Information Sharing and Lender Specialization:
Evidence from the U.S. Commercial Lending Market*

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Abstract

We examine how information sharing affects lender specialization. Using the introduction of a U.S. commercial credit bureau, we document that lenders use their comparative advantage in lending to enter new markets after joining the bureau. We exploit the staggered joining of members to show that a lender's specialization responds to information shared by other members joining the bureau, but only after the lender itself has become a member. Small lenders account for the majority of geographic and industry expansion, while large lenders increase their exposure to small firms. After joining the bureau, contract default rates are lower and less volatile, suggesting that the portfolio changes we document reduce lender risk. Our results help rationalize why intermediaries regularly forego rents when voluntarily sharing information, and document how information asymmetries can hinder expansion.

Keywords: lending, specialization, credit registries, credit scores, collateral, information sharing, transparency.
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1. Introduction

Developments in information technology have led to significant advances in information sharing. In most modern credit markets, lenders exchange contract terms and delinquency records through information sharing arrangements, (Djankov, McLiesh, and Shleifer 2007). Such arrangements operate on a voluntary basis in our largest credit markets: private bureaus provide near universal coverage of individuals in the US, UK, Japan, Germany, and Canada while mandated registries have negligible presence (World Bank 2015).[1]

Exchanging credit files reduces information asymmetries between borrowers and lenders, improving monitoring and screening capabilities for lenders and enhancing credit access for borrowers. However, because these same features increase competition for borrowers, it is not clear why lenders voluntarily share information (Pagano and Jappelli 1993). One possible motive is that adverse selection problems operate as entry barriers in credit markets (Dell'Ariccia et al. 1999). Sharing information can therefore facilitate contract growth, but do lenders then focus or expand their exposures?

On one hand, specialization fosters comparative advantages in screening and monitoring (Winton, 1999; Paravisini et al. 2015). Focusing not only allows the lender to earn rents on their expertise (Sharpe 1990; Rajan 1992; Petersen and Rajan 1994; Boot 2000; Ioannidou and Ongena 2010), but also provides protection from heightened competition (Boot and Thakor 2000; Hauswald and Marquez 2006). On the other hand, delegated monitoring hinges on lenders being sufficiently diversified such that they can credibly transform short-term liabilities into loans that require costly monitoring and enforcement (Diamond 1984; Boyd and Prescott 1986). Information sharing can facilitate entry into new markets and allow lenders to realize benefits of diversification.

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[1] Voluntary information sharing is also the norm in insurance markets (Cohen 2005), where companies report claim and fraud information to private third party intermediaries.

We provide evidence that lenders expand their state and industry exposures after sharing information. However, individual lenders' expansion patterns are significantly influenced by their specialization. State and industry expansion leverages existing collateral expertise, and entry into new asset markets can be predicted by the similarities between the lender's existing and new collateral exposures. We also find that the portfolio changes we document reduce risk for lenders and improve credit access for firms.

We use a panel of 14,251 firms' credit files to study the portfolios of 207 lenders voluntarily joining a U.S. equipment finance credit bureau, PayNet, in a staggered pattern between 2001 and 2014.[2] PayNet provides a useful setting for studying the effects of information sharing on the scope of lenders' portfolios. Equipment expenditures comprise 72% ($1.2 trillion) of private fixed non-residential investment in the U.S (BEA 2013), and the majority are financed with loans and leases (IHS 2013). Eight of the 10 largest lenders in this sector are PayNet members, and the bureau contains over $1.3 trillion in contracts. Most borrowers are opaque, 40% experience payment delinquencies, and even within the same industry (collateral market) the standard deviation of delinquency rates across states in a given quarter is 16% (15%). This suggests that adverse selection problems act as a meaningful entry barrier, and that the availability of local information can shape entry decisions.

We begin by examining the exposures in each lender's portfolio during the two-year period surrounding their bureau entry. Controlling for lender and time fixed effects, we find lenders grow the amount of credit and number of contracts in their portfolio. Moreover, lenders increase their geographic and industrial footprint by 9.3% and 11.8%, respectively, in the year after joining. Economically, this translates into contracting in 1.5 additional states and 2.8 additional industries for the average lender in our sample. To address the possibility

[2] PayNet launched in 2001 to serve the U.S. equipment finance sector, which, unlike the consumer finance or mortgage market, did not yet have a widely adopted credit-reporting and scoring system.

that broader developments in credit markets or unobservable shifts in lenders' business models explain our results, we conduct two placebo analyses. In the first, we counterfactually shift lenders' bureau entry dates back one year, and in the second, we randomly assign bureau entry dates to lenders. We find no evidence of expansion in either test. Our results also survive collapsing the sample to address concerns about serial correlation in our exposure measures, and controlling for time trends in lender scope.

To reinforce our results, we exploit shocks to a lender's information set arising from *other lenders* joining the bureau. To illustrate, consider the exposures of two lenders, Lender A joining in 2004 and Lender B in 2011. If a third lender (Lender C) specializing in agricultural equipment financing enters the bureau and shares their contracts in 2006, we predict a larger change in agricultural equipment exposure in 2007 for Lender A than Lender B. The appeal of this approach is that, although Lender A voluntarily joins the bureau, they have no say over whether or when Lender C joins after. Examining the full sample of lenders and collateral types, and accounting for lender-quarter effects, lender-collateral type effects, and collateral type-specific trends, we find member exposures are more responsive to changes in the contract repository. A one standard deviation increase in the number of bureau contracts for a typical collateral type increases the number of states and industries in members' portfolios by 3.3%. By comparison, we detect no change in non-members' exposures as the bureau coverage evolves. This indicates our expansion findings are driven by the availability of information in the bureau, rather than unobservable lender business model changes or conditions in collateral markets.

Next, we examine our main results in the context of organizational theory. Credit relationships are shaped by the size and structure of the lender (Berger et al. 2005; Berger and Udell 2006; Liberti and Mian 2009). Small lenders are likely to invest in relationships and employ monitoring technologies specific to the given sector, for example, while large lenders are predisposed to employ monitoring technologies that are scalable and transferable across markets. We split the sample according to total credit before joining the bureau, and find that, as a group, the state and industry expansion we document is primarily driven by small lenders. While small lenders increase the number of states (industries) in their portfolio by 16.0% (17.5%), large lenders expand an economically and statistically insignificant 2.7% (3.4%).

Why, then, do large lenders share information? Stein (2002) argues that small, decentralized lenders possess a competitive advantage in markets where borrower information is predominantly soft, as for most small firms. By introducing credit reports and scores sourced from verified, contract-level information, PayNet provided a new source of hard information about small firms. We find larger lenders contract more with small firms after joining, consistent with the bureau leveling the playing field with respect to contracting with small firms. While exposure to small borrowers declines with bureau membership on average, large lenders increase their small firm client share by 2.6%, a more than one-third increase over their pre period mean. The evidence helps us understand the incentives of different types of lenders to share information, and documents an expansion channel uniquely associated with credit scoring technologies.

Our third set of tests studies several aspects of portfolio risk around lenders' entry to the bureau. If exposure diversification is beneficial (Diamond 1984; Boyd and Prescott 1986), but hindered by adverse selection, then information sharing should facilitate portfolio reallocation toward new markets. Consistent with this, portfolio concentration measured by the Herfindahl-Hirschman Index (HHI) of geographic and industry exposures declines post-bureau. Further, portfolio delinquencies are not only lower, indicating improved screening and monitoring, but also less volatile in the time-series after a lender joins the bureau, indicating that the expansion efforts we document lead to safer portfolios.

Our fourth set of tests explores the expansion paths lenders pursue upon joining the bureau. In our setting, expertise in the asset being financed, or collateral, is a comparative advantage because lenders earn rents on their ability to predict default and recover collateral (Carey et al. 1998; Benmelech et al. 2005). We find significant expansion within collateral expertise: lenders expand their geographic (industrial) exposures by 4.8% (5.6%) *within* the collateral types they specialized in prior to joining.

Next, we examine whether collateral expertise is associated with expansion along the extensive margin. Related collateral types, such as computers and copiers, often involve a similar set of vendors, borrowers, and monitoring technologies. We construct an index measuring the degree of relatedness between each pair of collateral types by identifying the collateral pairs most commonly found together in lenders' portfolios. Our approach follows Bryce and Winter (2009) and employs the insight embodied in the survivor principle (Stigler 1968) by presuming that activity patterns of lenders indicate how resources and knowledge are shared across activities. Our index produces pairwise relatedness measures consistent with this intuition: telecommunications equipment is categorized as highly related to computer and copy equipment, but not railroad equipment, for example.

Lenders enter new collateral markets exhibiting the most relatedness with existing exposures. Moreover, this link strengthens after bureau entry, suggesting information sharing accelerates entry into related collateral markets. Our estimates indicate a one standard deviation increase in similarity between the new collateral type and those already in the lender's portfolio increases the new collateral exposure by between five and eleven percent after bureau entry. This evidence documents that, although the bureau reduces information asymmetries between lenders, some degree of adverse selection remains and lenders mitigate this by relying on their collateral expertise when entering new markets.

Finally, we examine how the bureau affects access to credit for firms. The number of lending relationships increases by 4.3% and average credit increases by 7.3% during the two-year window in which their credit file is first shared. Then, we examine financial flexibility by identifying whether the firm starts new contracts only upon the conclusion of old ones, or is able to access finance off the "maturity cycle". We find the likelihood of off-cycle contract origination increases by 4.0% with credit file availability.

Our research design exploits several unique features of PayNet. First, lenders enter the bureau in a staggered pattern, which helps us identify lender-specific shifts in exposures separate from aggregate trends, and alleviate concerns about portfolio changes being driven by changes in credit demand. Second, lenders report ongoing and historical contract data, including contract size, geography, industry, and collateral type, which enables us to compare portfolios in the pre- and post-information sharing regimes. Third, the bureau estimates and sells its own proprietary credit scores using quantitative inputs such as prior delinquencies, payment history, and outstanding contracts across all lenders. This limits the capacity for an individual lender to strategically report, which can happen for bureaus that simply redistribute members' own credit scores (Giannetti et al. 2015).

