's earliest contract in the PayNet database, measured at origination.
Borrowing History	The number of years since the start of the borrower's earliest contract in the PayNet database, measured at origination.
Serious Delinquency	An indicator equal to 1 for borrower-lender pairs in which the borrower has experienced a delinquency of more than 90 days or major default event (bankruptcy, legal action, repossession, collection, or write-off) during the past three years, and 0 otherwise.
Non-Serious Delinquency	An indicator equal to 1 for borrower-lender pairs in which the borrower has experienced a delinquency of less than 90 days but no serious delinquency or default event during the past three years, and 0 otherwise.

Appendix C: Supplemental Information about the Process of Becoming a PayNet Member

Although PayNet requires lenders to contribute both past and present contracts, lenders vary in the number of contracts they are capable of providing from the pre- and post-join period for several reasons. First, a newly formed lender will naturally not have open contracts prior to its inception; mergers and spinoffs can present similar issues. Second, a number of the lenders in my sample joined in 2012 or later, which prevents me from analyzing the long-term relationship survival or change in credit for these lenders' clients. Third, many lenders did not have sophisticated electronic-based record keeping prior to joining or have since disposed of records with inactive clients, making it impractical to assemble a long history of their lending activity to contribute to the bureau.

Given that my tests examine changes in borrowers' relationship status and credit around lenders' join dates, such issues could contaminate my results by creating the appearance of an increase in credit over time when in reality the increase is due to the omission of old contracts from my dataset. PayNet does not keep track of whether members are able to provide pre-join contracts, so to prevent this from happening, I exclude 31,683 contracts from lenders that did not provide contracts back to at least the 1999 period, and those joining in 2012 or later. I also exclude 28,547 contracts from four lenders with an abnormal (over 30%) spike in open contracts from the year before to the year after joining the bureau, out of concern that these lenders did not provide all of their historical contracts during the implementation. Because the largest lenders contributing the most contracts in my sample tended to provide ample history, these restrictions are not particularly costly in terms of sample size, because they only reduce my observations by 12% to 442,742.

To ensure a usable sample for my tests, I require each randomly chosen borrower to have at least one open contract within the two-year period both before their lender joins the bureau, and at least one open contract with any lender in the two-year period after. To assess any survival bias that this requirement imparts in my tests, I compare this main sample to a holdout sample of borrowers without the minimum contract requirement. Main sample borrowers are larger and have more contracts and more lending relationships, but the terms, industry composition, and payment performance are similar across the two samples.

Table 1: Sample Selection and Descriptive Statistics for Contracts

Panel A: Sample Selection	*Contracts*
Initial Observations	531,451
Eliminate contracts missing contract amounts and/or maturity information	(28,479)
Eliminate all contracts from lenders without sufficient pre-join contracts	(60,230)
Final Sample	442,742

Panel B: Descriptive Statistics for Contracts

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
Loan Contract	16.9%	37.5%	0.0%	0.0%	0.0%	442,742
Lease Contract	83.1%	37.5%	100.0%	100.0%	100.0%	442,742
Contract Amount (dollars)	123,148	671,095	9,869	28,081	87,111	442,742
Contract Term (months)	45.6	17.6	36.0	48.0	60.0	442,742
Payment Frequency (times per year)	11.0	3.1	12.0	12.0	12.0	420,346
Contract has Guarantor	16.9%	37.5%	0.0%	0.0%	0.0%	397,314
Contract Always Paid on Time	40.0%	49.0%	0.0%	0.0%	100.0%	442,742
Worst Delinquency for Contract: Late by <=30 days	24.5%	43.0%	0.0%	0.0%	0.0%	442,742
Worst Delinquency for Contract: Late by 31-60 days	19.0%	39.2%	0.0%	0.0%	0.0%	442,742
Worst Delinquency for Contract: Late by 61-90 days	7.4%	26.2%	0.0%	0.0%	0.0%	442,742
Worst Delinquency for Contract: Late by >90 days	9.2%	28.9%	0.0%	0.0%	0.0%	442,742
Maximum Days Past Due	31.5	70.4	0.0	9.0	32.0	442,742
Borrower Settled Contract prior to Maturity	31.1%	46.3%	0.0%	0.0%	100.0%	442,742

