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

José Liberti, Jason Sturgess, and Andrew Sutherland+

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Abstract

We examine how developments in financial technology that improve information sharing affect lender specialization. Using the introduction of a U.S. commercial credit bureau, we document that lenders leverage their collateral expertise to enter new markets after joining. We exploit the staggered joining of members to show that a member lender's exposure responds to information shared by new lenders entering the bureau but only when the newly shared information is related to the lender's own specialization. Small lenders account for most of geographic expansion, while large lenders increase their exposure to small firms. Our results help explain why intermediaries regularly forego rents when voluntarily sharing information and show how financial technology that mitigates information asymmetries can shape the boundaries of lending.

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+ Liberti: Northwestern University and DePaul University, jliberti@depaul.edu; Sturgess: DePaul University, jason.sturgess@depaul.edu; Sutherland: MIT, ags1@mit.edu.

1. Introduction

Developments in technology in financial markets, or fintech, have led to significant advances in the way financial intermediaries both use and share information. Using information technology, lenders have been able to find better matches between credit and users of capital. In most modern credit markets, lenders exchange contract terms and delinquency records through information sharing arrangements (Djankov, McLiesh, and Shleifer 2007). Many of these arrangements operate voluntarily in our largest credit markets: private bureaus provide near universal coverage of individuals in the U.S., U.K., Japan, Germany, and Canada, while mandated registries have negligible presence (World Bank 2015).

Sharing information reduces information asymmetries between borrowers and lenders, which improves monitoring and screening for lenders and enhances credit access for borrowers. However, because these same features increase competition for borrowers, it is unclear why lenders voluntarily share information (Pagano and Jappelli 1993). One possible motive is to overcome adverse selection problems that can operate as entry barriers in credit markets (Dell'Ariccia et al. 1999). In this paper, we examine whether voluntary information sharing enables specialized lenders to enter new markets at the expense of foregoing rents.

The literature emphasizes the role of specialization for financial intermediaries in producing information. Specialization fosters comparative advantages in screening and monitoring (Winton, 1999; Paravisini et al. 2015). Specializing not only allows the lender to earn rents on its 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; Dell'Ariccia 2001; Dell'Ariccia and Marquez 2004; Hauswald and Marquez 2006). Furthermore, specialized lenders likely have a competitive advantage contracting with similarly specialized borrowers, which could enhance access to credit. On

the other hand, traditional banking theories of delegated monitoring hinge 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).

We provide evidence that lenders expand credit and their geographic exposures after sharing information. This expansion is more pronounced in markets with significant barriers to entry, such as states where enforcement of noncompetition clauses prevents the hiring of a competitor's loan officers. Individual lenders' expansion patterns also are significantly influenced by their specializations. Credit and geographic expansion leverages 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 improve credit access for firms.

Conducting a study of this nature presents several empirical complications. First, one needs to identify an event that isolates a lender's exposure to the technology shock and to be able to track a lender's portfolio before and after the event. Second, it is difficult to separate the effects of information sharing on lending from the lender's decision to enter the bureau. Third, it is hard to disentangle the effects of information sharing on a lender's decision to enter new markets from the supply and demand of capital.

To overcome these complications, we study the portfolios of 207 lenders voluntarily joining a U.S. equipment finance credit bureau, PayNet, in a staggered pattern between 2001 and 2014.[1] The staggered entry allows us to address the concern that the shock might relate to a single credit event but does not solve the endogenous voluntary entry decision by a lender. To mitigate this concern, our empirical design exploits the fact that lenders specialize in lending against collateral types and that the voluntary entry of other lenders within a

[1] 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 nonresidential 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 $1.4 trillion in contracts.

collateral type provides exogenous variation in the information environment of incumbent lenders. Of course, it is possible that entry of new lenders is correlated with demand shocks. The final piece in our identification strategy is to compare lending patterns of incumbent lenders with lending patterns of non-members around the entry of new lenders. We are able to do this because all lenders supply their history of lending data, which allows us to exploit lenders that are not yet members as a counterfactual to current member lenders. In this way, we can examine how a member lender's exposure in a particular collateral type responds to an information shock, due to the new entrant, while absorbing the contemporaneous change in exposure in the same collateral type for a nonmember.

Our identification strategy is perhaps best illustrated with an example. Consider the exposures of the following lenders: Lenders A and B, which both specialize in agriculture equipment lending. However, lender A joins the bureau in 2004 and lender B joins in 2008. Now consider a third lender, Lender C, specializing in agricultural equipment financing that enters the bureau and shares its contracts in 2006. We predict a larger change in agricultural equipment exposure in 2007 for Lender A, who observes the new information from lender C in the bureau, than Lender B. To the extent that lenders A and B are exposed to similar economic shocks then any differential increase in lending around lender C joining the bureau can be attributed to information sharing. Further, we observe a natural placebo in our setting: lending by lender A in non-agricultural equipment types should not respond to the shocks to information originating from the specialized agricultural lender C joining the bureau.

We begin by examining the exposures—measured as total credit, total contracts, and the number of states—in each lender's portfolio during the two years surrounding its bureau entry. Lenders increase the amount of credit and number of contracts in their portfolios after joining the bureau and beginning to share information. They also increase their geographic footprint by 9.3% in the year after joining. Economically, this translates into contracting in

1.5 additional states for the average lender in our sample. This suggests that adverse selection problems act as a meaningful entry barrier and that the availability of local information can shape entry decisions.[2]

To establish a role for specialization, we focus on lender expertise in the asset being financed or collateral. Lenders frequently specialize by collateral type when offering secured financing because the contract terms, default probabilities, resale markets, and enforcement mechanisms tend to be similar within a collateral type (Loutskina and Strahan 2011; Eisfeldt and Rampini 2009; Murfin and Pratt 2017). These similarities can foster economies of scale for screening borrowers and provide a comparative advantage, because lenders earn rents on their ability to predict default and recover collateral (Carey et al. 1998; Benmelech et al. 2005). Therefore, a lender's expertise likely leads it to favor borrowers with collateral that the lender has experience financing. Lending to clients with familiar collateral also helps shelter the lender from the heightened competition that can accompany information sharing. Consistent with this, we find significant expansion within collateral expertise: lenders expand credit and their geographic exposure by 6.7% (5.4%), respectively, *within* the collateral types they specialized in before joining.

To better understand this collateral specialization channel, we examine how lenders' exposures at the collateral-level respond to shocks to their information set arising from *other lenders* joining the bureau, while absorbing lender-specific shocks using lender-quarter fixed effects. Members increase their exposures in a collateral type in response to new lenders sharing information in the bureau, but only when the shock is relevant to that collateral type. A one standard deviation increase in the number of bureau contracts for a typical collateral type increases a member's credit exposure to that collateral type by 16%. By comparison, we detect no change in nonmembers' exposures. We find parallel results when we drill the

[2] Most borrowers in PayNet are opaque. Forty percent 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%).

analysis down to the collateral-region level: shocks in bureau coverage for a given collateral type-region lead to lender increases in exposure in that same collateral type-region but, once again, for members only. Further, in placebo tests we show that members' exposures to a given collateral type do not respond to shocks to coverage in other collateral types. This set of findings indicates that specialization is being driven by the availability of information in the bureau, rather than by unobservable lender business model changes or conditions in collateral markets.

To reinforce our results, we then examine how the effects of information sharing and specialization vary with entry barriers. Lenders face adverse selection problems when entering new markets (Dell'Ariccia et al. 1999). These problems arise because firms repeatedly borrow from the same lender, giving the lender an information advantage over potential new entrants. One way entrants can overcome this advantage is to hire local loan officers, who will have collected soft information on potential borrowers (Gao, Martin, and Pacelli 2017; Liberti 2017). However, loan officers' employment agreements may include noncompete clauses (Wang 2017), though states vary in their enforcement of these clauses (Garmaise 2011; Jeffers 2017). We find greater reliance on hard information—credit reports and scores gained from information sharing—for expansion in states where soft information is more difficult to acquire because of the stronger enforcement of noncompete clauses.