Our paper contributes to the literature exploring the scope of lenders' exposures. While economists have long been interested in the boundaries of the firm, there is abundantly more evidence from industrial than credit markets. This is despite considerable regulatory scrutiny of lenders' portfolio concentrations (Basel 2000; OCC 2011) and the fundamental link between financial intermediation and diversification. There remains limited direct evidence linking lender scope to information sharing. Liberti et al. (2015) and Paravisini and Schoar (2015) show that the range of loan officer activities increases with credit score availability. Several papers link lender scope to adverse selection. Acharya et al. (2006) and Berger et al. (2010) show that diversification, while beneficial, can be costly in terms of lower returns when adverse selection is greater. Berger et al. (2016) find that lenders with new exposures to an industry are significantly more likely than incumbents to request audits from borrowers.

Our findings also contribute to a growing literature exploring the impact of credit scores and information sharing on credit markets.[3] Credit scores are vital to both lender monitoring and small firms' access to capital (Berger and Udell 2006), in part because many firms do not report financial statements or tax returns to their lender (Allee and Yohn 2009; Cassar et al. 2015; Minnis and Sutherland 2016). We document that information sharing not only enhances credit access for firms, but also leads to more diversified portfolios, which can support lending to riskier borrowers (Acemoglu and Zilibotti 1997, Acharya et al. 2011). Because we study a private credit bureau, our results are more relevant to settings with voluntary information sharing, and perhaps less generalizable to cases where credit reporting is mandatory.

Last, our study offers a potential explanation for why lenders voluntarily share proprietary contract information. Lenders enter new markets by leveraging collateral expertise, which suggests information frictions exist across states and sectors even within an asset class. Further, lenders' portfolios become more diversified after they join the bureau, consistent with models of diversified delegated monitoring. Collectively, our findings indicate that information frictions pose barriers to diversification and that lenders cannot efficiently replicate their commercial credit exposures through hedging or securitization. Indeed, there is scant securitization in commercial lending, and in the equipment finance market in particular (Whelan 2015).[4] These facts and our results suggest that information

[3] See, among others, Padilla and Pagano (2000), Ongena and Smith (2001), Jappelli and Pagano (2002); Musto (2004) Brown et al. (2009), Ioannidou and Ongena (2010), Gopalan et al. (2011), Doblas-Madrid and Minetti (2013), Gonzales-Uribe and Osorio (2014), and Sutherland (2016).

[4] Securitization issuance for equipment contracts was just $16 billion in 2015, representing less than 2% of financing volume. Mester (1997) highlights the delayed development of credit scoring and securitization technologies in commercial lending relative to the credit card, auto, and mortgage credit markets. She attributes

asymmetries impede lender expansion, and that sharing information is a plausible means of mitigating these information asymmetries.

2. Institutional Setting and Empirical Design

2.1 The PayNet Credit Bureau

Our tests exploit the introduction of the PayNet equipment finance bureau in 2001.[5] PayNet was founded by former equipment finance executives to fill a gap in the U.S. small business lending market: while delinquency and contract information has been voluntarily shared among consumer lenders for decades, until 2001 commercial lenders in the equipment finance market regularly originated contracts without knowing how the borrower had performed on similar contracts in the past (Ware 2002). As a result, lenders often had to phone or fax competitors for this information. Existing repositories such as Dun & Bradstreet or Experian lacked contract-level detail, and focused on trade credit information and had limited information on longer term, larger obligations that were comparable to typical equipment finance contracts.

The U.S. equipment finance market is highly concentrated. As of 2014, the single largest lender (GE Capital) controls over 20% of industry net assets; the ten (25) largest lenders control 64% (85%) of industry net assets (Monitor 2015). Although many smaller banks occasionally provide equipment financing to existing clients, few have dedicated equipment finance offerings and the U.S. market is typically characterized as being served by fewer than a thousand lenders. Firms in this market seek loans and leases to finance a variety of vehicles, equipment, and computers. The most common types of business fixed

the disparity to a lack of standardization in commercial credit contracts.

[5] Sutherland (2016) exploits the introduction of PayNet to show information sharing reduces switching costs for firms, conditional on their credit history, and reduces lenders' investments in relationships. Doblas-Madrid and Minetti (2013) use an earlier version of the PayNet database to investigate the impact of lender information sharing on firms' performance. Their results reveal that information sharing reduces contract delinquencies and defaults, particularly for informationally opaque firms.

investments involve trucks and buses, communications equipment, medical equipment, general industrial equipment, and computers (Bureau of Economic Analysis 2015).

PayNet operates on the principle of reciprocity: lenders may only participate by agreeing to share all past, present, and future credit files with other members. In return, members can query, for a fee, PayNet's proprietary credit score and probability of default for each firm. These proprietary scores are estimated using all ongoing and past contract information for each borrower across all contracts in the bureau, including contract terms, contract type, collateral type, years in business, years borrowing, industry, location, and delinquency history and patterns[6] Lender identities remain anonymous in the bureau. Misreporting and falsification of information is punished by PayNet with exclusion from the database.

To become members, lenders undertake a significant up-front investment in information technology (IT) to allow PayNet to "pull" information directly from the their IT systems on a recurring basis. Lenders must also submit to PayNet audit and testing exercises to verify complete and accurate information sharing of all contracts, resolve any legal issues associated with the disclosure of client information, and develop systems to process the credit reports made available by the bureau. According to PayNet, the joining processes average six months, consuming two months for some lenders and a year for others largely depending on the compatibility between the lender's pre-existing IT infrastructure and the PayNet interface.

Since late 2001, over 250 lenders have joined PayNet, including eight of the 10 largest lenders in the segment as well as a number of smaller captives and regional banks. As of June 2015, the PayNet database contained over $1.3 trillion of debt obligations from 23

[6] PayNet collects additional borrower-specific information from external data sources including demographic data such as number of employees and revenues, public filings and trade data in order to verify the accuracy of contributed information.

million contracts.[7] The growth of the bureau has also led to the development of the Thomson Reuters/PayNet Small Business Lending Index, which measures the volume of new commercial loans and leases and is regularly cited by the business media. Figure 1 provides a timeline of lenders' entry to the bureau from its launch to the spring 2014, the end of our sample.

2.2 Empirical Design

Our main tests examine the geographic and industry exposure of lenders around their entry to the PayNet bureau. Since lenders join in a staggered pattern, our empirical design employs an event study that compares lenders' exposures before and after entering the bureau. Choosing an event window involves balancing two objectives. On one hand, analyzing a narrow event window limits the risk of capturing cofounding events. On the other hand, the effects of bureau membership on portfolio exposures may take time to manifest, supporting a longer window. Our tests use an event window that tracks lenders in the four quarters prior to joining the bureau through the four quarters after joining. Examining portfolio exposures in the year prior to joining captures the period when PayNet is starting to access a lender's data. Tracking lenders through the year after joining the bureau permits sufficient time for new relationships to form, considering firms typically have multiple ongoing contracts, roughly half of which mature within a two-year period. Event time t=0 is measured as the last day of the quarter prior to the quarter in which a lender joins the bureau.

We estimate:

$$y_{i,t} = \alpha_i + \alpha_t + \beta \times Post_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $y_{i,t}$ is the log exposure measure for lender *i* at event time *t*, measured in quarters around bureau entry. For each lender-quarter, we construct our portfolio proxies using our

[7]PayNet signs non-disclosure agreements that prevent the revelation of members' identities. However, industry publications have named Citi, De Lage Landon, Farm Credit Leasing Services Corporation of Minnesota, and Wells Fargo as members of PayNet (Jackson 2000, 2001; Ware 2002).

panel of credit files. Our exposure measures include the natural logarithm of credit, number of contracts, and number of unique exposures to U.S. states/territories and three-digit SICs. α_i is a lender fixed effect that controls for time invariant lender characteristics such as whether the lender is a bank, independent finance company, or captive. α_t is a year fixed effect that controls for macroeconomic conditions. *Post* is a dummy variable equal to one for observations after the lender has joined the bureau. The specification stacks the event window for each lender and tests for common effects of a lender joining the bureau on portfolio exposure. We cluster standard errors at the lender level. Because the event window is specific to each lender, and these windows are then stacked in our analysis, it is unlikely our results can be explained by time-varying factors such as business cycles or growth opportunities that affect the equipment lending market. We subject this assumption several robustness tests.

Our next set of tests exploit the entry of one lender to the bureau as a shock to the information set available to current members. If information asymmetries influence expansion decisions, then members' portfolio allocations will respond to changes in the stock of information the bureau contains on each exposure type. By comparison, non-members' allocations should be insensitive to what information is in the bureau. We use the following specification to test this proposition:

$$y_{i,j,t} = \alpha_{i,j} + \alpha_{i,t} + Trend_j + \beta \times Information_{j,t} + \gamma \times Post_{i,t} \times Information_{j,t} + \varepsilon_{i,j,t} \quad (2)$$

where $y_{i,j,t}$ is the log dollar amount of contracts that lender *i* has in collateral type *j* in period *t*. $\alpha_{i,j}$ are lender-collateral fixed effects, which control for time-invariant differences in lenders' offerings for each collateral market (e.g., relationship model, customer segment focus). We account for lenders' choice to participate in the bureau, the timing of their entry, and their overall condition and strategy by including lender-quarter fixed effects, $\alpha_{i,t}$. $Trend_j$ is a collateral-specific trend variable, which accounts for growth in each collateral offering.

$Post_{i,t}$, defined above is absorbed by the lender-quarter dummies; $Information_{j,t}$ is the log number of contracts recorded in the bureau measured at the collateral type-quarter level. We limit the sample to non-zero collateral exposures, but note our results are not sensitive to studying the intensive and extensive margins together. Our tests use the full time series, to expose each lender to sufficient variation in *Information*.

The advantage of this specification over (1) is that changes in $Information_{j,t}$ are exogenous to individual lenders. Stated differently, although a lender decides when to join the bureau, they have no say over which others join after and contribute contracts of any given exposure type. Our hypothesis is that non-members' exposures do not respond to changes in bureau information (β is zero), while members' expand their exposures by using available bureau information (γ is positive).

Next, we examine *how* lenders exposures evolve. One possibility is that lenders identify new geographies or sectors into which they can expand by leveraging their existing expertise, such as the collateral types in which they currently specialize. Then, lenders would exhibit expansion not only in aggregate, but also within collateral types at the intensive margin.

Lenders could also expand along the extensive margin by entering new collateral types. If information sharing facilitates entry to new markets, we should observe lenders allocating credit in a manner that suggests they use the credit file information made available to them. In particular, lenders can learn both about the demand for financing different types of collateral, and identify collateral types that are related to those they currently lend against. Although PayNet does not allow lenders to "mine" the data (e.g., by downloading all the borrowers in a given zip code or collateral market), lenders can easily query the credit reports of their clients or new applicants, and learn about their exposures with *other* lenders. In fact, one would expect lenders to occasionally review their clients' credit reports to prepare for contract renewals and negotiations, and to look for signals of broader problems following missed payments.