Table 1: Sample Selection and Descriptive Statistics for Contracts

Panel C: Contract Count by Equipment Type and Start Year

Equipment Type	*Contracts*	*% of Total*	*$-Weighted*
Agricultural	49,053	11.1%	5.4%
Aircraft	349	0.1%	2.2%
Automobiles	2,116	0.5%	0.3%
Boats	85	0.0%	0.5%
Buses & Motor Coaches	1,476	0.3%	0.7%
Construction & Mining	65,772	14.9%	20.4%
Computer	28,222	6.4%	13.5%
Copier & Fax	138,926	31.4%	5.5%
Energy	68	0.0%	0.3%
Forklift	16,270	3.7%	1.6%
Logging & Forestry	1,415	0.3%	0.4%
Medium/Light Duty Trucks	10,235	2.3%	1.9%
Medical	5,204	1.2%	3.4%
Manufacturing	10,396	2.3%	5.4%
Office Equipment	5,875	1.3%	0.9%
Printing & Photographic	1,962	0.4%	1.1%
Railroad	354	0.1%	1.8%
Real Estate	843	0.2%	0.5%
Retail	9,739	2.2%	1.9%
Telecommunications	9,092	2.1%	1.1%
Truck	63,148	14.3%	23.5%
Unknown	19,241	4.3%	7.2%
Vending	1,692	0.4%	0.2%
Waste & Refuse Handling	1,209	0.3%	0.4%
Total	442,742	100.0%	100.0%

Start Year	*Contracts*	*% of Total*
Before 1996	26,381	6.0%
1996	14,439	3.3%
1997	17,118	3.9%
1998	21,875	4.9%
1999	23,107	5.2%
2000	22,298	5.0%
2001	22,200	5.0%
2002	22,706	5.1%
2003	26,023	5.9%
2004	30,457	6.9%
2005	29,626	6.7%
2006	30,405	6.9%
2007	28,369	6.4%
2008	26,208	5.9%
2009	18,076	4.1%
2010	20,423	4.6%
2011	21,886	4.9%
2012	20,027	4.5%
2013	18,329	4.1%
2014	2,789	0.6%
Total	442,742	100.0%

This table presents the sample selection (Panel A), descriptive statistics (Panel B), and equipment types and start years (Panel C) for observations used in the analyses. Delinquency variables in Panel B are measured across both open (ongoing) and closed contracts. See Appendix B for variable definitions.

Table 2: Descriptive Statistics for Borrowers and Lenders

Panel A: Descriptive Statistics for Borrowers

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
Borrower Size (total contracts outstanding, in dollars)	1,370,910	12,100,000	41,039	129,170	454,310	19,878
Age (years)	11.4	3.4	9.1	11.3	13.5	19,878
Borrowing History (years)	7.5	3.8	5.2	7.7	10.0	19,878
Number of Contracts Outstanding	6.2	43.5	1.1	1.8	3.5	19,878
Number of Types of Equipment being Financed	1.4	0.8	1.0	1.0	1.6	19,878
Has Paid Late on a Current Contract	59.9%	32.6%	34.0%	68.8%	88.5%	19,878
Has Paid 90+ Days Late on a Current Contract	6.9%	15.9%	0.0%	0.0%	3.9%	19,878

Panel B: Borrower Count by Industry

Industry	*# Borrower*
Consumer Non-Durables	2,275
Consumer Durables	1,919
Manufacturing	1,192
Energy	1,588
Chemicals	579
Business Equipment	4,191
Telecommunications	229
Missing	7,905
Total	19,878

Panel C: Descriptive Statistics for Lenders

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
Average Contract Amount	194,911	209,589	44,447	124,035	303,089	61
Average Borrower Size	17,146,570	25,093,750	3,939,679	11,933,450	20,163,430	61
Average Number of Open Contracts	1,437.7	2,095.5	157.2	510.2	1,901.9	61
% Contracts Always Paid on Time	42.2%	20.5%	27.2%	38.6%	53.5%	61
% Contracts Worst Delinquency: Late by <=30 days	23.5%	14.4%	12.8%	20.7%	32.8%	61
% Contracts Worst Delinquency: Late by 31-60 days	17.7%	9.9%	10.1%	18.7%	24.3%	61
% Contracts Worst Delinquency: Late by 61-90 days	6.5%	4.9%	2.8%	5.3%	9.1%	61
% Contracts Worst Delinquency: Late by >90 days	10.2%	10.0%	4.6%	6.8%	10.9%	61

This table presents descriptive statistics for Lenders and Borrowers. All figures in Panels A and C are derived from within-borrower or lender averages of quarterly observations. Lender figures only reflect the relationships with borrowers in my sample. Delinquency variables are measured across both open (ongoing) and closed (past) contracts. See Appendix B for variable definitions.