Next, we examine whether collateral expertise is associated with expansion into related collateral types. Following Bryce and Winter (2009), 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.[3] Our index produces pairwise relatedness measures consistent with this intuition. For example, telecommunications

[3] The approach 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.

equipment relates highly to computer and copy equipment but not railroad and logging equipment.

We find that lenders, on average, enter new collateral markets that most relate to existing exposures. This effect is relatively higher after bureau entry and when there are shocks to bureau coverage for the related collateral, suggesting that information sharing accelerates entry into related collateral markets. Our estimates indicate that a one standard deviation increase in similarity between the new collateral type and those already in the lender's portfolio increases the number of contracts in the new collateral exposure by 4 percent after bureau entry.

Small and large lenders may respond differently to the information shared when a competitor enters the bureau. Small lenders likely invest in soft information and employ monitoring technologies specific to the given sector (Stein 2002; Berger et al. 2005; Liberti and Mian 2009), while large lenders are likely to employ monitoring technologies that are scalable and transferable across markets. Splitting the sample according to total credit before joining the bureau, we find that small lenders drive the majority of credit, contract, and state expansion we document. For example, while small lenders increase the number of states in their portfolio by 16.0%, there is no effect for large lenders.

Large lenders may want to replicate the decentralized organizational structures of small lenders, who possess a competitive advantage in markets where borrower information is predominantly soft, as for small firms (Stein 2002). Where this replication is costly, PayNet can provide a valid substitute by offering access to information on small borrowers from small lenders. Implicitly, PayNet provides a new source of hard information that replaces the need to collect soft information. We find that larger lenders contract more with small firms after joining the bureau, consistent with this view. This evidence helps us

understand the incentives of different types of lenders to share information and demonstrates an expansion channel uniquely associated with credit scoring technologies.

Overall, we show that specialized lenders enter new credit markets after information sharing. One implication is that borrowers should have better access to specialized lenders, which should improve their access to credit. Consistent with this, we show that, after a borrower first has a credit file in the bureau, it increases its number of lenders by 6.0% and credit by 11.8%, respectively. We further show that access to specialized lenders enhances financial flexibility. That is, borrowers are more likely to start "off-cycle" relationships, as opposed to starting new relationships only upon the conclusion of old contracts.

Our study provides evidence that fintech can change the competitive landscape by reshaping the boundaries of lending. In doing so, it offers a potential explanation for the voluntary sharing of proprietary contract information by lenders joining a credit bureau. Lenders enter new markets by leveraging collateral expertise, which suggests information frictions exist across states even within an asset class. Collectively, our findings indicate that financial technology that mitigates information asymmetries allows lenders to enter new markets by matching their expertise with the collateral of borrowers.

We also contribute 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 (e.g., Berger and Ofek 1995; Rajan et al. 2000; Campa and Kedia 2002), despite considerable regulatory scrutiny of lenders' portfolio concentrations (Basel 2000; OCC 2011).[4] 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

[4] The evidence on the scope of lending has focused on diversification. Laeven and Levine (2007) show that diversified banks trade at a discount to banks that specialize in a single lending activity. Examining geographic expansion using U.S. bank branching deregulation as a quasi-experiment, Goetz et al. (2016) present evidence that banks engaging in geographical diversification lower their risk, while Acharya et al. (2011) show that bank diversification improved access to credit and resulted in diversification of real output.

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. (2017) find that banks with new exposures to an industry are significantly more likely than incumbents to request audits from borrowers.

The rest of the paper is organized as follows. Section 2 presents the institutional setting. Section 3 describes the empirical design. Section 4 presents the results and Section 5 concludes.

2. Institutional Setting

2.1 The PayNet Credit Bureau

The PayNet equipment finance bureau was introduced in 2001.[5] Since then, 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.[6] As of March 2017, the PayNet database contained over $1.4 trillion of obligations from 23 million contracts.

Figure 1 provides a timeline of lenders' entry to the bureau from its launch to the spring 2014, the end of our sample. Figure 2 plots the change in bureau coverage for the five most common collateral types. Although the bureau naturally grows over time, we note the five types experience shifts at different points—the across-type correlation is just 0.33. Together, these figures show that staggered entry, combined with specialization in collateral types by lenders, produces rich variation in the stock of contracts over time.

PayNet was founded to fill a gap in the U.S. small business lending market: while delinquency and contract information has been voluntarily shared among consumer lenders

[5] Sutherland (2017) uses the launch of PayNet to show information sharing reduces switching costs for small borrowers and compels lenders to be more transactional in their interactions with borrowers. Doblas-Madrid and Minetti (2013) use an earlier version of the PayNet database to investigate the impact of lender information sharing on firms' payment performance. Their results reveal that information sharing reduces contract delinquencies and defaults, particularly for informationally opaque firms.

[6] The U.S. equipment finance market is highly concentrated. As of 2014, the final year of our sample, the single largest lender (GE Capital) controlled over 20% of industry net assets, and the 10 (25) largest lenders controlled 64% (85%) of industry net assets (Monitor 2015).

for decades, until 2001 commercial lenders in the equipment finance market regularly originated loans without knowing how the borrower had previously serviced similar liabilities (Ware 2002). Repositories such as Dun & Bradstreet and Experian lacked contract-level detail.

Like other voluntary credit bureaus, PayNet operates on the principle of reciprocity. Lenders may participate only if they agree to share all past, present, and future credit files with other members. PayNet does not sell or otherwise make bureau information available to nonmembers. Members can query, for a fee, PayNet's credit file, proprietary credit score, and probability of default for each firm.[7] Lender identities remain anonymous in the bureau.

Several features of PayNet and the U.S. secured commercial credit market serve to ensure the accuracy of shared information. First, lenders must retroactively share all equipment finance contracts to become members. This is necessary for us to compare lenders before and after entry. Second, to become members, lenders undertake a significant upfront investment in information technology to allow PayNet to pull information directly from their internal systems. Lenders are also subject to PayNet's initial testing and ongoing audits to verify complete and accurate information sharing.

Third, PayNet cross-checks data against several sources, including the information shared by other lenders with similar exposures, the lender's prior information, trade and macroeconomic data, and public filings. In the United States, lenders make UCC financing statement filings to establish their legal right to collateral if the firm defaults. Because these filings are public and secretaries of state maintain searchable online records dating back to the 1990s or earlier, PayNet can easily verify that a lender has shared a given contract.

[7] Proprietary credit scores and default probabilities 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.

Finally, misreporting and falsification of information is punished by PayNet with exclusion from the database. Lenders misreporting also expose themselves to litigation from borrowers and other bureau members.

2.2 Sample and Descriptive Statistics

We construct our dataset from a panel of 20,000 randomly chosen firms' credit files, detailing payment histories and contract terms between 1998 and 2014. For each firm, we observe every contract with lenders that have ever joined PayNet, including those beginning and maturing before the lender joins. For each contract, we observe the amount, collateral type, maturity, payment frequency, guarantor requirement, and payment history as well as the state, industry, and age of the firm. In our initial tests, we study contracts open during an event window spanning one year before to one year after the lender joins the bureau. This requirement reduces the sample to 14,251 firms and 109,095 contracts between these firms and 207 lenders.[8]

Table 1 summarizes the contract features and exposures for lenders in our sample. We average each variable within lender during the last year before entry. The average (median) contract size is \$192,258 (\$75,034). Next, we measure the number of outstanding contracts, and the number of unique states and collateral types.[9] The average (median) lender has 482.2 (31.4) contracts with the 14,251 borrowers in our sample. During the pre-period, the typical lender is exposed to 15.7 states or U.S. territories (including Guam, Puerto Rico, and the Virgin Islands). There is considerable variation in geographic exposures—the largest lenders contract in practically every state, while smaller and more specialized lenders typically

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

[9] Unfortunately, some lenders are missing industry fields for many of their contracts. To present a consistent sample, we do not report analyses for sector exposures. In untabulated tests, we find a similar pattern of results for sector exposures as our credit and state exposure measures.

compete in just a handful of markets. Of the 23 collateral type categories in PayNet, the average (median) lender is involved in just 5.2 (3.0) before joining.