To test for extensive margin effects, we examine if new collateral type entry in the period after joining the bureau is correlated with lenders' collateral expertise. For each pair of collateral types, we calculate a relatedness score, which attempts to measure underlying similarities in lending technology and expertise across collateral types.[8] We detail the construction of our relatedness index in Appendix B. Our tests estimate:

$$y_{i,j,t} = \alpha_i + \alpha_j + \beta \times Post + \delta \times Relatedness_{i,j} + \gamma \times Post \times Relatedness_{i,j} + \varepsilon_{i,j,t} \quad (3)$$

where $y_{i,j,t}$ is the log dollar amount of contracts that lender *i* has in collateral type *j* in period *t*, for only collateral types that lender *i* has zero exposure for in the pre period. We include collateral type fixed effects, α_j. $Relatedness_{-i,j}$ captures the relatedness between lender i's existing collateral types and collateral type j. If lenders enter related markets after joining, γ will be positive. Our tests are run on a collapsed sample.

3. Sample and Descriptive Statistics

We construct our dataset from a panel of 20,000 randomly chosen firms' credit files, detailing the payment history and contract terms with 218 lenders between 1980 and 2014. For each contract, we observe the amount, collateral type, contract type, maturity, payment frequency, guarantor requirement, and payment history, as well as the state, industry, and age of the firm. For our tests, we require lenders to have non-missing contract amount and term information in the event window spanning one year before to one year after joining the

[8] This approach follows Bryce and Winter (2009), and employs the insight embodied in the survivor principle (Stigler 1968) by presuming that activity patterns of lenders are sound indicators of how resources and knowledge relate across diverse activities, such as lending against different collateral types. We presume that two collateral types are related, and hence likely rely on the same lending technology, if we always observe them in a lender's portfolio, but unrelated if we never observe them in the same portfolio.

bureau. This requirement reduces the final sample to 207 lenders, 14,251 firms, and 109,095 contracts between lenders and firms.[9]

Table 1 summarizes the sample. Before bureau entry, the average contract size is $192,156, and 24% (76%) of contracts are loans (leases).[10] Twenty six percent of the typical lender's contracts have experienced a delinquency, and the average delinquency is 50 days. Next, we measure exposures, but omit lenders with insufficient industry information in our industry exposure analysis.[11] Prior to entry, the average (median) lender has $56.3 million ($3.4 million) of credit through 491.2 (34) contracts with the 14,251 borrowers in our sample. The typical lender is exposed to 15.9 states or U.S. territories (including Guam, Puerto Rico, and the Virgin Islands), and 23.1 industries (measured at the three-digit SIC level). There is considerable variation in these exposures—the largest lenders contract in practically every state and industry, while the specialized lenders typically compete in just a handful of markets. We also document heterogeneity in the concentration of exposures by measuring the Herfindahl-Hirschman Index (HHI). Exposure and concentration increase and decrease, respectively, for both geographic and industrial exposure following bureau membership.

4. Results

4.1 Portfolio Dynamics

We begin by studying the dynamics of lenders' exposures around the time they join PayNet to assess the validity of our setting for testing the effects of information sharing on lender scope. We treat bureau entry as a shift in the information environment facing each lender. In Figure 2, we plot our four exposure measures in the eight quarters around bureau

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[9] Not all firms in our initial sample have contracts in the event window (e.g., some have contracts only before our event window begins or after it ends, or both).

[10] We classify loans and revolver contracts as loan contracts, and conditional sale, lease-purchase, leveraged lease, rental lease, true lease, and other contracts as leases.

[11] We omit these observations to avoid measurement error in our concentration variables induced by having a large percentage of contracts from unknown industries. We do not omit these lenders from our geographic exposure analysis, but note that our results are not sensitive to this choice.

entry. There is a clear discontinuity in the credit and contracts outstanding, as well as the number of states and industries in lenders' portfolios around the entry date. Furthermore, there is little evidence that lenders expanded contract portfolios in the periods prior to entry.

4.2 Information Sharing and Lender Scope

Our main tests assess how lenders' exposures evolve in the event window using (1). Table 2, columns 1 and 2 show that lenders significantly increase both the amount of credit granted and number of portfolio contracts upon entering the bureau. Portfolio credit (contracts) increases by 22.1% (17.2%) from the year before to year after bureau entry. Is this growth characterized by expansion or specialization? Columns 3 and 4 reveal lenders increase the number of state and industry exposures by 9.3% and 11.8%, respectively. For the average lender, this represents an additional 1.5 states and 2.7 industries relative to the pre-entry exposures.

Other developments aside from information sharing could also contribute to the expansion patterns we document. For example, advances in technology during the 2000s gave rise to alternative information sources for lenders (e.g., public filings searchable on the web, competing credit report products), and reduced the costs of screening unfamiliar firms. While our results are robust to a single shock to information because of the stacked empirical design, such possibilities could still threaten identification. Related, the decision to join a credit bureau could be just one of multiple endeavors lenders undertake to adapt their business model to new markets. Our next two sets of tests attempt to more directly tie our expansion findings to information shared in the bureau, and isolate the most plausible alternative explanations for our results.

First, we assess the sensitivity of our results to a series of specification adjustments that consider time effects and lenders' entry decisions in multiple ways. To begin, we modify (1) by replacing the year fixed effects with an event time trend. Table 3, Panel A, Column 1 studies log credit. We find a marginally insignificant 5.4% increase in portfolio size after joining (t-stat of 1.52). The attenuation may reflect the trend variable absorbing the sharp post-entry increase shown in Figure 2. Next, in column 2 we shift the lender's entry date back by one year. If the lender was undergoing other portfolio changes prior joining that account for our findings, then we should continue to find significant evidence of expansion in this placebo test. We do not. In column 3 we counterfactually assign random entry dates to lenders, and report an insignificant average coefficient from 1,000 simulations.

In column 4, we test if the effects of information sharing vary according to when the lender joins. On one hand, we might expect greater expansion for late joiners because they have a richer set of bureau information to draw upon. On the other hand, the first members could enjoy an early mover advantage by targeting the expansion markets where entry barriers are lowest. To explore these possibilities, we interact *Post* with a dummy variable, *Early Join*, equal to one if the lender joins during the first half of our sample (before 2008). We find that expansion efforts are unrelated to the entry timing. Last, to address concerns about serial correlation in our portfolio variables, we repeat our analysis by collapsing the pre and post period into single observations for each lender (Bertrand et al. 2004), and continue to cluster by lender. Column 5 shows that collapsed results are very similar to our main results in Table 2, column 1.

We repeat this battery of tests for the contract count, as well as the number of state and industry exposures in Panels B, C, and D. Our findings largely mirror those in Panel A. We continue to find significant growth in state and industry exposures (though not contracts) after controlling for time trends. None of our placebo tests show significant expansion, and our results are not sensitive to controlling for the timing of bureau entry or collapsing the sample. To summarize, the evidence in Table 3, combined with figure 2, provides confidence that our main results are not simply driven by secular trends or business model changes unrelated to bureau membership.

Nevertheless, one may remain concerned that our tests thus far use voluntary bureau entry to study variation in exposures. Despite our best efforts to demonstrate the robustness of our findings, identifying and properly controlling for confounding factors associated with voluntary reporting is difficult without knowing who the lenders are. Our second set of tests take a lender's decision to join the bureau as given, and measure how their exposures evolve relative to changes in the information available in the bureau using (2). Several arguments motivate this alternative approach. Lenders specialize in specific collateral markets; therefore, the bureau often experiences spikes in the number of certain types of contracts when individual lenders join. Moreover, although a lender decides whether and when to join, they do not select which others follow. This provides a natural experiment to study how exposures respond to changes in information. Our prediction is that members, who regularly query the bureau for credit files of applicants and existing clients, are significantly more likely to enter a given exposure as the coverage for this exposure improves. By comparison, non-members' exposures should not be sensitive to changes in bureau information.

Table 4 presents the results of estimating (2). For all exposure types (credit, contracts, states, and industries) we find an insignificant coefficient on *Information*, the log number of contracts available in the bureau for that collateral type in that quarter. This suggests non-members do not adapt their exposures in response to the repository of information available in the bureau. On the other hand, we find a significantly positive coefficient on *Post* * *Information* for all exposure types, except for sector exposures (2.1% growth, t-stat 1.56). Economically, a one standard deviation increase in *Information* results in a 3.3% shift in state and industry exposures for members. Because we account for lender-quarter effects, these results cannot reflect lender-level developments coinciding with entry to the bureau, such as M&A, or changes in senior management or overall lending strategy. Moreover, we note our findings are robust to alterative specifications that consider different measures of *Information* (e.g., an indicator for the period after the lender with the most contracts in that collateral type joins), different fixed effect combinations, and examining both the intensive and extensive margins.

In sum, this section presents evidence that lenders offered more credit and significantly expanded their geographic and industry exposures after joining the bureau. We attribute these developments to information sharing by using trend controls and placebo tests, and by demonstrating that only member lender portfolios evolve with exogenous changes in bureau coverage.

4.3 Information Sharing and Lender Size

Prior work argues lender size influences the type of information used to screen and monitor firms. Small creditors, in light of their decentralized organizational structure, tend to be relationship lenders and are more capable of using discretion or soft information to evaluate credit applications (Stein 2002; Petersen 2004; Berger et al 2005; Liberti and Mian 2009). By comparison, large lenders are thought to be more transactional in their interactions with borrowers, and rely more heavily on hard information such as credit scores.

The heterogeneity in lenders' approach to client interactions has two implications for our study. First, small lenders who possess a competitive advantage in relationship-based contracting are likely to have few exposures beyond the regions and sectors they have the most experience dealing with (Berger and Udell 2006). Stated differently, the relationship-based approach to credit is not easily scalable, and this limits the ability of the small lenders relying on this approach to enter new markets. By comparison, large lenders inclined to rely on hard information in contracting are likely to have a broader span of exposures, because their lending technology is scalable in that it requires less first-hand, repeated interaction with borrowers. Empirically, we find a positive correlation between size and exposure span: large lenders, defined to have above median credit, have portfolios that span 25 geographies (47 industries), while small lenders have portfolios that span just seven geographies (five industries), with the difference across lender type statistically significant at the 1% level. This line of reasoning suggests that small lenders have more to gain in terms of exposure expansion when joining a credit bureau.