Table 3: Descriptive Statistics for Relationships

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
Relationship Length at Contract Origination (years)	5.7	5.2	0.9	4.5	9.3	442,742
No Relationship at Contract Origination	16.8%	37.4%	0.0%	0.0%	0.0%	442,742
Number of Ongoing Relationships (borrowers)	1.6	1.1	1.0	1.1	1.7	19,878
Number of Ongoing Relationships (lenders)	379.1	494.8	49.8	239.9	497.7	61
Relationship Ends within Next Year	14.8%	35.5%	0.0%	0.0%	0.0%	32,331
Relationship Ends within Next Two Years	29.5%	45.6%	0.0%	0.0%	100.0%	24,407
Relationship Ends within Next Three Years	42.3%	49.4%	0.0%	0.0%	100.0%	14,551
Relationship Ends within Next Four Years	53.2%	49.9%	0.0%	100.0%	100.0%	12,673

This table presents descriptive statistics for borrower-lender relationships. The relationship ending probabilities are included for only the observations used in my Table 4 regressions. The number of ongoing relationship figures are derived from within-borrower or lender averages of quarterly observations, and lender figures only reflect the relationships with borrowers in my sample.

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

Panel A: Relationship Exits, Prepayments, and Change in Credit

	(1) Exit from Relationship after 1 year	(2) Exit from Relationship after 2 years	(3) Exit from Relationship after 3 years	(4) Exit from Relationship after 4 years	(5) Δ Pr (Borrower Prepays Contract) 4 year window	(6) Δ Log Credit 2 year window	(7) Δ Log Credit 4 year window
Join	0.034*	0.083***	0.122**	0.163**	0.029	-0.040	-0.071
	[1.91]	[3.10]	[2.59]	[2.51]	[0.66]	[-1.11]	[-1.23]
R2	0.351	0.383	0.423	0.436	0.348	0.328	0.371
N	32,331	24,407	14,551	12,673	24,407	32,331	24,407
Fixed Effects	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter
Clustering	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year
Sample	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers

These tests examine the change in relationship status and credit outstanding for the set of borrowers with more than one outstanding lending relationship at the time one of their lenders joined the bureau. The dependent variable in columns 1 through 4 is an indicator for whether the borrower exits the relationship within various periods of the join quarter. The dependent variable in column 5 is the change in probability that the borrower settled a contract before maturity over the four year window surrounding the join quarter. The dependent variable in columns 6 and 7 is the change in average log credit over the two and four year window surrounding the join quarter. See Appendix B for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the quarter-year level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively.

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

Panel B: Robustness Analysis for Exit Tests

	(1) Exit from Relationship after 2 years	(2) Exit from Relationship after 2 years	(3) Exit from Relationship after 2 years	(4) Exit from Relationship after 2 years	(5) Exit from Relationship after 2 years	(6) Exit from Relationship after 2 years	(7) Exit from Relationship after 2 years
Join	0.083***	0.079***	0.082*	0.094***	0.096***	0.000	0.113***
	[3.10]	[6.09]	[1.73]	[3.03]	[3.48]	[0.01]	[2.85]
R2	0.383	0.423	0.545	0.477	0.395	0.320	0.592
N	24,407	189,944	12,569	10,137	20,889	3,518	12,175
Fixed Effects	Borrower-Quarter	Borrower, Lender	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter
Controls	No	Yes	No	No	No	No	No
Clustering	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year
Borrower Sample	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Single Equipment Type Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Only Pairs Existing before 2000
Lender Sample	All Lenders	All Lenders	Constant Exposure Lenders	All Lenders	Only Large Lenders	Only Small Lenders	All Lenders

These tests present robustness analysis for the column 2 result in Panel A (column 1 provides the original result to facilitate comparison). The dependent variable in columns 1 through 7 is an indicator for whether the borrower exits the relationship within two years of the join quarter. Column 2 examines the change in relationship status without a borrower-quarter fixed effect. Controls include recent payment performance for both borrowers and the lenders' portfolios. Column 3 includes only lenders that do not expand their equipment type exposure during the year after entering the bureau. Column 4 includes only borrowers that contract for one type of equipment in the dataset. Column 5 (6) includes only lenders with an above- (below) median number of contracts in the sample. Column 7 analyzes only the sample of borrower-lender pairs that contracted together prior to 2000. See Appendix B for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the quarter-year level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively.