3. Empirical Design

In this section, we develop the research design for the tests. First, using a simple event study, we study how the lenders' portfolios change after information is shared by tracking each lender before and after they join the bureau. We build a lender-quarter panel where the event time t = 0 is measured as the last day of the quarter before the quarter in which each lender joins the bureau. The event window includes four quarters before and four quarters after the entry. This narrow event window helps us isolate the effects of information sharing from marketwide and lender-specific developments unrelated to information sharing, such as the arrival of alternative information sources or unobservable business model changes.[10]

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, lender exposure measures include the dollar credit, number of contracts, and number of unique exposures to U.S. states/territories. *Post* is a dummy variable equal to one for observations after the lender has joined the bureau and 0 otherwise. α_i and α_t are lender and time fixed effects. Because lenders join the bureau in a staggered pattern, time-varying factors, such as business cycles or growth in the equipment lending market, are unlikely to bias our tests. Throughout, we cluster standard errors by lender.

The second specification mitigates the concern that voluntary entry by a lender may be endogenous. The empirical design exploits the voluntary entry of other lenders to the

[10] Our results are quantitatively and qualitatively similar using wider windows.

bureau to provide plausibly exogenous variation to the information environment available to current members. The research design allows us to study the response of a member's exposure of a collateral type to changes in the stock of information shared in the bureau for the same collateral type. Nonmembers' allocations should not be affected by the information shared in the bureau. The specification is:

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

where $y_{i,j,t}$ is the log exposure measure that lender *i* has on collateral type j in period *t*, measured in quarters around bureau entry. For each lender-collateral-type quarter, lender exposure measures include the dollar credit, number of contracts, and number of unique exposures to U.S. states/territories. $Information_{j,t}$ is the log number of contracts recorded in the bureau for collateral type j in quarter *t*. $Post_{i,t}$, defined above, is absorbed by the lender-quarter fixed effects. $\alpha_{i,j}$ are lender-collateral fixed effects, which control for time-invariant differences in lenders' offerings for each collateral type. $\alpha_{i,t}$ are lender-quarter fixed effects, which absorb the lender's decision to participate in the bureau, the timing of entry, or any unobservable event unrelated to information sharing.

We examine the full sample rather than an event window to expose each lender to sufficient variation in the stock of information. Specifically, it takes time for the lender to access credit files and for the collateral markets it competes in to experience meaningful changes in bureau coverage.

The research design allows us to compare how different metrics changed for lenders in two categories. The advantage of specification (2) is that changes in $Information_{j,t}$ are exogenous to individual lenders. Although a lender's decision to join the bureau is endogenous, she has no control on the decision of other lenders to join the bureau. Our hypothesis is that nonmembers' exposures do not respond to changes in bureau information

(β is not significant), while members expand their exposures for existing collateral types by using available bureau information (γ > 0).

The last tests examine whether lenders enter new collateral markets after information is shared in the bureau. If information sharing facilitates market entry, we should observe lenders allocating credit in a manner that suggests they use the credit information in the bureau. In particular, they can learn about the demand for financing different types of collateral and identify collateral types that are related to those they currently lend against.

We examine the correlation between a lender entering a new collateral market in the period after joining the bureau and its own collateral expertise. For each pair of collateral types, we calculate a relatedness score. This score captures underlying similarities in lending technology and expertise across collateral types. We detail the construction of our relatedness index in Appendix B. Our tests estimate a specification similar to (2):

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

where $y_{i,j,t}$ is the log dollar amount or number of contracts that lender *i* has in collateral type *j* in period *t*. $Relatedness_{i,j}$ captures the maximum relatedness between lender *i*'s existing collateral types and new collateral type *j*. $\alpha_{i,j}$ and $\alpha_{i,t}$ are lender-collateral and lender-quarter fixed effects, respectively. If lenders enter related markets when expanding their collateral offerings, we expect the coefficient δ to be positive.[11] If information sharing enhances the lender's ability to leverage its collateral expertise when entering new collateral markets, then we expect the coefficient on γ to be also positive. Finally, we examine whether entry into related collateral markets is stronger after other lenders in related collateral markets join the bureau by including the interaction term *Post* × *Relatedness*× *Information* in specification (3).

[11] The coefficient on Relatedness in specification (3) is absorbed when we include lender-collateral fixed effects.

4. Results

4.1 Lending Portfolio around Bureau Entry

We start by studying lenders' exposure around the time they join PayNet. In Figure 3, we plot the unconditional lenders' average exposure measures in the eight quarters surrounding lenders' bureau entry. Following the entry date, there is a distinctive increase in the outstanding credit, number of contracts, and state exposures in lenders' portfolios. There is no indication that lenders systematically shift their portfolios in the periods before entry.

4.2 Information Sharing and Lender Specialization

We begin our analysis by estimating (1) to assess how lenders' exposures evolve during the eight-quarter event window. Table 2, Panel A, columns 1 and 2, show that lenders significantly increase both the amount of credit granted and number of contracts upon entering the bureau.[12] Portfolio credit (contracts) increases by 22.1% (17.2%) from the year before to the year after entry. Column 3 reveals lenders increase the number of state exposures by 9.3%. For the average lender, this represents an additional 1.5 states.

Other developments aside from information sharing could also contribute to the expansion patterns we document. Our staggered empirical design and inclusion of year fixed effects make it unlikely that a single shock could explain voluntary entry or generate our results. However, the decision to join a credit bureau could be driven by unobservable decisions by lenders. We perform two robustness tests in Table A1 of our online appendix to tie our expansion findings to the timing of information shared in the bureau.

First, we counterfactually assign random entry dates to lenders and measure the average coefficient from 1,000 simulations. Columns 1–3 report no evidence of expansion for any of our exposure measures around the placebo entry dates. Second, to address

[12] Our sample contains 1,605 observations (slightly less than eight per lender) because a few small lenders do not have contracts in every single quarter.

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. The collapsed results resemble our original findings.

In our next tests, we establish whether asset type specialization is associated with lenders' expansion patterns. In Table 2, Panel B, we examine how our three exposure measures evolve with information sharing *within* collateral type. We estimate (1) at the lender-collateral type-quarter level. We only include observations from collateral types that the lender has exposure to in the quarter before joining. Defining our sample this way allows us to control for lender-collateral type (instead of just lender) fixed effects and study changes in the intensive margin exposures for each of the lender's collateral offerings.

We show in columns 1 and 2 an increase in the amount of credit and number of contracts outstanding within pre-existing collateral types, though the increase in contracts is marginally insignificant (t-statistic 1.45). Next, in column 3, we show that the number of states within a collateral type increases by 5.4% after the lender joins the bureau. For a typical collateral type, this translates into 0.4 new states (5.4% x 7.2 average state exposures) in the post-period. Together, our Table 2 results suggest that lenders expand upon joining the bureau and that collateral specialization helps explain this expansion.

4.3 Lender Exposures and Shocks to Information

Confounding factors associated with voluntary bureau entry may explain our previous findings on specialization. To mitigate this concern, we turn to specification (2), which takes a lender's decision to share information as given and measures how its exposures respond to the information shared by others in the bureau. This approach hinges on the plausible assumption that the entry decision of a second lender, which provides a shock to the information environment, is exogenous to the incumbent's specialization.

Given lenders' specialty by collateral type, the focus of their collateral exposures within specific regions, and the staggered entry of our setting, the bureau's information does not evenly grow for each exposure type. We exploit this variation in contract growth across collateral types to identify the effect of information shocks on lender specialization. For example, we can pinpoint that a lender's specialization in a specific collateral type follows from a shock to that collateral type and not to growth in the number of contracts in the bureau per se. In Figure 2 we plot the growth in the number of contracts by collateral type and observe both that there is time-series variation in contract growth and idiosyncratic growth at the collateral type-level.