Second, this heterogeneity in lending technology and client type across lender sizes could result in bureau credit files capturing different types of information contributed by small and large lenders. Because small firms are less likely to have audited financial reports, analyst or media coverage, or credit report information from other sources (e.g., Dun & Bradstreet or Experian), small lenders have certain advantages over larger lenders in establishing relationships with them. Thus, information sharing has implications not only for the geographic and industry composition of the lender's portfolio, but also for the size of their typical client.

We perform two tests to offer evidence on these predictions. First, in Table 5, we examine how our main results differ by lender size. Controlling for lender and year fixed effects, we find that small lenders drive the majority of the expansion documented in our main results. The change in credit amounts (number of contracts) for large lenders, although positive, lags the rate of growth for small lenders by 22.5% (24.1%). State and industry exposures follow a similar pattern. While small lenders increase their geographic (sector) footprint by 16.0% (17.5%), large lender expansion is a statistically insignificant 2.7% (3.4%). In untabulated robustness tests, we confirm our inference that small lenders drive the expansion is not sensitive to including time trends, event quarter fixed effects, or adding business model controls that consider each lender's mix of lease and loan offerings.

Our second set of tests in this section examines how lender size relates to any change in the borrower size composition of portfolios. We define *Small Clients* as a dummy variable equal to one for borrowers in the smallest quartile of total credit measured at the industry-quarter level. Next, we measure the percent of the lender's clients that are classified as small firms in each quarter. In columns 1 and 2 of Table 6, we show that the percentage of relationships allocated to small firms marginally declines, on average, in the year after bureau entry. However, when we examine client composition by lender size, we find that larger lenders significantly *increase* their interactions with small firms, while small lenders decrease the fraction of their client base allocated to this segment.[12] We again subject these findings to time trends, event time effects, and business model controls and find our results maintain. The 2.6% increase in small client exposure for large lenders we document is economically significant: prior to joining the bureau large lenders allocate only 7.3% of their portfolio to the most opaque segment of firms.

To summarize, the expansion in portfolio exposures documented in our main results is primarily driven by small lenders. Large lenders nevertheless incur nontrivial implementation costs and put relationship rents at risk in order to voluntarily share information. Why? Although large lenders see little change in the scope of their geographic and industry offerings, we find they significantly increase their exposure to small clients, precisely the segment that these lenders are predicted to have difficulty contracting with when credit scores are not available. Thus, it appears that larger transactional lenders use the bureau at least in part to access credit files for smaller firms. Of course, there may exist other benefits to large lenders of information sharing. For example, the monitoring cost savings may be more

[12] Because the unit of observation is lender-quarter, this does not necessarily indicate the total credit to small firms declines (i.e., the negative main effect could be overcome by the positive interaction effect since large lenders have more outstanding credit).

important for large lenders, given the scale of their operations.[13] Because we do not observe margin or overhead cost information, we leave the analysis of these possibilities to future research.

4.4 Lender Portfolio Risk

The theoretical rationale for diversification presented in Diamond (1984) hinges on risk reduction through the pooling of uncorrelated exposures. Our next tests examine several dimensions of lenders' portfolio risk around their entry to the bureau. First, we measure the HHI of geographic and industry exposures, equal to 0.40 (0.43) for the average lender in the pre period. Second, we measure the contract size-weighted portion of contracts that are delinquent in each quarter for each lender. For a typical lender about to join the bureau, 34% of the contracts are delinquent.[14] These delinquencies typically span 30 days for the median lender; for individual contracts, payments can fall anywhere from a few days to over a year behind. Third, we examine the link between exposure diversification and risk. If information sharing helps lenders reduce their portfolio risk, we should observe a smoother pattern in contract performance and less idiosyncratic risk in the form of spikes in delinquencies over time. We measure this by analyzing the time series volatility in the portion of contracts that are delinquent. We dollar weight each contract in the lender's portfolio so we are examining the dollar-weighted contract performance.[15] For each lender, we calculate the standard deviation of our measure during the pre and post period separately, providing us with one pre and post period observation for each lender.

[13] The bureau may also target large lenders for the launch for the bureau (e.g., by marketing to them or providing discounts) to establish credibility and ensure a sufficient pool of contracts to attract further members.

[14] Our delinquency figures are comparable to Doblas-Madrid and Minetti (2013), who access a sample of contracts for 15 lenders and find 60% of contracts experience at least one delinquency during the last year.

[15] This approach is motivated by investment portfolio theory. Holding an undiversified lending portfolio in a single sector results in loss exposure that is highly correlated across contracts, whereas holding a diversified lending portfolio is akin to holding the market portfolio, which should result in systematic loss. Simply put, the undiversified lender expects none, or all, of its portfolio to be delinquent, while the diversified lender can always expect some group of borrowers to be delinquent but very rarely all of them.

Our tests of each of the three measures use (1) on the collapsed sample. Our sample size differs across the tests because some lenders have incomplete industry data (column 2 of Table 7) or missing delinquency records (columns 3 and 4). Columns 1 and 2 show a significant reduction in both geographic and industry exposure concentration. Geographic (industry) concentration declines by 4.9% (6.1%), representing 12.2% (14.2%) of the pre-entry mean. In column 3, we show that the portion of delinquent contracts decreases by 8.8%. This indicates information sharing can improve lenders' screening abilities and heighten payment incentives for the average firm, and reinforces prior findings (Padilla and Pagano 2000; Doblas-Madrid and Minetti 2013; Bennardo et al. 2015). Last, column 4 finds that the volatility of the rate of delinquencies decreases by 3.0%, consistent with the expansion in portfolio exposures documented in our main results leading to less correlated payment problems within the portfolio.

Together, this evidence complements our main findings. Information sharing reduces the adverse selection problems associated with entering new markets. Upon joining the bureau, lenders expand, reduce exposure concentration, and reduce portfolio risk.

4.5 Information Sharing, Collateral Expertise, and Expansion Decisions

Lenders frequently specialize by asset type when offering secured commercial financing because the contractual terms, default probabilities, recovery markets, and enforcement mechanisms tend to be similar within an asset type, creating economies of scale. In this section, we examine how asset type specialization affects the manner in which lenders expand. We begin by examining whether lenders expand using the intensive margin. Although information sharing can improve the lender's ability to screen all unfamiliar firms, their pre-existing expertise likely favors certain markets. In particular, if a lender has expertise in a specific type of collateral, then one might expect the lender to exploit this advantage to reach new regions or industries.

In Table 8, we summarize lenders' exposures across the 23 collateral types observed in the bureau. Collateral types vary in terms of the number of lenders offering contracts, as well as the states and industries they span. For example, approximately half of our sample lenders contract in computers, with contracts found in 52 states and territories, and 378 of 423 3-digit SIC industries in our sample. By comparison, only nine lenders offer contracts for boats, found in 19 states and 20 industries. Furthermore, it is apparent that collateral types vary in their degree of specialization. Computer and bus/motor coach contracts, for example, are both found in practically every state, but 60% fewer lenders offer bus/motor coach than computer contracts.

In Table 9, we examine how information sharing affects the number of state or industry exposures *within* a given collateral type. Our specification for this analysis is the same as (1), except that our unit of observation is lender-collateral type-quarter, and we include lender-collateral type fixed effects instead of lender fixed effects. Given our predictions concern the use of a lender's collateral expertise, we only include observations where the lender has collateral type exposure prior to joining the bureau.

Column 1 and 2 demonstrate significant growth in the amount of credit and number of contracts outstanding within pre-existing collateral exposures. However, this expansion is not confined to the same states and industries the lender competed in prior to entering the bureau. Column 3 shows that the number of states within a collateral type increases by 4.8% after the lender is part of the bureau. For a typical collateral type, this translates into 0.4 new states (4.8% x 7.2 average state exposures) in the post period. We examine industry expansion in column 4. Our tests show that the number of industries within a collateral type increases by 5.6% after the lender is part of the bureau, equivalent to 0.6 new industries.

Next, we examine the choice of entry into collateral types that a lender joins for the first time after information sharing. One possible expansion channel is that lenders enter new collateral types sharing features with the ones in which they already specialize. For example, computers and copiers likely involve a similar set of vendors, borrowers, and screening and monitoring procedures. On the other hand, there is likely scant overlap in lending features for computers and logging or railroad equipment. We predict that, if lenders expand by leveraging their existing expertise as shown in Table 9, then this very expertise could be employed to enter new collateral exposures.

To test this prediction, we require a measure of the degree of relatedness between two collateral types. Unfortunately, we are not aware of such an index. Therefore, we employ the insight embodied by the survivor principle (Stigler 1968) by assuming that the contracting patterns of lenders on collateral types are good indicators of how distinct collateral types share resources and knowledge. Under this argument, collateral types more related in terms of lending technology should be more frequently observed together in the lenders in our sample.

We follow Teece et al. (1994) and Bryce and Winter (2009) and develop an index of collateral type relatedness. We detail the construction of the index in Appendix B. To summarize, for each pair of possible collateral types, we first count the number of lenders contracting in both. This count variable reveals the frequency with which collateral types overlap in lenders' portfolios. Second, we adjust the count measure to account for the probability of overlap one would observe if collateral types were randomly allocated to lenders, given the number of lenders and the observed quantities of each collateral type in the market. Third, we control for the dollar values of contracts to account for the fact that collateral types may not be related if, although observed together frequently, they account for only a small fraction of a lender's portfolio, on average.

Fourth, we allow for indirect relatedness by converting relatedness to a distance and applying a shortest path algorithm. In other words, it is possible that two collateral types, A and B, are rarely observed together in a contract portfolio, but each are highly related to a third collateral type, C, which means that A and B are also highly related. Finally, we convert the distance measure back into a standardized relatedness measure by subtracting the mean and dividing by the standard deviation.[16] Our tests employ two variations of this measure: the first (second) uses the maximum (average) pairwise relatedness between the lender's current collateral types and a given collateral type in which the lender does not have exposure.

Summary statistics for our relatedness index are presented in Appendix C. The index appears to produce pairwise similarity scores that capture underlying similarities in collateral features. For example, computers and copiers are scored as highly related (99.3), while railroads and copiers are unrelated (15.8). Thus, according to our prediction, if our relatedness measure captures the degree of similarity in monitoring technology, a lender in copiers but not computers nor railroad equipment in the pre period is far more likely to begin lending against computers than railroad collateral. Our framework suggests this effect strengthens once they join the bureau.