Table 5: Relationship Dynamics, Credit History, and Changes in Credit around Lenders' Entry to Credit Bureau

Panel A: By Credit History

	(1)	(2)	(3)	(4)	(5)	(6)
	Exit from Relationship after 2 years	Δ Log Credit 4 year window	Exit from Relationship after 2 years	Δ Log Credit 4 year window	Exit from Relationship after 2 years	Δ Log Credit 4 year window
	Clean Record	Clean Record	Mixed Record	Mixed Record	Bad Record	Bad Record
Join	0.086***	0.083	0.094**	-0.165**	0.026	-0.142**
	[3.60]	[1.56]	[2.46]	[-2.44]	[0.90]	[-2.74]
R2	0.360	0.367	0.397	0.381	0.396	0.377
N	8,677	8,677	12,730	12,730	3,000	3,000
Fixed Effects	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter
Clustering	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year
Sample	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers

These tests examine the change in relationship status and credit outstanding for the set of borrowers with more than one outstanding lending relationship at the time one of their lenders joined the bureau. The dependent variable in columns 1, 3, and 5 is an indicator for whether the borrower exits the relationship within two years of the join quarter. The dependent variable in columns 2, 4, and 6 is the change in average log credit over the four year window surrounding the join quarter. The sample in columns 1 and 2 (3 and 4, 5 and 6) is restricted to borrowers with a clean (mixed, bad) credit record. See Appendix B for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the quarter-year level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively.

Table 5: Relationship Dynamics, Credit History, and Changes in Credit around Lenders' Entry to Credit Bureau

Panel B: By Track Record Length and Credit History

	(1)	(2)	(3)	(4)	(5)	(6)
	Exit from Relationship after 2 years	Δ Log Credit 4 year window	Exit from Relationship after 2 years	Δ Log Credit 4 year window	Exit from Relationship after 2 years	Δ Log Credit 4 year window
	Long Record	Long Record	Short Record	Short Record	Entire Sample	Entire Sample
Join	0.115***	-0.211***	-0.015	0.350***	0.005	0.416***
	[4.04]	[-3.89]	[-0.50]	[7.28]	[0.06]	[3.17]
Join * Bad Record * Log Record Length					-0.107*	0.188*
					[-1.94]	[2.02]
Join * Clean Record * Log Record Length					0.063*	-0.236***
					[1.88]	[-6.47]
Join * Bad Record					0.271	-0.515*
					[1.51]	[-1.72]
Join * Clean Record					-0.136	0.666***
					[-1.46]	[6.13]
Join * Log Record Length					0.031	-0.201***
					[0.82]	[-3.75]
R2	0.389	0.382	0.376	0.401	0.386	0.395
N	18,656	18,656	5,751	5,751	24,407	24,407
Fixed Effects	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter	Borrower-Quarter
Clustering	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year
Sample	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers

These tests examine the change in relationship status and credit outstanding for the set of borrowers with more than one outstanding relationship at the time one of their lenders joined the bureau. The dependent variable in columns 1, 3, and 5 is an indicator for whether the borrower exits the relationship within two years of the join quarter. The dependent variable in columns 2, 4, and 6 is the change in average log credit over the four year window surrounding the join quarter. The sample in columns 1 and 2 (3 and 4) is restricted to borrowers with a long (short) track record. See Appendix B for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the quarter-year level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively.

Table 6: New Relationships After Borrower's Credit File is Available in Bureau

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	New Relationship	New Relationship	New Relationship	New Relationship	New Relationship	New Relationship	New Relationship
	2 year window	4 year window	4 year window	4 year window	4 year window	4 year window	4 year window
	<u>All Borrowers</u>	<u>All Borrowers</u>	<u>Clean Record</u>	<u>Mixed Record</u>	<u>Bad Record</u>	<u>Short Record</u>	<u>Long Record</u>
Post	0.031**	0.049**	0.064***	0.014	0.054	-0.032	0.082***
	[2.59]	[2.04]	[3.38]	[0.39]	[1.47]	[-0.76]	[5.40]
R2	0.633	0.667	0.650	0.663	0.696	0.715	0.652
N	24,796	23,433	14,369	7,011	2,053	6,738	16,695
Fixed Effects	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower
Clustering	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year
Sample	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers	Multiple-Relationship Borrowers

These tests examine the change in probability that a borrower establishes a new relationship from the period before to the period after their information is first available in the bureau. The dependent variable in columns 1 through 7 is an indicator for whether the borrower starts a new relationship during various windows. All observations are collapsed into equal length pre- and post-periods for the borrower around the time its credit file is first available in the bureau. See Appendix B for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the quarter-year level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively.