Table 3 presents the results of estimating specification (2). In column 1, we find an insignificant coefficient on *Information*, suggesting that, for nonmembers, lending within a collateral type is insensitive to the stock of bureau credit files for that collateral type. We find a positive and significant coefficient on *Post* × *Information* (7.0%), indicating that members' lending responds to increases in the availability of credit files for a given collateral type. In contrast, we find no significance for the coefficient in *Information*, which captures the response of nonmembers to the stock of information in the bureau. Economically, a one standard deviation increase in *Information* for a collateral type results in a 16.2% rise in credit within that collateral type 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.[13]

Next, in column 2, we add a collateral-specific trend to specification (2) to ensure our results are not explained by a spurious correlation between increases in bureau information for a collateral type and growth in demand for financing of that collateral type. We find

[13] In Table A2 of the online appendix, we show that our findings are robust to examining both a lender's existing and new collateral types and alterative specifications that consider different measures of information.

similar results: members' outstanding credit increases with the coverage for individual collateral types, while nonmembers see no such change.

Last, we add a geographic dimension to our analysis, which allows us to more directly ascribe exposure changes to the availability of collateral-specific, local information. We aggregate collateral exposures within the nine census regions, because we lack sufficient observations to group contracts by collateral type-state-quarter.[14] We include region-quarter fixed effects and region-collateral specific trends to account for changes in credit demand that may coincide with growth in the bureau information. Column 3 presents the results. We find a significantly positive coefficient for the interaction *Post* × *Information* but nothing on the main effect *Information*. Columns 4–6 (7–9) repeat our tests for the number of contracts (state exposures) within a collateral type or collateral type-region. We find a similar pattern of exposure response to *Information* as our first tests. Last, we modify our *Information* variable to include stale contracts, defined as contracts closing up to four, eight, or 12 quarters ago. Lenders may find such contracts useful for aiding expansion, albeit less useful than contracts open today. Table A3 of the online appendix shows that the coefficient on *Post* × *Information* declines monotonically as additional stale information is considered. This result is consistent with the availability of timely, exposure-specific information driving the increases in credit, contracts, and states in our main tests.

Table 4 performs two additional sets of robustness tests for our Table 3 results. First, rather than measure the stock of information as the log number of bureau contracts for a given collateral type, we use *Information Placebo*, equal to the log number of all bureau contracts *excluding that collateral type*. If the exposure growth we document in Table 3 arises spuriously and is unrelated to improved screening and monitoring using bureau files,

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

then we should continue to find a significant coefficient on the interaction term. In columns 1–3, we show that there is no expansion resulting from changes in *Information Placebo* for each of credit, contracts, and state exposures, for either members or nonmembers. This reinforces that our prior findings are indeed driven by the availability of credit files for a given collateral type.

Second, we test whether 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 information to draw upon. On the other hand, the first members could enjoy an early mover advantage by targeting the expansion markets with the fewest competitors where entry barriers are lowest. To explore these possibilities, we add interactions with the indicator variable *Early Join*, equal to one if the lender joins during the first half of our sample (before 2007). In columns 4–6, we show that expansion efforts are unrelated to the timing of entry to the bureau (*Post* × *Information* × *Early Join* is consistently insignificant).

Our results present consistent evidence that lenders offer more credit and contracts and significantly expand their geographic exposures after joining the bureau. Information sharing and collateral specialization are central to this expansion. Bureau member exposures to a collateral type evolve with exogenous changes in bureau coverage for that collateral type, while nonmembers experience no such change.

4.4 Lender Exposures and Barriers to Entry

Entrants can overcome the incumbents' information advantage of borrowers by hiring local loan officers. States differ in the enforceability of loan officers' employment-agreement noncompete clauses. Lenders may rely more on hard information to expand in regions where

it is difficult to acquire soft information through hiring local loan officers.[15] In contrast, information sharing may be less useful for expansion in regions with weak enforcement, since it is easier to hire loan officers. We study how lenders' exposure respond to information shocks when information acquisition varies across states.

We classify states according to their enforcement of noncompete clauses. Using the index from Garmaise (2011), we assign individual states to strong (score at least 6), medium (4 or 5), and weak (3 or less) enforcement-region categories.[16] This allows us to develop a sample with a comparable number of observations in each category. The results in Table 5 mirror our Table 3 findings. In strong and medium enforcement states, bureau members expand their credit, contracts, and state exposures in response to bureau coverage of individual collateral types, while nonmembers do not. Weak enforcement states experience no such expansion, for either members or nonmembers. These results carry two implications. First, they document a new channel through which noncompete clause enforcement serves as a barrier to lender expansion. Second, our findings show how lenders can substitute hard information for soft information in overcoming the adverse selection problems presented by expansion.

4.5 Expansion Decisions and Collateral Expertise

Our tests so far concern how lenders expand their exposures within an existing collateral offering upon entering the bureau. Next, we examine whether lenders enter new collateral markets given their specific expertise.

[15] In Florida (the state with the highest enforcement score in our sample), Centennial Bank sued a former employee and a rival bank, after the employee violated his noncompete agreement by going work for that rival. The lawsuit claims that the rival "was undergoing efforts to expand geographically from Alabama to several other states, principally Florida" (Stockfisch 2016).

[16] Because we define regions in these tests according to state non-enforcement levels rather than the census geographic categories, the number of observations differ in this test from our Table 3, columns 3, 6, and 9 tests.

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 technologies. On the other hand, there is likely scant overlap in lending features for computers and logging or railroad equipment. We test whether lenders expand into new collateral exposures by leveraging their expertise.

Following Teece et. al (1994) and Bryce and Winter (2009), we develop an index of collateral type relatedness. 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 for the probability of overlap we 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 comprise only a small fraction of a lender's portfolio, on average. Fourth, we allow for indirect relatedness by translating 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.[17] Appendix B explains the construction of the index in detail.

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

Our tests consider the maximum pairwise relatedness between the lender's current collateral types and a given collateral type in which the lender does not have exposure.[18] Appendix C presents summary statistics for our relatedness index. Although our tests use the standardized relatedness measure, we present percentiles to facilitate interpretation.

Our index produces 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). Moreover, within a collateral type, our index scores high in comparable related assets (e.g., for computers, the highest relatedness scores are assigned to telecommunications, copier and fax, and office equipment). If our relatedness measure captures the degree of similarity in screening and monitoring technologies, a lender in copiers in the pre-period is more likely to have new collateral exposure in computers than in railroad equipment. Our framework suggests this effect strengthens once they join the bureau.

In Table 6, we summarize lenders' exposures across the 23 collateral types observed as well as the most related collateral types for each asset. Collateral types vary in terms of the number of lenders offering contracts and the states they span. For example, approximately half of our sample lenders contract in computers, with contracts found in 52 states and territories. By comparison, only nine lenders offer contracts for boats, with contracts found in 19 states. Furthermore, 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.

[18] In Table A4 of the online appendix, we show that our results are similar if we instead measure the average pairwise relatedness.

Table 7 tests for expansion into related collateral types using specification (3). We restrict our sample to collateral types the lender was not exposed one year before entering PayNet. Column 1(4) shows that, on average, lenders are more likely to increase credit (contracts) in related collateral types. (The coefficient on *Relatedness* is positive and significant.) This relation strengthens after the lender enters the bureau, as *Post* × *Relatedness* is positive and significant as well. In columns 2 and 5, we add lender-collateral-type fixed effects and results are similar. In the post-period, a one standard deviation increase in the relatedness between the new and existing collateral types increases the lender's contracts in the new collateral type by 4.4%. Given our fixed effect structure, expansion into related collateral types cannot be explained by lender-level business model shifts or time-invariant features of individual lenders' collateral offerings.

Columns 3 and 6 retain the same fixed effect structure as columns 2 and 5 and add our *Information* variable to link collateral market expansion to bureau coverage. Interestingly, the coefficient on *Post* × *Relatedness* itself is no longer significant. Instead, expansion into related collateral types in the post-period is moderated by the availability of credit files in that collateral type. These results complement our earlier findings. Lenders' collateral expertise influences their expansion decisions, and expansion efforts rely upon information available in the bureau.