Because our predictions concern the extensive margin, in Table 10 we restrict our sample to collateral types the lender was not exposed to one year before entering. The results show that a lender is likely to enter new collateral markets in the post period (the coefficient on *Post* is positive and significant). Moreover, the effect is much stronger for collateral types that are related to the lender's collateral expertise (the coefficient on *Relatedness * Post* is positive and significant), regardless of whether we consider the maximum or average similarity between the given collateral type and those already in the lender's portfolio. Economically, a one standard deviation increase in the relatedness between the new and existing collateral types increases the lender's exposure to the new collateral type by five (eleven) percent in the year after joining, using the maximum (average) relatedness measure.

[16] We find similar results if we ignore contract amounts or do not allow for indirect relatedness when constructing the index.

To summarize, the results in this section show that lenders leverage their experience in their existing collateral exposures to enter new states and industries. These results offer direct evidence on how information sharing facilitates expansion by tracing the changes in lender exposures documented in our main results.

4.6 Information Sharing and Firm's Credit Relationships

Our final set of tests examines contracting from the borrower perspective. Since our main results suggest that information sharing puts lenders in a better position to contract with unfamiliar firms, we expect the typical borrower to have more lending relationships once their credit file is available in the bureau. To examine this, we measure each firm's lending relationships throughout the four-year window surrounding the first instance their file appears in PayNet. An important feature of these tests is that firms have no say over whether, when, or how their credit history is shared, which mitigates concerns that contemporaneous changes in demand for credit could affect our results.

We restrict our analysis to firms that have open contracts in both the pre and post period. For each of these 12,675 borrowers, we examine how the number of relationships, total credit, and origination of new contracts changes after being included in the credit bureau in a borrower fixed effect estimation. We tabulate both a full sample test with a trend variable, and a collapsed test.

Column 1 of Table 11 shows that the number of lending relationships for the typical borrower increases by 4.3% in the post period. Economically, there are 11% fewer firms in the post period with just one lending relationship with a bureau member. Next, we examine how this affects total borrowing. Column 2 measures the (log) total credit for all relationships in the bureau (including ones not observable to bureau members at the time but observable to us because of the backfilling requirement). We find a statistically significant increase in total credit of 7.3%. Our results build upon the survey evidence documenting improved access to finance following the introduction or reform of credit bureaus in developing countries (Brown et al. 2009; Love et al. 2013; Peria and Singh 2014).

Next, we examine whether the timing of credit access changes with file availability. To do this, we create an indicator variable measuring *when* firms are borrowing, equal to one if firm started a new contract or lending relationship without having an old contract maturing that quarter or a surrounding quarter. The intuition for this "off cycle" financing variable is that not being tied to the maturity cycle of current contracts provides financial flexibility for the firm. Prior to information sharing, 28.3% (14.1%) of firms begin contracts (new lending relationships) off cycle. Columns 3 and 4 show that access to finance significantly improves once credit files are available. The likelihood of starting a new contract (relationship) off cycle increases by 5.5% (5.3%) relative to the pre period mean. We also present non-collapsed results with a trend control in columns 5-8, and find similar inferences with the exception of our total credit test.

5. Conclusion

Extant research has analyzed the effect of lender specialization on profitability and risk, including the observed shift from interest income products to activities that generate fees, trading revenues, and other non-interest income. Although these studies have advanced our understanding of the economies of scope in credit markets, they have not explored how lending is constrained by information frictions. In this paper, we examine whether lenders voluntarily share information to overcome such frictions. Using the staggered entry of lenders into an equipment finance credit bureau, we show lenders expand their portfolios in terms of geographic and industry reach after joining: the number of exposures increases while exposure concentration decreases. Small lenders drive the bulk of the expansion. Why do large lenders share information? Motived by prior research on organizational structure, we show information sharing enables large lenders to increase their offerings to small firms.

Lenders enter new states and sectors not randomly, but by leveraging their collateral type expertise. When lenders enter a new collateral market, they are most likely to enter one closely related to their existing collateral exposures. After joining the bureau, the frequency and volatility of delinquencies decline. Firms' financing options expand in terms of the number of lenders and the timing of their access to capital. Together, our results support theoretical research arguing that information asymmetries influence the structure of credit markets, and provide a rationale for voluntary information sharing.

Regulators regard diversification and transparency as desirable credit market features supporting financial stability and economic growth (Basel 2000, OCC 2011). Moreover, the flow of credit can be impeded by information asymmetries. Because reporting costs are largely fixed, small borrowers are highly exposed to information frictions when accessing credit markets (Petersen and Rajan 1994). Therefore, our results also contribute to the debate on whether credit reporting should be mandatory (Committee on Financial Services 112-157). Alternatively, private credit bureaus can be subsidized, which would preserve the option for lenders to decline participation if the proprietary and direct costs of joining are too high. Future research can weigh the merits of these proposals.

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Appendix A: Variable Definitions

Variable	Description
Share	The ratio of the lender's credit (measured as the dollar amount of the contract) within a state, industry, or collateral type to total credit for the lender in a given quarter. The unit of observation is lender-quarter-state, industry, or collateral type. The formula is as follows (denotes state, industry, or collateral type; *j* denotes lender; *t* denotes quarter): $$Share = \frac{Credit_{ijt}}{\sum_{i=1}^{I} Credit_{ijt}}$$
Early Join	An indicator equal to one for lenders entering the bureau before the median lender (before 2008), and zero otherwise.
Information	The log number of contracts that have been contributed to the bureau to date for a given collateral type, updated quarterly.
Large Lender	An indicator equal to one for lenders with above median credit in the quarter before entering the bureau, and zero otherwise.
% Portfolio Small Clients	The percent of the lender's clients in the smallest quartile of total credit within their industry-quarter.
HHI	A Hirschman Herfindahl index (HHI) measure, equal to the sum of the squares of the geographic or industry shares for the lender. The unit of observation is lender-quarter. The formula is as follows (*i* denotes state or industry; *j* denotes lender; and *t* denotes quarter): $$HHI_{jt} = \sum_{i=1}^{N} \left(Share_{ijt}\right)^2$$
Portion of Contracts Delinquent	The percent of the lender's contracts that are currently delinquent.
Log Std Dev Is Delinquent	The natural logarithm of the time series standard deviation of Portion of Contracts Delinquent.
Relatedness	A measure of the degree of similarity between two collateral types. In our tests, we measure either the maximum or average relatedness between a new collateral type and the lender's existing collateral offerings. Appendix B describes the construction of the relatedness measure.
Starts New Contract (Relationship) Off Cycle	An indicator equal to one for borrowers that started a new contract (lending relationship) in a quarter without having another contract maturing that quarter or a surrounding quarter.

Appendix B: Construction of the Collateral Type Relatedness Index

The construction of the collateral type relatedness index is motivated by Teece et al. (1994) and Bryce and Winter (2009), and involves the following steps:

Step 1: Estimating the collateral type dyad count. We begin by observing how many times two collateral types (a collateral type dyad) are observed together in the same lender.

We start with $K = 207$ lenders contracting in $I = 23$ collateral types. Let $C_{ik} = 1$ if lender k contracts in collateral type *i*, and 0 otherwise. The number of lenders active in collateral type *i* is $n_i = \sum_{k=1}^{k=207} C_{ik}$, and the number of lenders active in both collateral type *i* and collateral type *j* is $J_{ij} = \sum_{k=1}^{k=207} C_{ik} C_{jk}$.

Step 2: Estimating the collateral type dyad relatedness. Next, we scale the collateral dyad count to control for the observed frequency of each collateral type. Specifically, J_{ij} cannot be taken directly as a measure of relatedness, and must be adjusted for the number of lenders appearing in the dyad if lenders were randomly assigned to collateral types.

To measure the distribution of the collateral dyad, X_{ik} consider the probability that *x* out of *K* lenders receive a random assignment to both collateral types *i* and *j*. For this random model, we take the collateral type sizes n_i and n_j and the population size *K* as given, and ask how many times do the n_j *j*'s overlap with the n_i *i*'s consistent with the observed x.

i. Start with the n_j lenders in collateral type *j*.
ii. From these n_j lenders, allocate the x lenders in the overlap with collateral type *i* to x of the n_i observations. This can happen in $\binom{n_i}{x}$ways.
iii. Allocate the remaining $n_j - x$ lenders who are in collateral type j to the $K - n_i$ lenders not in the overlap. This can happen in $\binom{K-n_i}{n_j-x}$ ways.
iv. Normalize the sorts in (ii) and (iii) by the total number of ways the n_j lenders can be sorted, i.e. the number of ways one can choose n_j lenders from *K* lenders, $\binom{K}{n_j}$.

Then, the probability of observing an overlap of x is given by the hypergeometric random variable:

$$P\left[X_{ij} = x\right] = \frac{\binom{n_i}{x}\binom{K-n_i}{n_j-x}}{\binom{K}{n_j}} \tag{1}$$

with a mean of:

$$\mu_{ij} = E\left(X_{ij}\right) = \frac{n_i n_j}{K} \tag{2}$$

and variance of:

$$\sigma_{ij}^2 = \mu_{ij}\left(1 - \frac{n_i}{K}\right)\binom{n_i n_j}{K} \tag{3}$$

We are now in a position to compare the observed dyad J_{ij} with the expected dyad, $E[X_{ij}]$, by estimating the standardized dyad:

$$\tau_{ij} = \frac{J_{ij} - \mu_{ij}}{\sigma_{ij}} \tag{4}$$

When the τ_{ij} is positive and large, it indicates systematic exposure by lenders into pairs of collateral types. I.e. types are related if lenders finance collateral types that share similar monitoring technologies.

Step 3: Estimating the weighted collateral type dyad relatedness. A shortfall of the standardized measure estimated in step 2 is that it does not reflect the economic importance of the dyad frequency of collateral types *within* a lender. For example, two activities each contributing only 1% - 2% of the lenders' contract pool may be only weakly related, whereas two collateral types that each secure close to half of the contract pool are likely related more strongly. If the pattern is consistent across all lenders operating in two collateral types, then this should be reflected in the relatedness score of the dyad.

We account for the dyad weights as follows. The weight is determined by comparing for each dyad the relative weights, s_i and s_j, of total contract pool that are attributable to each activity *i* and *j* of the dyad. The minimum of these two weights, $min[s_i, s_j]$, is then selected for each lender and averaged across all lenders operating in the dyad. The minimum weight is selected because it represents an ``upper bound'' measure of how closely related the two industries could be when they appear together. If collateral type A, having a weight of 0.01, is combined with collateral type B, having a weight of 0.70, the 0.01 is selected to provide information on the importance of the dyad to that lender. These minimum weights are then averaged across all lenders operating in the dyad to create the dyad weight.