Table 7: Relationship Dynamics and Changes in Credit around Lenders' Entry to Credit Bureau for Single Relationship Borrowers

	(1)	(2)	(3)	(4)	(5)	(6)
	Exit from Relationship after 1 year	Exit from Relationship after 2 years	Δ Log Credit 2 year window	Δ Log Credit 4 year window	New Relationship after 1 year	New Relationship after 2 years
Join Cohort	0.038	0.029	0.003	0.024	0.085***	0.139***
	[0.60]	[0.43]	[0.03]	[0.20]	[2.89]	[4.32]
R2	0.423	0.338	0.094	0.085	0.126	0.130
N	1,091	1,091	1,091	1,091	1,091	1,091
Fixed Effects	Industry	Industry	Industry	Industry	Industry	Industry
Borrower Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender Controls	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Lender	Lender	Lender	Lender	Lender	Lender
Sample	Single-Relationship Borrowers	Single-Relationship Borrowers	Single-Relationship Borrowers	Single-Relationship Borrowers	Single-Relationship Borrowers	Single-Relationship Borrowers

These tests examine the change in relationship status and credit outstanding for the set of borrowers starting contracts between 1997 and 1999 that mature in 2003. The sample is restricted to borrowers that had relationships with only one lender when the contract began. The dependent variable in columns 1 and 2 (5 and 6) is an indicator for whether the borrower exits their existing relationship (commences a new relationship) within one or two years of the beginning of 2004. The dependent variable in columns 3 and 4 is the change in average log credit from their main lender over the two and four year window surrounding the beginning of 2004. Join Cohort is a treatment variable equal to one for borrower-lender pairs where the lender joined the bureau before January 1, 2003, and zero for pairs where the lender joined the bureau after January 1, 2004. See Appendix B for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the lender level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively.

Table 8: Contract Terms for Borrowers Starting New Relationships

	(1) Log Maturity	(2) Log Payment Frequency	(3) Guarantor?	(4) Log Average Contract Size
New Relationship	0.014	-0.006	0.019**	-0.309***
	[0.82]	[-0.69]	[2.51]	[-9.65]
New Relationship * Post	-0.066***	0.018	-0.038***	0.118***
	[-2.91]	[1.55]	[-4.14]	[3.04]
R2	0.249	0.714	0.452	0.417
N	93,646	90,676	80,936	93,646
Fixed Effects	Borrower-Quarter, Contract Type	Borrower-Quarter, Contract Type	Borrower-Quarter, Contract Type	Borrower-Quarter, Contract Type
Clustering	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year

These tests examine whether borrowers get different contract terms relative to existing contracts when they initiate a new relationship after their credit file is available in the bureau. When more than one contract is outstanding between the borrower and lender, I use the dollar-weighted average terms of the contract. See Appendix B for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the quarter-year level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively.

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

Panel A: Descriptive Statistics

	Serious Delinquency	Non-Serious Delinquency
Borrower-Lender Pairs with delinquency type	10,291	42,242
Renewal occurs within 3 years after delinquency	3,814	20,989
Borrower subsequently improves to having perfect record with lender for 3 years	1,644	17,529
Borrower subsequently improves to having mixed record with lender for 3 years	2,178	
Borrower subsequently deteriorates to having serious delinquency		8,061

Panel B: Contract Renewals after Delinquencies

	(1) Renewal after Serious Delinquency	(2) Renewal after Non-Serious Delinquency	(3) Renewal after Serious Delinquency	(4) Renewal after Non-Serious Delinquency
Post Join	-0.097***	-0.094***	-0.073*	-0.042
	[-5.06]	[-4.14]	[-1.70]	[-1.35]
R2	0.799	0.614	0.944	0.875
N	31,113	215,397	9,631	40,850
Fixed Effects	Relationship	Relationship	Relationship	Relationship
Clustering	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year
Sample	Entire Sample	Entire Sample	Collapsed Sample	Collapsed Sample

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