4.6 Information Sharing and Lender Size

Differences in lender size may affect the response to new information and help illuminate the incentives of different types of lenders to share information. Large lenders may want to replicate the decentralized organizational structures of small lenders since small lenders have an advantage in collecting soft information relative to large lenders (Stein 2002; Berger et al 2005; Liberti and Mian 2009). Large lenders can then use PayNet as a substitute

for soft information acquisition by accessing information on small borrowers from small lenders.

In Table 8, we test whether this is true by estimating specification (1) using the same event window as in Table 2. We find that small lenders drive most 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%) (columns 1 and 2). State exposures follow a similar pattern (column 3). While small lenders increase their geographic footprint by 16.0%, large lender expansion is statistically insignificant 2.7%.

Our second set of tests in this section examines how lender size relates to changes in the borrower size composition of portfolios. We define *Small Clients* as a dummy variable equal to one for borrowers below the median of total credit measured at the collateral type-quarter level. Next, we measure the percentage of the lender's clients that are classified as small firms in each quarter. In column 1 of Table 9, we show that the percentage of relationships allocated to small firms remains relatively constant, on average, in the year after bureau entry. However, when we examine client composition by lender size in column 2, we find that larger lenders increase lending to small borrowers by 2.5%. This is economically significant when compared with the average allocation of 19.1% to small firms by large lenders pre-entry.

Although large lenders see little change in the scope of their geographic offerings, we find that large lenders contract more with small borrowers after joining the bureau. This is consistent with the view that PayNet offers a new source of hard information that replaces the need for collecting soft information.

4.7 Information Sharing and Firm's Credit Relationships

Our final set of tests examines contracting activity from the borrower perspective. Since our main results show that information sharing puts lenders in a better position to leverage their expertise, we expect the average borrower to have more lending relationships and more credit once its file is available in the bureau. To examine this, we record the number of lending relationships and credit outstanding for each firm each quarter. We restrict our analysis to borrowers that have open contracts in both the pre- and post-period. Two features of our tests allow us to offer reliable estimates of the effect of information sharing on borrowers' activities. First, lenders, not borrowers, decide to enter the bureau so entry is plausibly exogenous to the borrower. Second, we control for industry-quarter fixed effects to account for contemporaneous changes in demand for credit with a sector and borrower fixed effects to account for time-invariant firm characteristics.

Column 1 of Table 10 shows that the number of lending relationships for the average borrower increases by 6.0% in the post-period. Economically, there are 17% fewer borrowers in the post-period with just one lending relationship with a bureau member. Next, we examine how this affects total borrowing. Column 2 shows a statistically and economically significant increase in total credit of 11.8%. 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).

Finally, 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 lending relationship without having an old contract maturing that quarter or a surrounding quarter. The intuition for this "off cycle" variable is that not being tied to the maturity cycle of current contracts provides financial flexibility for the borrowers. Prior to information sharing, 14.1% of firms begin new lending relationships off cycle.

Column 3 shows that access to finance significantly improves once credit files are available. The likelihood of starting a new relationship off cycle increases by 0.7%.

Overall, our results show that information sharing improves access to specialized credit, suggesting that voluntary sharing of information also enhances a borrower's access to capital. Thus, our findings contribute to a growing literature exploring the impact of credit scores and information sharing on credit markets.[19]

5. Conclusion

We provide evidence that developments in financial technology that advance the way financial intermediaries both use and share information have the potential to change the competitive landscape of lending. Information sharing allows specialized lenders to access new markets, which fosters greater competition and enhances access to credit when borrowers are also specialized. In addition, technology that allows for the transfer or hardening of soft information, traditionally produced by smaller lenders, reduces the requirement of lenders to collect this information and potentially reduces hold-up problems associated with small and medium enterprise financing.

Our findings contribute to the understanding of not only the role of voluntary information sharing in financial markets but also of the rationale why intermediaries regularly forego rents when voluntarily sharing information. Our results highlight that, while adverse selection exists in credit markets, lenders will willingly share borrower information to overcome information asymmetries regarding new borrowers in new markets.

Finally, our study is also important for understanding the role of fintech in credit markets. Early literature has mostly focused on fintech as an incubator for new lenders and how these new lenders compare with traditional lenders, especially in terms of efficiency

[19] See, among others, Padilla and Pagano (2000), Jappelli and Pagano (2002), Musto (2004); Berger and Udell (2006), Brown et al. (2009), Gopalan et al. (2011), Doblas-Madrid and Minetti (2013), Gonzales-Uribe and Osorio (2014), Cassar et al. (2015), Balakrishnan and Ertan (2017), and Sutherland (2017).

(Philippon 2015) or regulation (Philippon 2016; Buchak et. al. 2017). We show that fintech also has the potential to reshape traditional credit markets.

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Appendix A: Variable Definitions

Variable	Definition
Log Credit	The log total value of all open contracts for the lender.
Log Contracts	The log number of all open contracts for the lender.
Log States	The log number of states the lender is currently exposed to through its borrowers.
Post	An indicator equal to one for quarters after the lender has joined the bureau 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.
Information Placebo	The log aggregate number of open contracts for all collateral types *excluding type j* appearing in the bureau that quarter.
Early Join	An indicator equal to one for lenders entering the bureau before 2007 and zero otherwise.
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.
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 percentage of the lender's clients in the smallest quartile of total credit within their industry-quarter.
Post File	An indicator equal to one for the period after the borrower first appears in the bureau and zero otherwise.
Log # Lending Relationships	The log number of lenders currently providing the borrower with credit.
Log Total Credit	The log total value of all open contracts for the borrower.
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 and zero otherwise.

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 that 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:

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

We can now compare the observed dyad J_{ij} with the expected dyad, $E[X_{ij}]$, by estimating the standardized dyad:

$$\tau_{ij} = \frac{J_{ij} - \mu_{ij}}{\sigma_{ij}}. \quad (4)$$

When the τ_{ij} is positive and large, it indicates systematic exposure by lenders into pairs of collateral types. That is, 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

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

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 collateral types 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 percentile that represents the cumulative area under the distribution and ranges between 0 and 100. 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

This figure plots the timeline of entry to the PayNet credit bureau for the 207 lenders in our sample from its launch in 2001 to the spring 2014, the end of our sample.

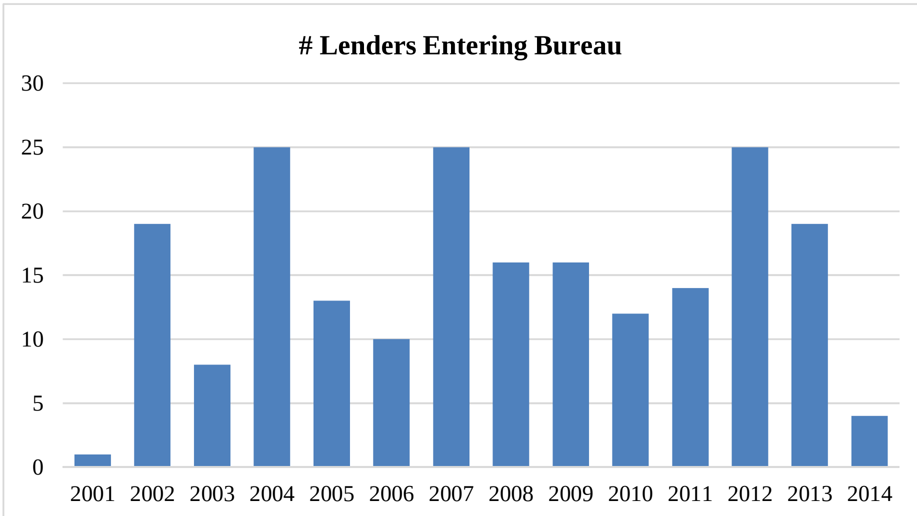


Figure 2: The Stock of Bureau Information by Collateral Type

This figure plots the change in bureau coverage for the five most common collateral types in our sample (copiers and fax, trucks, construction and mining equipment, agricultural equipment, and computers). Collateral types are summarized in Table 6. Each series measures the growth in number of open contracts in the bureau that year as a percentage of maximum all time open contracts in the bureau for the collateral type.