The average weight S_{ij} produced by all lenders operating in the dyad is

$$S_{ij}^{min} = \frac{\sum_k min_k[s_i, s_j] C_{ik} C_{jk}}{\sum_k C_{ik} C_{jk}} \tag{5}$$

To adjust the standardized measures by the weight, the scores in (4) are first converted to a distance matrix such that all measures are positive, and a smaller measure reflects high relatedness. The distance matrix is computed by identifying the maximum τ_{ij} among the set of normalized scores, and subtracting all scores from this value.

Following this transformation, cell values in the distance matrix are divided by (5), such that those dyads with a small weighting are transformed to be "more" distant: The resulting matrix can be evaluated as a network in which the values in matrix cells are the distances between nodes *i* and *j*. The network is comprised of collateral type vertices connected by arcs having weight (length) inversely proportional to relatedness.

Step 4: Estimating relatedness using shortest paths
The weighted distance measure in step 3 allows only for direct relatedness, and not indirect relatedness. For example, consider that collateral types *x* and *y* have distance "2" and *y* and *z*

have distance “3”, and the distance for *x* and *z* is unobserved. To account for this, we employ a shortest path measure, which implies that *x* and *z* must have a distance of 5.

The shortest path method produces a distance measure for dyads that are not directly connected in the network, and it substitutes a shortest path distance for a direct link between two industries when the path distance is shorter than the direct distance.

To complete construction of the index, the weighted distance matrix, which is now filled with shortest path scores, is converted to a similarities matrix, where the greatest values rather than the lowest values represent the highest relatedness. This is done simply by subtracting each computed path length score from the maximum computed path length, which implicitly sets the least related dyad to a value of zero and the most related dyad to some positive value. Following the similarities transformation, index scores are further transformed in two ways. First, the similarities score is standardized by subtracting the mean of the distribution from each value and dividing by the standard deviation.

Plots of the distribution of all normalized (not percentile) dyad relatedness index scores are presented in Appendix C.

Appendix C: Collateral Type Relatedness Index

The table presents relatedness scores for 23 collateral type pairs from the 207 lenders observed in the sample. Relatedness scores are distributed approximately normally. Normalized values, or z-scores, range from a low of -2.45 to a high of 2.64 standard deviations from the mean. To facilitate interpretation, the relatedness scores have been transformed into a value that represents the cumulative area under the distribution and ranges between 0 and 100. Therefore, the scores can be interpreted as a percentile. An index score of 70 implies that 70% of collateral type dyads are less related than the focal score, whereas 30% are more related.

Collateral Type	AIR	AUTO	BOAT	BUS	CNST	COMP	COPY	ENGY	FORK	LOG	MDTR	MEDC	MFG	OFFC	PRNT	RAIL	REAL	RETL	TELE	TRCK	VEND	WAST
AGRI	18.5	40.2	4.0	50.0	90.2	81.5	80.8	50.7	87.0	79.3	86.6	76.1	74.3	77.9	54.7	14.9	92.0	75.4	81.2	87.3	60.1	43.1
AIR		10.9	64.9	16.7	25.0	35.1	33.7	8.0	17.8	9.8	17.0	30.4	21.7	31.9	19.2	35.5	11.6	30.1	34.1	42.8	17.4	14.1
AUTO			1.1	51.4	68.8	59.8	60.5	7.2	56.2	19.9	68.1	56.9	73.2	65.2	46.7	6.2	67.8	61.2	60.9	63.4	39.1	23.9
BOAT				2.5	5.1	9.4	8.7	0.4	3.6	0.7	2.9	6.9	4.7	7.6	4.3	13.4	1.8	6.5	9.1	11.2	3.3	2.2
BUS					47.5	38.4	37.7	10.5	55.8	23.6	85.9	32.6	48.2	35.9	41.3	21.0	28.3	42.0	38.0	64.5	26.1	27.5
CNST						79.0	78.3	26.4	89.5	69.2	83.7	73.6	87.7	75.7	81.9	24.6	69.9	86.2	78.6	89.9	67.4	72.5
COMP							99.3	32.2	83.3	40.9	45.7	97.1	94.2	98.2	80.4	15.2	59.1	96.7	99.6	63.8	91.3	48.6
COPY								31.2	82.6	39.5	44.9	97.5	93.1	98.6	79.7	15.9	58.3	96.0	100.0	62.7	90.6	49.3
ENGY									22.8	21.4	22.5	27.9	19.6	29.3	12.3	1.4	28.6	27.2	31.5	23.2	15.6	8.3
FORK										44.2	55.1	76.4	84.8	85.1	61.6	24.3	64.1	77.5	83.0	65.9	75.0	76.8
LOG											52.2	37.0	36.2	38.8	29.7	5.8	57.6	36.6	39.9	53.3	25.4	67.0
MDTR												40.6	50.4	42.4	43.8	18.1	62.3	47.8	45.3	84.1	29.0	56.5
MEDC													91.7	95.7	74.6	18.8	53.6	94.9	97.8	58.0	88.8	43.5
MFG														93.8	88.4	13.0	51.8	94.6	93.5	73.9	84.4	51.1
OFFC															77.2	14.5	55.4	95.3	98.9	59.4	89.1	46.4
PRNT																26.8	30.8	85.5	80.1	54.3	66.7	62.0
RAIL																	12.7	13.8	16.3	12.0	10.1	20.3
REAL																		52.9	58.7	65.6	37.3	25.7
RETL																			96.4	69.6	92.8	44.6
TELE																				63.0	90.9	49.6
TRCK																					46.0	48.9
VEND																						34.8
WAST																						

Figure 1: Number of Sample Lenders Entering the Bureau by Year

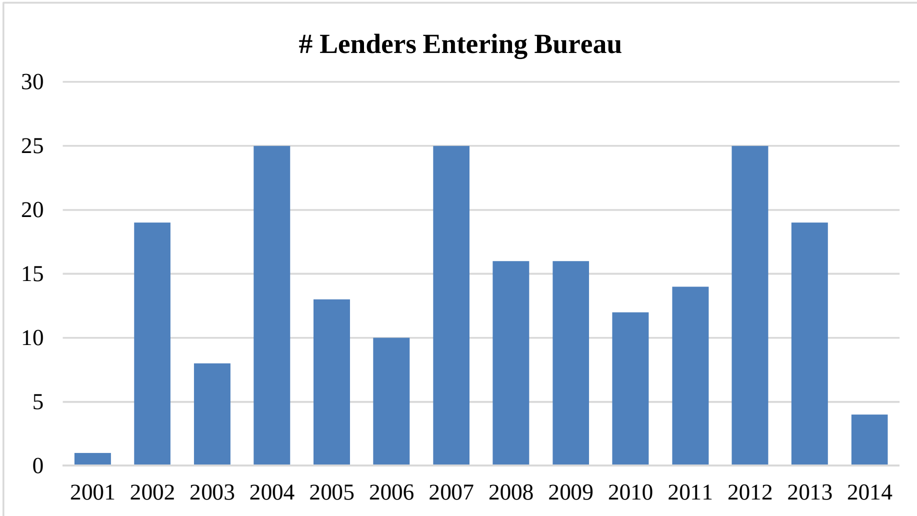
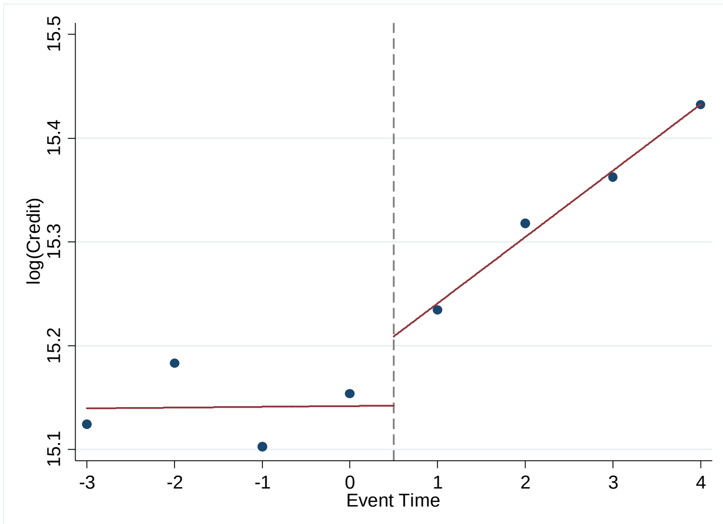
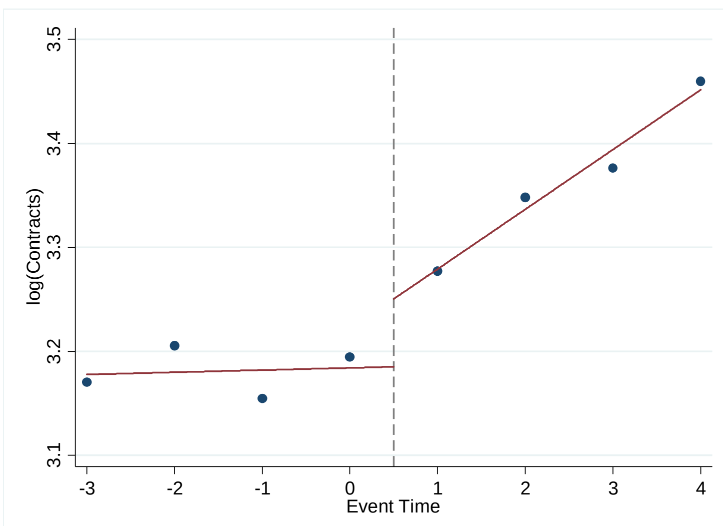
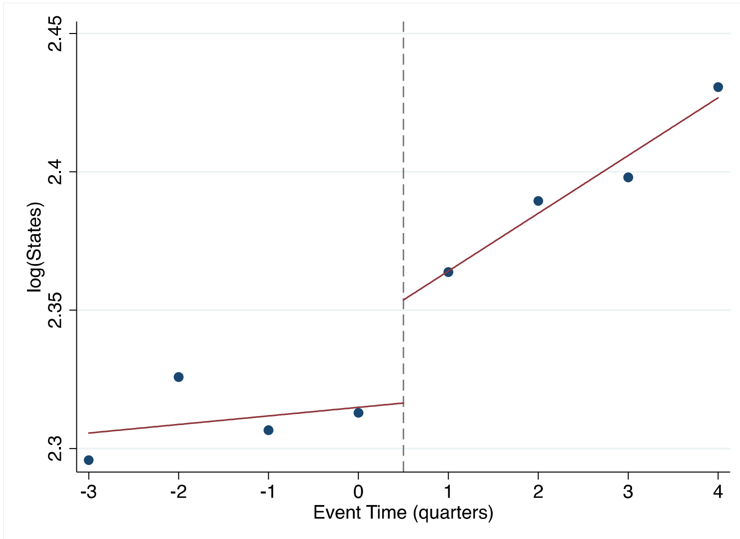


Figure 2: Lending Dynamics around Bureau Entry

This figure plots the exposure dynamics for lenders during the four quarters before and after joining the bureau. The graphs present the natural logarithm of credit, contracts, and number of state and industry exposures, respectively. T=1 is defined as the end of the quarter in which the lender joins the bureau. The line presents the coefficient estimate of exposure on event time in the pre- and post-periods separately.






2.45
2.4
2.35
2.3
log(States)
-3
-2
-1
0
1
2
3
4
Event Time (quarters)

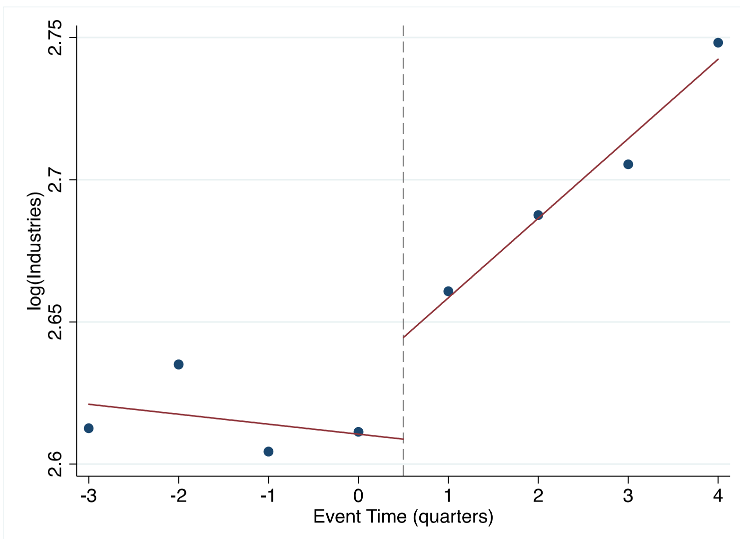

2.75
2.7
2.65
2.6
log(Industries)
-3
-2
-1
0
1
2
3
4
Event Time (quarters)

Table 1: Summary Statistics

This table describes the contract features and exposures for lenders in our sample. The unit of observation is lender-quarter, and the sample spans the two-year period surrounding the lender's entry to the bureau. For industry exposures, we exclude lenders with insufficient industry information for our portfolio measures. See Appendix A for variables definitions.

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
Average Contract Features (Post=0)						
Contract Size	192,156	292,538	40,840	75,801	223,081	793
Lease Contract	76.4%	39.6%	54.8%	100.0%	100.0%	793
Loan Contract	23.6%	39.6%	0.0%	0.0%	45.2%	793
Contract Has Delinquency	26.0%	24.6%	3.7%	20.0%	41.0%	367
Days Currently Delinquent	50.0	92.4	17.2	29.8	46.0	296
Average Contract Features (Post=1)						
Contract Size	191,113	262,386	41,372	77,311	225,875	812
Lease Contract	75.9%	39.7%	54.5%	100.0%	100.0%	812
Loan Contract	24.1%	39.7%	0.0%	0.0%	45.5%	812
Contract Has Delinquency	15.4%	19.9%	0.0%	9.4%	20.7%	783
Days Currently Delinquent	54.9	113.2	17.3	29.0	49.0	566
Lender Features (Post=0)						
Credit	56,317,950	159,719,100	560,994	3,377,120	27,718,390	793
Contracts	491.2	1292.8	8.0	34.0	178.0	793
# State Exposures	15.9	15.9	3.0	8.0	27.0	793
HHI State	0.40	0.32	0.11	0.30	0.61	793
# Industry Exposures	23.1	46.3	2.0	6.0	18.0	573
HHI Industry	0.43	0.31	0.16	0.37	0.66	573
Lender Features (Post=1)						
Credit	56,497,860	150,118,800	784,834	3,336,387	29,174,900	812
Contracts	498.0	1311.0	10.0	37.5	190.0	812
# State Exposures	16.5	15.7	3.5	9.0	28.0	812
HHI State	0.36	0.30	0.10	0.26	0.51	812
# Industry Exposures	23.9	46.4	3.0	7.0	19.0	592
HHI Industry	0.39	0.29	0.14	0.33	0.53	592

Table 2: Information Sharing and Lender Exposures

This table models lenders' exposures as a function of bureau membership. The dependent variable in columns 1 (2, 3, and 4) is the log dollar amount of credit (log number of contracts, states and industries) in the lender's portfolio. *Post* is an indicator equal to one for quarters after the lender has joined the bureau. We include lender and year fixed effects in all columns. The sample spans the two-year period surrounding the lender's entry to the bureau. Column 4 includes only lenders with sufficient industry information for our tests. Reported below the coefficients are t-statistics calculated with standard errors clustered at the lender level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Log Credit	(2) Log Contracts	(3) Log States	(4) Log Industries
Post	0.221***	0.172***	0.093***	0.118***
	[5.32]	[4.84]	[5.21]	[4.53]
Adj R2	0.966	0.972	0.963	0.964
N	1,605	1,605	1,605	1,165
Fixed Effects	Lender, Year	Lender, Year	Lender, Year	Lender, Year
Clustering	Lender	Lender	Lender	Lender
Sample	T-3 to T+4	T-3 to T+4	T-3 to T+4	T-3 to T+4

Table 3: Information Sharing and Lender Exposures- Robustness Analysis

This table provides robustness analysis of our Table 2 results. Panel A (B, C, and D) studies credit (contracts, states, and industries). *Post* is an indicator equal to one for quarters after the lender has joined the bureau. *Early Join* is an indicator equal to one for lenders joining before 2008. We include lender fixed effects in all columns, and an event quarter trend variable in columns 1-3. Column 2 provides a placebo analysis where we counterfactually shift the lender's bureau entry date back by four quarters. Column 3 provides a placebo analysis where we run 1,000 trials in which we randomly assign bureau entry dates for each lender. Column 5 collapses the sample into single pre and post period observations for each lender. The sample spans the two-year period surrounding the lender's entry to the bureau, and Panel D includes only lenders with sufficient industry information for our tests. Reported below the coefficients are t-statistics calculated with standard errors clustered at the lender level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively. See Appendix A for variables definitions.

Panel A: Credit

	(1)	(2)	(3)	(4)	(5)
	Log Credit	Log Credit	Log Credit	Log Credit	Log Credit
Post	0.054	-0.001	0.000	0.299***	0.287***
	[1.52]	[-0.04]	[-0.01]	[4.26]	[6.67]
Post * Early Join				-0.011	
				[-0.13]	
Adj R2	0.966	0.972		0.965	0.970
N	1,605	1,551		1,605	409
Trend	Yes	Yes	Yes	No	No
Fixed Effects	Lender	Lender	Lender	Lender	Lender
Clustering	Lender	Lender	Lender	Lender	Lender
Sample	T-3 to T+4	Placebo	Placebo	T-3 to T+4	Collapsed T-3 to T+4

Panel B: Contracts

	(1) Log Contracts	(2) Log Contracts	(3) Log Contracts	(4) Log Contracts	(5) Log Contracts
Post	0.037	-0.004	0.000	0.253***	0.223***
	[1.20]	[-0.15]	[0.04]	[4.46]	[7.07]
Post * Early Join				-0.017	
				[-0.24]	
Adj R2	0.973	0.979		0.972	0.978
N	1,605	1,551		1,605	409
Trend	Yes	Yes	Yes	No	No
Fixed Effects	Lender	Lender	Lender	Lender	Lender
Clustering	Lender	Lender	Lender	Lender	Lender
Sample	T-3 to T+4	Placebo	Placebo	T-3 to T+4	Collapsed T-3 to T+4

Panel C: States

	(1) Log States	(2) Log States	(3) Log States	(4) Log States	(5) Log States
Post	0.030*	0.002	0.000	0.128***	0.127***
	[1.93]	[0.13]	[0.07]	[4.04]	[6.30]
Post * Early Join				-0.009	
				[-0.24]	
Adj R2	0.964	0.971		0.963	0.962
N	1,605	1,551		1,605	409
Trend	Yes	Yes	Yes	No	No
Fixed Effects	Lender	Lender	Lender	Lender	Lender
Clustering	Lender	Lender	Lender	Lender	Lender
Sample	T-3 to T+4	Placebo	Placebo	T-3 to T+4	Collapsed T-3 to T+4

Panel D: Industries

	(1) Log Industries	(2) Log Industries	(3) Log Industries	(4) Log Industries	(5) Log Industries
Post	0.042*	-0.013	0.000	0.152***	0.167***
	[1.90]	[-0.71]	[-0.02]	[3.61]	[5.77]
Post * Early Join				0.005	
				[0.10]	
Adj R2	0.964	0.972		0.963	0.960
N	1,165	1,132		1,165	297
Trend	Yes	Yes	Yes	No	No
Fixed Effects	Lender	Lender	Lender	Lender	Lender
Clustering	Lender	Lender	Lender	Lender	Lender
Sample	T-3 to T+4	Placebo	Placebo	T-3 to T+4	Collapsed T-3 to T+4

Table 4: Exposure Responses to Information Shocks

This table models lender exposures using (2). The unit of observation is lender-collateral type-quarter. The dependent variable in columns 1 (2, 3, and 4) is the log dollar amount of credit (log number of contracts, states and industries) in the lender's portfolio. *Post* is an indicator equal to one for quarters after the lender has joined the bureau. *Information* is the log number of contracts that have been contributed to the bureau to date for a given collateral type. We include lender-collateral fixed effects, lender-quarter fixed effects, and collateral-specific trends in all columns. The sample includes all quarters for each lender, and column 4 includes only lenders with sufficient industry information for our tests. Reported below the coefficients are t-statistics calculated with standard errors clustered at the lender level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Log Credit	(2) Log Contracts	(3) Log States	(4) Log Industries
Information	0.006	-0.010	0.001	-0.007
	[0.16]	[-0.43]	[0.13]	[-0.46]
Post * Information	0.077***	0.060***	0.021**	0.021
	[2.62]	[3.29]	[2.13]	[1.56]
Adj R2	0.874	0.896	0.886	0.905
N	48,678	48,678	48,678	30,999
Lender x Collateral Type FEs?	Yes	Yes	Yes	Yes
Lender x Quarter FEs?	Yes	Yes	Yes	Yes
Collateral Type-Specific Trends?	Yes	Yes	Yes	Yes
Clustering	Lender	Lender	Lender	Lender
Sample	Full	Full	Full	Full

Table 5: Information Sharing and Exposures by Lender Size

This table models the number of lender exposures as a function of bureau membership and lender size. The dependent variable in columns 1 (2, 3, and 4) is the log dollar amount of credit (log number of contracts, states and industries) in the lender's portfolio. *Post* is an indicator equal to one for quarters after the lender has joined the bureau. *Large Lender* is an indicator equal to one for lenders with an above median dollar amount of contracts in the quarter before joining the bureau. We include lender and year fixed effects in all columns. The sample spans the two-year period surrounding the lender's entry to the bureau. Column 4 includes only lenders with sufficient industry information for our tests. Reported below the coefficients are t-statistics calculated with standard errors clustered at the lender level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively. Below the table, we present test statistics for Post + Post * Large Lender. See Appendix A for variables definitions.