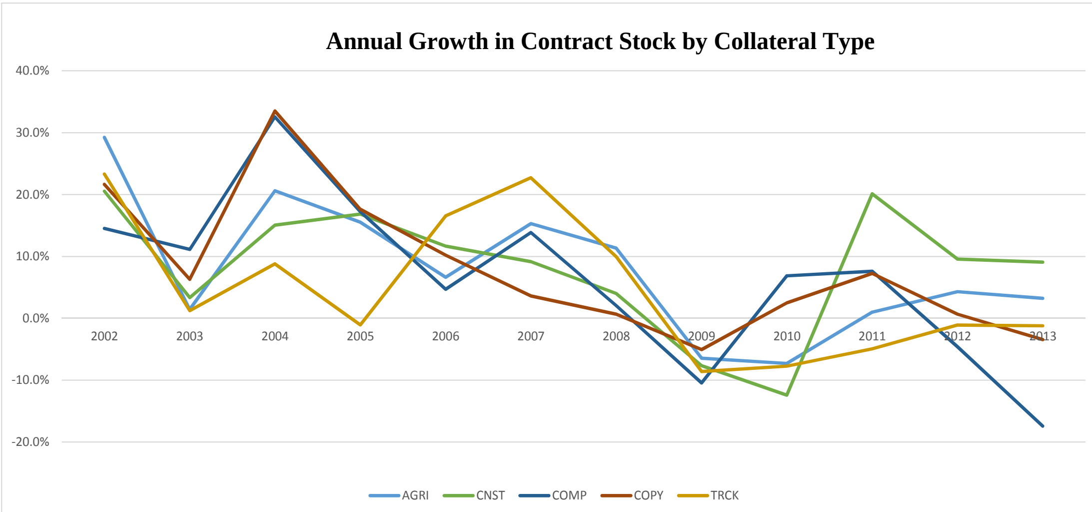
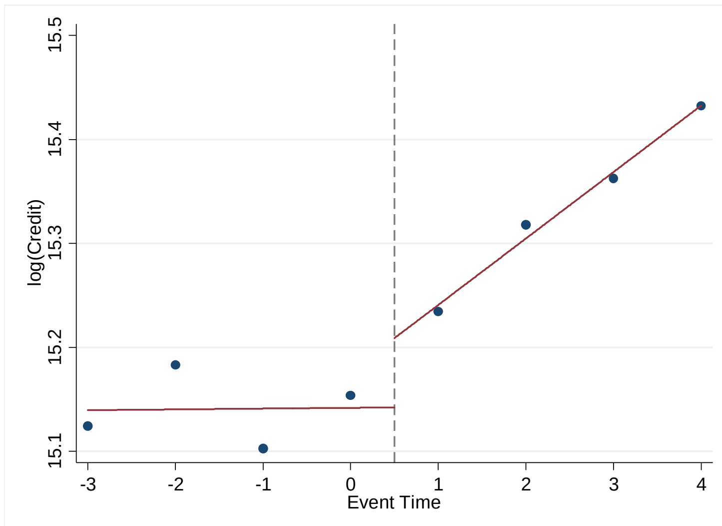
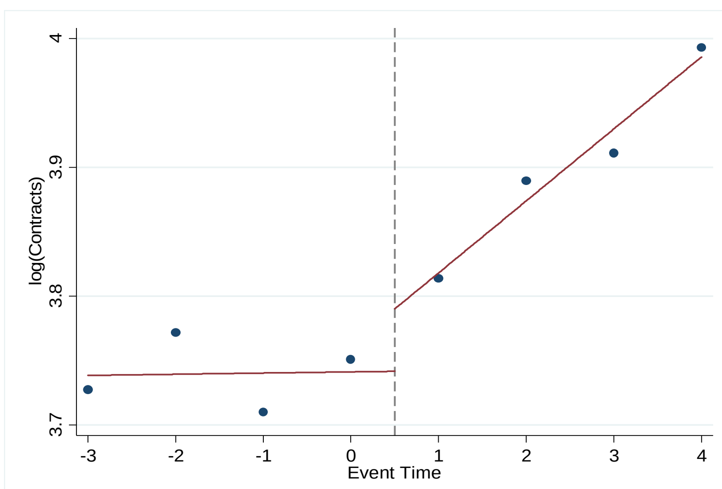


Figure 3: Lending Dynamics around Bureau Entry

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 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.





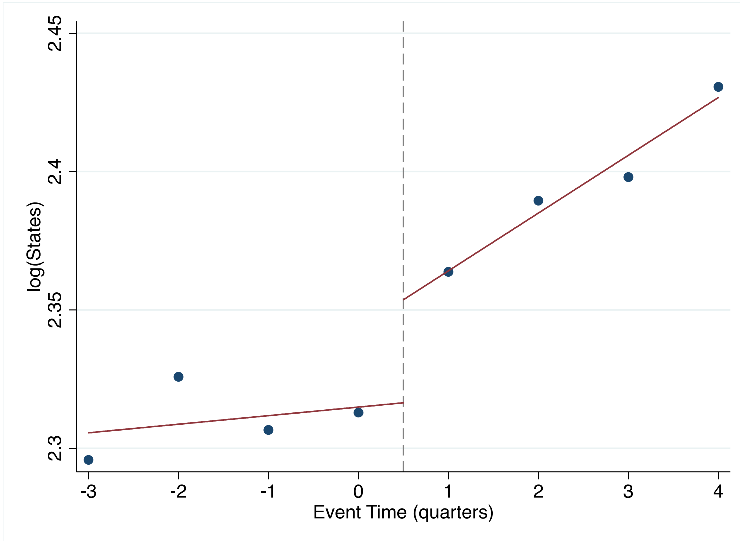

2.45
2.4
2.35
2.3
log(States)
-3
-2
-1
0
1
2
3
4
Event Time (quarters)

Table 1: Summary Statistics

This table describes the contract features and exposures for lenders in our sample. We present within-lender average features for the year before bureau entry. The unit of observation is lender. See Appendix A for variables definitions.

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
Average Lender Features						
Contract Size ($)	192,258	283,233	40,991	75,034	227,602	207
# Contracts	482.2	1,283.2	7.3	31.3	174.3	207
# State Exposures	15.7	15.8	3.0	7.9	26.5	207
# Collateral Types	5.2	5.0	1.0	3.0	7.8	207

Table 2: Information Sharing and Lender Exposures

This table models lenders' exposures as a function of bureau membership using (1). Panel A studies lender exposures each quarter, while Panel B studies exposures within a collateral type for lenders each quarter. The dependent variable in column 1 (2,3) is the log dollar amount of credit (log number of contracts, log number of states) in the lender's portfolio. *Post* is an indicator equal to one for quarters after the lender has joined the bureau. The sample spans the two years surrounding the lender's entry to the bureau. In Panel B, the sample is restricted to collateral types that the lender was exposed to in the quarter before joining. The unit of observation in Panel A (B) is lender-quarter (lender-collateral type-quarter). 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: Lender Exposures

	(1) Log Credit	(2) Log Contracts	(3) Log States
Post	0.221***	0.172***	0.093***
	[5.32]	[4.84]	[5.21]
Adj R-Sq.	0.966	0.972	0.963
N	1,605	1,605	1,605
Lender FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes

Panel B: Lender Exposures within Collateral Type

	(1) Log Credit	(2) Log Contracts	(3) Log States
Post	0.067*	0.051	0.054**
	[1.87]	[1.45]	[2.25]
Adj R-Sq.	0.978	0.976	0.942
N	7,401	7,401	7,401
Lender x Collateral FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes

Table 3: Exposure Responses to Information Shocks

This table models how lenders' exposures respond to changes in the bureau stock of information using (2). The dependent variable in columns 1–3 (4–6, 7–9) is the log dollar amount of credit (log number of contracts, log number of states) for a given collateral type or collateral type-region in the lender's portfolio. *Post* is an indicator equal to one for quarters after the lender has joined the bureau. In columns 1–2, 4–5, and 7–8 (3, 6, and 9), *Information* is the log number of open contracts appearing in the bureau that quarter for a given collateral type (collateral type-region). The sample includes all quarters but is restricted to collateral types that the lender was exposed to in the quarter before joining. The unit of observation in columns 1–2, 4–5, and 7–8 (3, 6, and 9) is lender-collateral type-quarter (lender-collateral type-quarter-region). 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log Credit	Log Credit	Log Credit	Log Contracts	Log Contracts	Log Contracts	Log States	Log States	Log States
Information	0.017	-0.013	0.028	0.013	-0.022	0.020	0.012	-0.004	0.004
	[0.57]	[-0.37]	[1.41]	[0.52]	[-1.00]	[1.37]	[1.02]	[-0.38]	[1.02]
Post * Information	0.070**	0.047*	0.098***	0.074***	0.047**	0.098***	0.029**	0.009	0.012***
	[2.53]	[1.93]	[4.05]	[3.29]	[2.58]	[6.10]	[2.57]	[0.89]	[3.12]
Adj R-Sq.	0.868	0.875	0.696	0.887	0.894	0.748	0.876	0.883	0.632
N	41,618	41,618	170,847	41,618	41,618	170,847	41,618	41,618	170,847
Lender x Collateral Type FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender x Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Quarter FEs			Yes			Yes			Yes
Collateral Type-Specific Trends	No	Yes	No	No	Yes	No	No	Yes	No
Region x Collateral Type Specific Trends			Yes			Yes			Yes

Table 4: Exposure Responses to Placebo Information Shocks and Entry Timing

This table studies whether lenders' exposures are sensitive to the addition of unrelated information to the bureau, or entry timing. The dependent variable in columns 1 and 4 (2 and 5, 3 and 6) is the log dollar amount of credit (log number of contracts, log number of states) for a given collateral type in the lender's portfolio. *Information Placebo* is the log aggregate number of open contracts *excluding type j* appearing in the bureau that quarter. *Post* is an indicator equal to one for quarters after the lender has joined the bureau. *Information* is the log number of open contracts appearing in the bureau that quarter for a given collateral type. *Early Join* is an indicator equal to one for lenders entering the bureau before 2007. The sample includes all quarters but is restricted to collateral types that the lender was exposed to in the quarter before joining. The unit of observation in is lender-collateral type-quarter. 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 Credit	(5) Log Contracts	(6) Log States
Information Placebo	0.050	0.046	0.030			
	[1.27]	[1.53]	[1.58]			
Post * Information Placebo	-0.039	-0.318	0.056			
	[-0.11]	[-1.16]	[0.45]			
Information				0.015	-0.031	-0.001
				[0.26]	[-1.01]	[-0.09]
Post * Information				0.082**	0.053*	0.022
				[2.02]	[1.76]	[1.34]
Information * Early Join				-0.024	0.015	0.002
				[-0.40]	[0.35]	[0.07]
Post * Information * Early Join				-0.053	-0.012	-0.022
				[-1.01]	[-0.31]	[-1.02]
Adj R-Sq.	0.875	0.894	0.883	0.875	0.894	0.883
N	41,618	41,618	41,618	41,618	41,618	41,618
Lender x Collateral Type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Lender x Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Collateral Type-Specific Trends	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Noncompetition Agreement Enforcement and Exposure Responses to Information Shocks

This table models how lenders' exposures respond to changes in the bureau stock of information as a function of noncompetition agreement enforcement. The tests are performed within region category, where region categories are defined as the group of states with strong, medium, and weak noncompetition agreement enforcement using the index from Garmaise (2011). The dependent variable in columns 1, 2, and 3 (4, 5, and 6; 7, 8, and 9) is the log dollar amount of credit (log number of contracts, log number of states) for a given collateral type-region category 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 open contracts appearing in the bureau that quarter for a given collateral type-region category. The sample includes all quarters but is restricted to collateral types that the lender was exposed to in the quarter before joining. The unit of observation lender-collateral type-region category-quarter. 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log Credit	Log Credit	Log Credit	Log Contracts	Log Contracts	Log Contracts	Log States	Log States	Log States
	Strong	Medium	Weak	Strong	Medium	Weak	Strong	Medium	Weak
Information	-0.007	0.023	0.039	0.034	0.024	0.040	0.007	0.011	0.000
	[-0.15]	[0.72]	[1.12]	[1.17]	[1.05]	[1.38]	[0.62]	[1.16]	[-0.01]
Post * Information	0.112**	0.080**	0.023	0.063**	0.079***	0.042	0.024**	0.024**	0.015
	[2.39]	[2.14]	[0.66]	[2.21]	[3.16]	[1.44]	[2.07]	[2.44]	[1.49]
Adj R-Sq.	0.835	0.853	0.854	0.875	0.876	0.875	0.815	0.845	0.837
N	26,180	32,118	31,511	26,180	32,118	31,511	26,180	32,118	31,511
Lender x Collateral Type FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender x Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Collateral Type Exposures

This table summarizes the number of lenders and states or territories (including Guam, Puerto Rico, and the Virgin Islands) with contracts for each collateral type. The final three columns present the most related collateral types, according to our index. * indicates significance in relatedness between two collateral types at the 10% level.

Collateral Type	# Lenders	# States	Most Related	Second Most Related	Third Most Related
Agricultural	67	49	Real Estate*	Construction & Mining*	Truck
Aircraft	16	32	Boat	Truck	Computer
Automobiles	56	51	Manufacturing	Construction & Mining	Medium/Light Duty Trucks
Boats	9	19	Aircraft	Railroad	Truck
Buses & Motor Coaches	40	46	Medium/Light Duty Trucks	Truck	Manufacturing
Construction & Mining	110	51	Agricultural*	Truck	Forklift
Computer	101	52	Telecommunications*	Copier & Fax*	Office Equipment*
Copier & Fax	53	52	Telecommunications*	Copier & Fax*	Office Equipment*
Energy	9	20	Agricultural	Telecommunications	Office Equipment
Forklift	50	50	Construction & Mining	Agricultural	Manufacturing
Logging & Forestry	30	42	Agricultural	Construction & Mining	Waste & Refuse Handling
Medium/Light Duty Trucks	67	49	Agricultural	Construction & Mining	Truck
Medical	79	48	Telecommunications*	Office Equipment*	Retail*
Manufacturing	97	51	Retail*	Computer*	Office Equipment*
Office Equipment	73	50	Telecommunications*	Copier & Fax*	Computer*
Printing & Photographic	53	46	Manufacturing	Retail	Construction
Railroad	16	26	Aircraft	Printing & Photographic	Construction
Real Estate	20	22	Agricultural*	Construction & Mining	Automobiles
Retail	99	52	Computer*	Telecommunications*	Copier & Fax*
Telecommunications	69	52	Copier & Fax*	Computer*	Office Equipment*
Truck	121	51	Construction & Mining	Agricultural	Medium/Light Duty Trucks
Vending	49	49	Retail*	Computer*	Copier & Fax*
Waste & Refuse Handling	37	45	Forklift	Construction & Mining	Logging

Table 7: Lender Exposures, Collateral Relatedness, and Bureau Information

This table models lenders' exposures within a collateral type as a function of relatedness to existing collateral types in the portfolio, bureau information, and bureau membership. The dependent variable in columns 1–3 (4–6) is the lender's log dollar amount (log number) of contracts in that collateral type. *Relatedness* is measured as the maximum of the pairwise relatedness scores between the lender's existing collateral type offerings and the given collateral type. *Post* is an indicator equal to one for the period after the lender has joined the bureau. *Information* is the log number of open contracts appearing in the bureau that quarter for a given collateral type. Columns 3 and 6 include all main and two-way effects but do not report them for brevity. The unit of observation is lender-collateral type-quarter. The sample includes all quarters but is restricted to collateral types that the lender was not exposed to one year before entering 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 variable definitions.