	(1) Log Credit	(2) Log Contracts	(3) Log States	(4) Log Industries
Post	0.333***	0.293***	0.160***	0.175***
	[4.49]	[4.92]	[4.95]	[4.51]
Post * Large Lender	-0.225**	-0.241***	-0.133***	-0.141***
	[-2.44]	[-3.36]	[-3.41]	[-2.80]
Adj R2	0.966	0.973	0.964	0.965
N	1,605	1,605	1,605	1,165
Fixed Effects	Lender, Year	Lender, Year	Lender, Year	Lender, Year
Clustering	Lender	Lender	Lender	Lender
Sample	T-3 to T+4	T-3 to T+4	T-3 to T+4	T-3 to T+4
Post + Post * Big Lender = 0	0.108	0.052	0.027	0.034
F-statistic	5.86	1.86	2.15	1.33
P-value	0.016	0.174	0.145	0.250

Table 6: Information Sharing, Small Client Exposure, and Lender Size

This table models the client size composition of the lender's portfolio as a function of bureau membership and lender size. The dependent variable in columns 1 and 2 is the percent of the lender's clients that are small firms, classified as those in the lowest total credit quartile at the industry-quarter level. *Post* is an indicator equal to one for quarters after the lender has joined the bureau. *Large Lender* is an indicator equal to one for lenders with an above median dollar amount of contracts in the quarter before joining the bureau. We include lender and year fixed effects in both columns. The sample spans the two-year period surrounding the lender's entry to the bureau. Reported below the coefficients are t-statistics calculated with standard errors clustered at the lender level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively. See Appendix A for variables definitions.

	(1) % Portfolio Small Clients	(2) % Portfolio Small Clients
Post	-0.011*	-0.024**
	[-1.83]	[-2.08]
Post * Large Lender		0.026**
		[2.06]
Adj R2	0.776	0.778
N	1,605	1,605
Fixed Effects	Lender, Year	Lender, Year
Clustering	Lender	Lender
Sample	T-3 to T+4	T-3 to T+4

Table 7: Information Sharing and Lender Portfolio Risk

This table models lender portfolio risk measures as a function of bureau membership. The dependent variable in columns 1 and 2 is the Herfindahl-Hirschman Index for geographic and industry exposures. The dependent variable in column 3 (4) is the contract-size weighted share of the lender's contracts that are currently delinquent (the log standard deviation of the contract-sized weighted share of the lender's contracts that are currently delinquent). *Post* is an indicator equal to one for quarters after the lender has joined the bureau. We include lender fixed effects in all regressions. For each lender, the sample is collapsed into a pre and post period spanning the four quarters before and four quarters after bureau entry. The sample in column 2 (3 and 4) is limited to lenders with sufficient industry (delinquency) information for our tests. Reported below the coefficients are t-statistics calculated with standard errors clustered at the lender level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively. See Appendix A for variables definitions.

	(1) HHI State	(2) HHI Industry	(3) Portion of Contracts Delinquent	(4) Log Std Dev Is Delinquent
Post	-0.049***	-0.061***	-0.088***	-0.030**
	[-5.17]	[-4.49]	[-3.49]	[-2.51]
Adj R2	0.901	0.851	0.402	0.043
N	409	297	132	132
Fixed Effects	Lender	Lender	Lender	Lender
Standard Errors	Lender	Lender	Lender	Lender
Sample	Collapsed T-3 to T+4	Collapsed T-3 to T+4	Collapsed T-3 to T+4	Collapsed T-3 to T+4

Table 8: Geographic and Industry Exposures by Collateral Type

This table summarizes the number of lenders, states (or territories including Guam, Puerto Rico, and the Virgin Islands), and industries with contracts for each collateral type.

Collateral Type	# Lenders	# States	# Industries
Agricultural	67	49	225
Aircraft	16	32	60
Automobiles	56	51	256
Boats	9	19	20
Buses & Motor Coaches	40	46	112
Construction & Mining	110	51	286
Computer	101	52	378
Copier & Fax	53	52	397
Energy	9	20	28
Forklift	50	50	240
Logging & Forestry	30	42	63
Medium/Light Duty Trucks	67	49	240
Medical	79	48	124
Manufacturing	97	51	300
Office Equipment	73	50	299
Printing & Photographic	53	46	170
Railroad	16	26	48
Real Estate	20	22	82
Retail	99	52	336
Telecommunications	69	52	325
Truck	121	51	265
Vending	49	49	201
Waste & Refuse Handling	37	45	96
Average	57	44	198
Median	53	49	225
Maximum	121	52	397

Table 9: Information Sharing and Collateral Expertise

This table models the lender's exposures *within* a collateral type as a function of bureau membership. The unit of observation is lender-collateral type-quarter. The dependent variable in columns 1 (2, 3, and 4) is the log dollar amount of credit (log number of contracts, states and industries) in the lender's portfolio. *Post* is an indicator equal to one for the period after the lender has joined the bureau. We include lender-collateral type fixed effects in all regressions. For each lender-collateral type offering, the sample is collapsed into a pre and post period spanning the four quarters before and four quarters after bureau entry. The sample is restricted to collateral type offerings with non-zero exposure for the lender in the pre period, and column 4 includes only lenders with sufficient industry information for our tests. Reported below the coefficients are t-statistics calculated with standard errors clustered at the lender level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Log Credit	(2) Log Contracts	(3) Log States	(4) Log Industries
Post	0.178***	0.132***	0.048***	0.056***
	[6.33]	[4.92]	[3.95]	[3.82]
Adj R2	0.983	0.984	0.969	0.972
N	1,890	1,890	1,890	1,746
Fixed Effects	Lender x Collateral Type	Lender x Collateral Type	Lender x Collateral Type	Lender x Collateral Type
Clustering	Lender	Lender	Lender	Lender
Sample	Collapsed	Collapsed	Collapsed	Collapsed

Table 10: Information Sharing and Collateral Relatedness

This table models lenders' collateral exposures as a function of relatedness to existing collateral types in the portfolio, and bureau membership. The unit of observation is lender-collateral type-quarter. The dependent variable is the lender's log dollar amount of contracts in that collateral type. *Relatedness* is a lender-level score of the similarity between a lender's existing collateral types and a new collateral type. In column 1 (2), the lender-level score is measured as the maximum (average) of the pairwise relatedness scores between the lender's existing collateral type offerings and the given collateral type which the lender did not have exposure to one year prior to entering the bureau. *Post* is an indicator equal to one for the period after the lender has joined the bureau. We include collateral type and lender fixed effects in all regressions. The sample spans the two-year period surrounding the lender's entry to the bureau. The sample is restricted to collateral types that the lender was not exposed to before entering the bureau, and is collapsed into a pre and post period spanning the four quarters before and four quarters after bureau entry. Reported below the coefficients are t-statistics calculated with standard errors clustered at the lender level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively. See Appendix A for variable definitions.

	(1) Log Credit	(2) Log Credit
Post	0.050***	0.075***
	[4.52]	[5.20]
Relatedness Max	0.033	
	[1.60]	
Relatedness Max * Post	0.107***	
	[4.22]	
Relatedness Avg		0.023**
		[2.03]
Relatedness Avg * Post		0.055***
		[4.03]
Adj R2	0.048	0.049
N	7,352	7,352
Fixed Effects	Collateral Type, Lender	Collateral Type, Lender
Clustering	Lender	Lender
Sample	Collapsed	Collapsed

Table 11: Information Sharing and Firm Credit Access

This table models borrower access to credit as a function of whether their credit file is available in the bureau. The dependent variable in columns 1 and 5 (2 and 6) is the log number of lending relationships (total credit). The dependent variable in columns 3 and 7 (4 and 8) is an indicator for whether the borrower starts a new contract (relationship) without having an old contract maturing in that quarter or a surrounding quarter. *Post* is an indicator equal to one for the period after the borrower first appears in the bureau. We include borrower fixed effects in all regressions. The sample is limited to borrowers with pre and post observations. In columns 1-4, the sample is collapsed into a pre and post period spanning the four quarters before and four quarters after the borrower's credit file is first available in the bureau. Reported below the coefficients are t-statistics calculated with standard errors clustered at the borrower level. *, **, *** indicate significance at the two-tailed 10%, 5% and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Log Avg # of Lending Relationships	(2) Log Avg Total Credit	(3) Starts New Contract Off Cycle	(4) Starts New Relationship Off Cycle	(5) Log # of Lending Relationships	(6) Log Total Credit	(7) Starts New Contract Off Cycle	(8) Starts New Relationship Off Cycle
Post	0.043***	0.073***	0.040***	0.051***	0.013***	0.004	0.055***	0.053***
	[29.31]	[11.85]	[7.03]	[10.88]	[10.80]	[0.80]	[13.95]	[17.43]
Adj R2	0.948	0.965	0.507	0.505	0.907	0.937	0.157	0.132
N	25,350	25,350	25,350	25,350	101,352	101,352	101,352	101,352
Trend	No	No	No	No	Yes	Yes	Yes	Yes
Fixed Effects	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower
Clustering	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower
Sample	Collapsed	Collapsed	Collapsed	Collapsed	T-3 to T+4	T-3 to T+4	T-3 to T+4	T-3 to T+4