	(1) Log Credit	(2) Log Credit	(3) Log Credit	(4) Log Contracts	(5) Log Contracts	(6) Log Contracts
Relatedness	0.358***			0.029**		
	[3.44]			[2.54]		
Post * Relatedness	0.534***	0.444***	0.159	0.057***	0.044***	0.001
	[5.22]	[5.50]	[1.08]	[4.50]	[4.99]	[0.05]
Post * Relatedness * Information			0.052*			0.007**
			[1.77]			[2.27]
Adj R-Sq.	0.234	0.555	0.555	0.231	0.606	0.607
N	157,254	157,254	157,254	157,254	157,254	157,254
Collateral Type FEs	Yes	No	No	Yes	No	No
Lender x Collateral Type FEs	No	Yes	Yes	No	Yes	Yes
Lender x Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: 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 column 1 (2 and 3) is the log dollar amount of credit (log number of contracts, log number of states) 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. The sample spans the two years 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. 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
Post	0.333***	0.293***	0.160***
	[4.49]	[4.92]	[4.96]
Post * Large Lender	-0.225**	-0.241***	-0.133***
	[-2.44]	[-3.36]	[-3.41]
Adj R-Sq.	0.966	0.973	0.964
N	1,605	1,605	1,605
Lender FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Post + Post * Large Lender = 0	0.108	0.052	0.027
F-statistic	5.86	1.86	2.15
P-value	0.016	0.174	0.145

Table 9: Information Sharing and Small Client Exposure by 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 percentage of the lender's clients that are small firms, classified as those below the median total credit at the collateral type-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 total credit in the quarter before joining the bureau. The sample spans the two years 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	-0.009	-0.021
	[-1.06]	[-1.52]
Post * Large Lender		0.025*
		[1.76]
Adj R-Sq.	0.848	0.848
N	1,605	1,605
Lender FEs	Yes	Yes
Year FEs	Yes	Yes

Table 10: Information Sharing and Firm Credit Access

This table models a borrower's access to credit as a function of whether its credit file is available in the bureau. The dependent variable in columns 1 and 2 is the log number of lending relationships and log total credit, respectively. The dependent variable in column 3 is an indicator for whether the borrower starts a new relationship without having an old contract maturing in that quarter or a surrounding quarter. *Post File* is an indicator equal to one for the period after the borrower first appears in the bureau. The sample is limited to borrowers with pre and post observations. 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 # of Lending Relationships	(2) Log Total Credit	(3) Starts New Relationship Off Cycle
Post File	0.060***	0.118***	0.007***
	[17.94]	[6.75]	[4.75]
Adj R-Sq.	0.675	0.747	0.009
N	674,985	674,985	674,985
Borrower FEs	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes

Online Appendix to:

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

May 2017

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

Table A1: Information Sharing and Lender Exposures

This table provides robustness analysis for our Table 2, Panel A, results. The dependent variable in columns 1 and 4, (2 and 5, 3 and 6) is the log dollar amount of credit (log number of contracts, log number of states) in the lender's portfolio. *Placebo Post* is an indicator equal to one after the placebo join date, where this date is randomly assigned 1,000 times for each lender. We report the median coefficient and t-statistics from the 1,000 trials. *Post* is an indicator equal to one for quarters after the lender has joined the bureau. The sample spans the two years surrounding the lender's entry to the bureau. The sample size in columns 1–3 is not reported because it varies for each entry date, as some lenders do not have contracts every quarter. Columns 4–6 collapse the sample into one-year pre and post periods for each lender. 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 Credit	(5) Log Contracts	(6) Log States
Placebo Post	-0.004	-0.002	-0.002			
	[-0.11]	[-0.08]	[-0.14]			
Post				0.287***	0.223***	0.127***
				[6.68]	[7.07]	[6.30]
# Lenders	207	207	207	207	207	207
Lender FEs?	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs?	Yes	Yes	Yes	No	No	No
Sample	Placebo	Placebo	Placebo	Collapsed	Collapsed	Collapsed

Table A2: Exposure Responses to Information Shocks

This table performs a robustness analysis of our Table 3 results. In Panel A, we relax our sample restriction by studying both the intensive (the lender's existing collateral types) and extensive (new collateral types) margins. In Panel B, *Information* is a dummy variable equal to one once the specialist lender in that collateral type has joined the bureau. The specialist lender in each collateral market is defined as the lender with the most contracts, conditional on this lender having at least 25% of its portfolio in the collateral type. *Post* is an indicator equal to one for quarters after the lender has joined the bureau. The unit of observation is lender-collateral type-quarter. 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: Intensive and Extensive Margins Combined

	(1) Log Credit	(2) Log Contracts	(3) Log States
Information	0.040	0.021	0.015
	[1.20]	[0.90]	[1.31]
Post * Information	0.081***	0.072***	0.029**
	[2.65]	[3.21]	[2.52]
Adj R-Sq.	0.868	0.890	0.879
N	48,678	48,678	48,678
Lender x Collateral Type FEs	Yes	Yes	Yes
Lender x Quarter FEs	Yes	Yes	Yes

Panel B: Alternative Measure of Information

	(1) Log Credit	(2) Log Contracts	(3) Log States
Information	0.060	0.008	0.003
	[0.57]	[0.11]	[0.08]
Post * Information	0.256***	0.199***	0.099***
	[2.88]	[3.36]	[3.11]
Adj R-Sq.	0.868	0.886	0.876
N	41,618	41,618	41,618
Lender x Collateral Type FEs	Yes	Yes	Yes
Lender x Quarter FEs	Yes	Yes	Yes

Table A3: Exposure Responses to Stale Information

This table alters the *Information* variable in our Table 3 analysis to include contracts that have already matured. We report the *Post * Information* coefficients for tests that include contracts that have matured as much as one, two, or three years ago in *Information*. *Post* is an indicator equal to one for quarters after the lender has joined the bureau. *Information* is the log number of contracts appearing in the bureau for a given collateral type. The sample includes all quarters but is restricted to collateral types that the lender was exposed to in the quarter before joining. The unit of observation is lender-collateral type-quarter. 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.

	Log Credit	Log Contracts	Log States
Information: only open contracts (original results)			
Post * Information	0.098***	0.098***	0.012***
	[4.05]	[6.10]	[3.12]
Information: open contracts + contracts maturing up to one year ago			
Post * Information	0.089***	0.092***	0.011***
	[3.66]	[5.63]	[2.79]
Information: open contracts + contracts maturing up to two years ago			
Post * Information	0.083***	0.086***	0.010**
	[3.38]	[5.22]	[2.50]
Information: open contracts + contracts maturing up to three years ago			
Post * Information	0.078***	0.080***	0.009**
	[3.19]	[4.88]	[2.32]

Table A4: Lender Exposures, Collateral Relatedness, and Bureau Information

This table provides robustness analysis for our Table 7 results. We reproduce all columns, except *Relatedness* is measured as the *average* of the pairwise relatedness scores between the lender's existing collateral type offerings and the given collateral type. The dependent variable in columns 1–3 (4–6) is the lender's log dollar amount (log number) of contracts in that collateral type. *Post* is an indicator equal to one for the period after the lender has joined the bureau. *Information* is the ratio of the number of open contracts appearing in the bureau that quarter for a given collateral type to the maximum number for that collateral type across all quarters. The unit of observation is lender-collateral type-quarter. The sample includes all quarters but is restricted to collateral types that the lender was not exposed to one year before entering 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 variable definitions.

	(1) Log Credit	(2) Log Credit	(3) Log Credit	(4) Log Contracts	(5) Log Contracts	(6) Log Contracts
Relatedness	0.195***			0.017***		
	[3.62]			[2.86]		
Post * Relatedness	0.274***	0.233***		0.030***	0.024***	
	[5.11]	[5.48]		[4.46]	[5.00]	
Post * Relatedness * Information			0.022			0.003*
			[1.31]			[1.68]
Adj R-Sq.	0.235	0.555	0.555	0.233	0.606	0.607
N	157,254	157,254	157,254	157,254	157,254	157,254
Collateral Type FEs	Yes	No	No	Yes	No	No
Lender x Collateral Type FEs	No	Yes	Yes	No	Yes	Yes
Lender x Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes