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Does function follow organizational form? Evidence from the lending practices of large and small banks ☆

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Abstract

Theories based on incomplete contracting suggest that small organizations have a comparative advantage in activities that make extensive use of "soft" information. We provide evidence consistent with small banks being better able to collect and act on soft information than large banks. In particular, large banks are less willing to lend to informationally "difficult" credits, such as firms with no financial records. Moreover, after controlling for the endogeneity of bank-firm matching, we find that large banks lend at a greater distance, interact more

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impersonally with their borrowers, have shorter and less exclusive relationships, and do not alleviate credit constraints as effectively.

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1. Introduction

One of the most enduring questions in economics was posed by Coase (1937): What determines the boundaries of the firm? The question is perhaps most often framed in terms of *vertical* integration—i.e., when can it make sense for upstream and downstream activities to be combined under the roof of a single firm? But one can also ask about the circumstances under which *horizontal* integration creates value. A good present-day illustration of this version of the question comes from the commercial banking industry, where ongoing consolidation raises the issue of whether the resulting large banks will behave differently than the small banks that they are displacing.

A partial answer to Coase's question comes from the work on transaction-cost economics of Williamson (1975, 1985) and Klein et al. (1978). These authors focus on the hold-up problems that can accompany market transactions, and argue that such problems can be mitigated by having the firm, rather than the market, mediate trade. While this approach is helpful in identifying the advantages of integration (i.e., a reduction in market hold-up problems), it is less clear on the disadvantages. As such, it is somewhat of a one-sided theory—unless one invokes factors outside the model, like unspecified "costs of bureaucracy," it has the awkward implication that efficiency would be best served by placing all of the economy's assets inside a single firm.

The disadvantages of integration emerge much more clearly in the framework of Grossman and Hart (1986), Hart and Moore (1990), and Hart (1995), henceforth GHM. At its most general level, the central insight of the GHM paradigm is that, in a world of incomplete contracts, agents' ex ante incentives are shaped by the extent to which they have control or authority over physical assets. Thus, for example, if firm A acquires firm B, the manager who was previously CEO of firm B might reduce his level of ex ante effort now that he is subordinate to the CEO of firm A and no longer has full control rights over B's assets; herein lies the potential cost of integration.

The GHM paradigm has strongly influenced subsequent work on the theory of the firm. But it has proved challenging to construct sharp empirical tests of the theory. As discussed in Whinston (2001), this is in part due to the fact that the predictions can be sensitive to specific assumptions, such as the nature of the non-contractible investments that need to be made ex ante. Another difficulty is that GHM focus on ownership of physical assets as the exclusive source of power and incentives in the firm, thereby abstracting from other considerations that might be present in a richer, more empirically realistic model. These considerations include differentially informed agents as in Aghion and Tirole (1997), incentive structures as in Holmstrom and Milgrom (1994) and Holmstrom (1999), or access to critical resources as in Rajan and Zingales (1998, 2001).

One strategy for dealing with these problems is to not take the original GHM models too literally as a basis for empirical testing, and to work instead with "second-generation" models that build on the basic GHM insights but that are more tailored to delivering clear-cut comparative static predictions, either for a specific type of investment or in a particular institutional setting. This strategy is followed by Baker and Hubbard (2003), whose work centers on the trucking industry and the question of whether drivers should own the trucks they operate, as well as by Simester and Wernerfelt (2003), who look at the ownership of tools in the carpentry industry.

In this paper, we take a broadly similar approach. Unlike the above-mentioned authors, however, our focus is not on how differences in technology influence the ownership of assets, but rather on how the nature of an organization affects both the way it does business and the kinds of activities that it can efficiently undertake. Specifically, we attempt to understand whether small organizations are better at carrying out certain tasks than large organizations. In this regard, our work is closer to Mullainathan and Scharfstein (2001), who document how producers of a particular chemical that are integrated with the downstream users of the chemical have investment behavior that differs from that of stand-alone producers.

Our starting point is the model in Stein (2002). This model adopts the basic GHM insight that the allocation of control affects incentives, but it does so in a setting that is more specific, and thus yields sharper empirical predictions. The predictions have to do with the differing incentives that are created in large and small firms for the production and use of various kinds of information. The model implies that small firms are at a comparative advantage in evaluating investment projects when the information about these projects is naturally "soft" and cannot be credibly communicated from one agent in the firm to another. In contrast, large firms do relatively well when information about investment projects can be easily "hardened" and passed along within the hierarchy.

This model applies naturally to the banking industry, where information is critical to the activity of lending. The model suggests that large banks will tend to shy away from small-business lending, because this is an activity that relies especially heavily on the production of soft information, something that is not their strong suit. For example, consider a loan officer trying to decide whether or not to extend credit to a small start-up company that does not have audited accounting statements. The best the loan officer may be able to do is to spend time with the company president in an effort to determine whether she is honest, prudent, and hardworking—i.e., the classic candidate for a "character loan." However, given that this information is soft and cannot be verifiably documented in a report that the loan officer can pass on to his superiors, the model predicts (as is explained in more detail below) that his incentives to produce high-quality information are weak when he works inside a large bank.

By contrast, when dealing with a larger company that has a well-documented track record, the decision to extend credit can be based more heavily on verifiable information, such as the company's income statements, balance sheet, and credit rating. In this case, the model suggests that a large bank will have no problem—indeed, it may do better—at providing incentives for information production.

To test this theory, we make use of a data set on small-business lending that has information not only about the small firms in the sample, but also about their primary bank lenders and the nature of the relationship between the two. The data thus allow us to investigate a number of hypotheses about how the "technology" of lending depends on variables such as bank size. If, as the theory suggests, large banks are at a comparative disadvantage in the production and use of soft information, one would expect this to influence their methods of lending.

We develop six basic pieces of evidence to support this case. First, and most simply, we find that bigger banks are more apt to lend to firms that are larger or that have better accounting records (a good example of hard information). Second, controlling for firm and market characteristics, we find that the physical distance between a firm and the branch office that it deals with increases with the size of the bank. This is consistent with the notion that large banks rely less on the sort of soft information that is typically available through personal contact and observation. Third and relatedly, we find that firms do business with large banks in more impersonal ways—i.e., they meet less often with their banker and instead communicate more by mail or phone.

Of course, a firm chooses the bank from which it borrows. That is, the match between a firm and its bank is to some extent endogenous, and is likely to be related to firm characteristics. Indeed, our first finding—that bigger banks match up with firms with better accounting records—is evidence of just this endogeneity. This suggests that we need to proceed carefully if, as in our second and third findings, we want to use bank size as a right-hand-side variable to explain certain aspects of the lending relationship. For example, perhaps large banks deal with their customers more impersonally not because they are incompetent at personal interaction, but because they tend to match with a type of customer for whom personal interaction is less appropriate.

To deal with this potential endogeneity problem, we try instrumenting for bank size with two variables: (i) the median size of *all* banks (weighted by number of branches) in the market where the firm is located, and (ii) a regulatory variable that measures how permissive the firm's state has been with respect to branching. Intuitively, if a firm borrows from a large bank because it is located in a market where there are only large banks (say because regulation has not artificially constrained bank size), this does not reflect an endogenous choice on the part of the firm, but rather an exogenous, geographically imposed limitation. We find that when we take this instrumental-variables (IV) approach, the estimated effect of bank size on distance and on the extent of impersonal communication is even larger than when we do not correct for endogeneity.

Our fourth and fifth findings are that bank-firm relationships tend to be stronger—both more long-lived and more exclusive—when the firm in question borrows from a small bank. These findings also emerge both with and without using IV, but again are more pronounced when an IV approach is employed. They are exactly what one would expect based on the theory, given that the soft information produced by small banks is more likely than hard information to be non-transferable. In other words, the theory suggests that small-bank lending should fit more closely with the kind of model in Rajan (1992), where accumulated soft information binds a borrower to its bank over time.

The sixth and final part of our empirical work is to test whether bank size affects the availability of credit to small businesses. If small firms need lenders that are willing to go deeper and acquire soft information, then we would expect those that are forced to go to large banks to be particularly credit constrained. One measure of the degree to which a firm is rationed by financial institutions is the amount of expensive trade credit it relies on (Petersen and Rajan (1994) and Fisman and Love (2003)). We find that all else equal, a firm that borrows from a larger bank is more prone to repay its trade credit late.

Interestingly, this last result holds *only* when we instrument for bank size. When firms are forced to borrow from large banks because there are no small banks around, they seem to face credit constraints—this is what the IV version of the regression tells us. At the same time, an ordinary-least-squares regression of credit constraints on bank size reveals an offsetting effect due to the endogeneity bias: those firms that are by nature the most difficult credits tend to match with smaller banks, as the theory would suggest.

While our empirical tests are primarily motivated by a model in the control-rights genre, it is important to note that some of the same predictions about the effects of bank size follow from other types of agency models. To take a leading example, Brickley et al. (2003) observe that officers and directors in their sample of small Texas banks own an average of nearly 70% of the stock of these banks. They then go on to propose a theory of small-bank/big-bank differences based on explicit incentive-contracting considerations. In particular, they argue that since managers of small banks have higher-powered ownership incentives, they will devote more effort to soft-information collection, and can be trusted to use this information in a way that is consistent with shareholder objectives. This differs from Stein's (2002) theory, which emphasizes the incentive effects of control rights rather than of direct share ownership.

Our view is that these two types of theories are broadly complementary, and it would be a mistake to try to argue that our basic empirical findings are solely the product of one mechanism or the other. Nevertheless, the two theories have some divergent implications, which in principle allow for a degree of separation.

Section 2 reviews both theories and fleshes out our main hypotheses more fully. Section 3 introduces our data set. Section 4 describes our empirical results. Section 5 discusses how our work fits with the related banking literature, and Section 6 concludes.

2. Hypothesis development

2.1. Overview of the theory

The logic of Stein's (2002) model can be sketched with an example. Imagine a loan officer in Little Rock who is responsible for deciding which small-business loans are worth making. The quality of the loan officer's judgment will depend on how good a job he has done in producing soft information, which in turn will be a function of his incentives. In the limiting case of a very small bank, the loan officer is also president of the bank, and has the authority to allocate the bank's funds as he sees fit. Given that he can count on having some capital to work with, he knows that his research efforts will not be wasted, and hence his incentives to do research are relatively strong. In other words, the decentralization inherent in a small bank rewards an agent who develops expertise by ensuring the availability of capital with which to lever that expertise.

In contrast, if the Little Rock loan officer is part of a large multi-branch hierarchy, the following problem arises. Suppose that he spends a lot of effort learning about local prospects. But then somebody higher up in the organization decides that overall lending opportunities are better in Tulsa, and cuts the capital allocation for Little Rock. In this case, because he doesn't get a chance to act on the soft information that he has produced, and because he cannot credibly pass it on, the loan officer's research effort goes to waste. Ex ante, this implies that the loan officer does less research in a hierarchical setting. Here, the authority to allocate capital is separated from expertise—i.e., the Little Rock loan officer can be left with no capital to work with—which dilutes the incentives to become an expert. This can be thought of as a specific manifestation of the key GHM idea that taking control away from an agent tends to weaken the agent's incentives.[1]

To further bring out the intuition of the model with soft information, consider this question: All else equal, will a large banking organization be better at making small-business loans if it is set up as single legal entity, or as a multi-bank holding company with a number of legally distinct subsidiaries? Several authors (e.g., Keeton, 1995; DeYoung et al., 1998) hypothesize that the multi-bank holding company structure is particularly inimical to small-business lending, because it adds extra layers of bureaucracy. However, Stein (2002) argues that just the opposite may be the case. To the extent that this structure makes it harder to move capital across the different subsidiaries, it can act as a partial precommitment by the CEO to run a decentralized operation—i.e., to not reduce individual agents' capital allocations. This should improve their incentives to gather soft information, and thereby benefit small-business lending.

[1] Aghion and Tirole (1997) also argue that agents' incentives can be blunted when they are in a hierarchy. A critical distinction is that in Stein (2002), a hierarchical structure *need not* weaken incentives—indeed, it only does so when information is soft. Thus the models have quite different empirical implications: the Aghion–Tirole model does not say anything about why large banks might be at more of a disadvantage with small-business loans than with credit cards or mortgages.

The model works very differently when the information produced by agents can be hardened and passed on to their superiors, as might be the case with the output from a credit-scoring model. Now, large banks might actually generate more investigative effort than small banks. This is because with hard information, agents can become advocates for their units—a Little Rock loan officer working inside a large bank who produces verifiable evidence showing that lending opportunities in his area are strong can increase his capital allocation. Here, separating authority from expertise actually improves research incentives, as lower-level managers struggle to produce enough information to convince their superiors that they should get a larger share of the bank's overall capital budget. Similarly, Rajan and Zingales (1998) observe that withholding ownership can in some cases spur effort by encouraging competition for power.

Although the explicit distinction between soft and hard information that Stein emphasizes is not typically drawn in the applied banking literature, it corresponds closely to the oft-discussed dichotomy between "relationship" lending and "transactions-based" lending (see, e.g., Berger and Udell, 2002). Moreover, it is a common hypothesis in this line of work that large banks will be at a disadvantage when it comes to relationship lending, but will do better with respect to transactions-based lending. For example, Berger et al. (1999) argue that "because of….organizational diseconomies…large complex financial institutions….would reduce services …to those customers who rely on relationships" (pp. 165–166).

2.2. Testable implications

2.2.1. The choice of bank

The most basic implication of the theory is that small banks have a comparative advantage in making loans based on soft information, while large banks have a comparative advantage in making loans based on hard information. This suggests that a firm about which there is more hard information should tend to borrow from a larger bank. One potential proxy for whether there is hard information about a firm is its size, since, e.g., large firms are more able to afford the fixed costs associated with regular audits. Of course, there can be other reasons why large firms and large banks go together. However, our data also allow us to infer whether a given firm keeps accounting records. This could serve as an alternative proxy for hard information, and we would therefore predict that firms with accounting records are more likely to borrow from larger banks.

2.2.2. The endogeneity of bank size and our instrumenting strategy

All the hypotheses that follow relate bank size to various aspects of the bank-firm lending relationship. In other words, we want to use bank size as a right-hand-side variable to explain the nature of the lending technology. But since firms can to a degree choose their banks—as we have just emphasized—there is an obvious endogeneity problem. In particular, a firm characteristic for which we have not controlled could explain why the firm chooses a bank of a certain size, as well as the aspect of the relationship we are interested in. For example, an entrepreneur with an

MBA might be better able to get a hearing from a loan officer in a large bank. This entrepreneur might also find it easier to generate spreadsheet reports that reduce the need for personal visits to the bank. Thus, he might be more apt to borrow at a distance, and to communicate with the bank impersonally. If so, we would see large banks lending impersonally and at a distance, but this would not necessarily reflect a causal consequence of bank size.

To address this potential bias, we need one or more instruments that are correlated with a firm's propensity to be matched with a bank of a particular size, but that are uncorrelated with characteristics of the firm that might influence the nature of the lending relationship. In our baseline specifications, we use two instruments: (i) the log of the median size of *all* the banks in the Metropolitan Statistical Area (MSA) or rural county in which the firm is located (weighted by the number of branches), and (ii) the fraction of the previous ten years during which the firm's state was neither a unit banking nor limited branching state. The idea is that if a firm is located in a state where regulation has not constrained bank size, and hence where large banks dominate its market, the firm will be pushed—independent of its own characteristics—in the direction of a large bank. We can then examine how this forced match shapes the bank-firm relationship.

Although our median-bank-size instrument varies at the level of the city or rural county, and our regulatory instrument varies only at the state level, the two are closely linked, with a univariate correlation of 0.472. Not surprisingly, states that have been permissive with respect to branching tend to have larger banks across all of their individual markets. In spite of this commonality, however, one might argue that the state-level regulatory variable is a purer instrument. Perhaps within a given state, some markets have certain attributes that tend to attract both banks of a certain size and firms with particular characteristics. For example, a vibrant big-city economy might draw both large banks and MBA-trained entrepreneurs.

An alternative estimation strategy that helps to address this critique is to dispense with the median-bank-size variable and to use the regulatory variable as the *only* instrument for bank size. This approach, which we experiment with below, is more conservative, but also considerably less powerful, because it makes use only of across-state variation, and loses the within-state across-market variation. Nevertheless, it leads to point estimates that are remarkably similar to those from our baseline instrumenting technique, although the standard errors are of course somewhat higher.

2.2.3. The effect of bank size on distance and mode of interaction

Coval and Moskowitz (2001) demonstrate the importance of physical distance for information-gathering, documenting that money managers do better when investing in the stocks of nearby companies. Similarly, being close to one's customers is likely to facilitate a loan officer's collection of soft information, but to have little impact on his ability to gather hard information. What we have in mind is that one important way for the loan officer to gather soft information is through face-to-face interaction with a potential borrower. Being nearby might also help the loan officer to better understand the nuances of the local business environment. Hard information, on the other hand, can by definition be easily summarized in a report, and hence can be faxed or emailed anywhere, making distance essentially irrelevant.

Now think of a firm that wants to borrow. If it is forced to choose among large banks (because, say, no small banks are around), we would not expect the firm to limit itself to those that are close, because large banks are unlikely to invest in acquiring soft information, making the lending technology more distance-independent. We would also expect the mode of communication between the firm and the bank to be more impersonal. By contrast, if only small banks are around and the firm is informationally opaque, we would expect it to pick a nearby bank, because small banks' information acquisition is sensitive to the "shoe-leather" cost of personal visits. We would also expect the contact between the firm and bank to be more personal in nature.

2.2.4. The effect of bank size on relationship length and exclusivity

If our findings about distance and mode of interaction reflect the fact that small banks are better at using soft information, we should see this manifested in two further ways. First, small banks should sustain longer relationships with their borrowers. The soft information that a small bank has gathered over time should give it a comparative advantage in providing its client firm with good lending terms. Moreover, because this soft information is not easily transferable by the firm, the banker might have a certain degree of market power (see Sharpe, 1990; Rajan, 1992), which would further tie the firm to the bank. If, on the other hand, a firm's relationship with a large bank is based on hard information, which is easily communicated to potential new lenders, the additional benefits of staying with the same lender, or the switching costs of moving to a new one, are likely to be lower. The length of time that a firm and its bank have dealt with each other should thus decrease with bank size.

A second implication, which follows from similar reasoning, is that the likelihood that a relationship between a firm and its bank is an exclusive one—i.e., that the bank is the firm's only lender—should also decrease with bank size. In other words, their greater reliance on soft information suggests that smaller banks should form both longer and more exclusive relationships with their customers.

2.2.5. The effect of bank size on credit availability

Since we argue that small banks form stronger, more information-intensive bonds with their borrowers, we might also expect them to do a better job of easing these firms' credit constraints. If we can document evidence consistent with this prediction, we will have identified an important "real" effect of bank size that would seem to be particularly difficult to explain away with alternative theories.

To form an operational measure of credit constraints, we follow Petersen and Rajan (1994) and look at the fraction of a firm's trade credit that is paid late. As Petersen and Rajan argue, stretching trade credit is a very expensive way to obtain finance, and a firm is likely to do so only when rationed by institutional lenders. So the final prediction of our theory is that firms should repay a higher fraction of their trade credit late if they borrow from larger banks. This is perhaps the test for which it is most critical to correct for the endogeneity of the firm's choice of bank, as one would expect particularly difficult credits to choose small banks. Without instrumenting for bank size, the test would therefore be biased against finding that small banks improve credit availability.

2.3. Alternative theories

As noted in the introduction, many of the above predictions about small-bank/big-bank differences can also be motivated in the context of a model based on explicit incentive-contracting considerations. Brickley et al. (2003) point out that managers of small banks tend to have higher-powered ownership incentives, and there are a variety of reasons to expect that such well-aligned incentives might facilitate a reliance on soft information. In spite of the similarities, however, one can imagine tests that might discriminate between the two theories. For example, if we had data on insider ownership, or on the nature of the pay-for-performance relation for each of the banks in our sample, we could check to see if—as Brickley, Linck, and Smith implicitly suggest—these variables eliminate the effect of bank size in our regressions. Unfortunately, we do not have such data, so our ability to disentangle the two theories is limited.

3. Data

3.1. Sources

Our primary data source is the Federal Reserve's 1993 National Survey of Small Business Finance (NSSBF), which covers the financing practices of a stratified random sample of firms. The survey was actually conducted in 1994 and 1995 based on a sample of firms that were in existence at the end of 1993. Some of the information collected—e.g., on the firm's most recent loan—comes from the calendar year 1994. To be in the sample, a firm must be a for-profit entity with fewer than 500 employees. Consequently, the firms in our sample are really quite small, with a mean book value of assets of $3.0 million, and a median of $680,000.

The survey's focus on small firms is ideal for our purposes, for several reasons. First, many of the firms in our sample do not have formal financial records. This makes it plausible that soft information might play an important in evaluating their creditworthiness. Second, these firms secure most of their external finance from debt markets, and a predominant share of this comes from banks. Thus there is the possibility that being matched with the "wrong" kind of bank could have a meaningful effect on their overall access to finance. Third, with such small firms, the decision of whether to borrow from a large or small bank is unlikely be driven by regulatory lending limits.

Although the survey includes a complete inventory of all of a firm's current loans, we focus on its most recent loan, and only if that loan is from a bank. This allows us to focus on a fairly static banking environment, and also ensures that we measure firms' and banks' characteristics at roughly the time that loans are originated. In particular, each observation in our sample is based on a firm that secured a loan from its bank between 1990 and 1994; 88% of these loans were originated in either 1993 or 1994.

Each firm is then matched with the specific bank from which it borrows. For the banks, we use the Consolidated Report of Condition and Income (a.k.a. the Call Reports) to obtain balance-sheet variables such as bank assets. We also use the FDIC Summary of Deposits to determine the locations of individual bank branches. Our baseline sample includes 1,131 firms for which we have data on the most recent lender.

3.2. Variable definitions

In the analysis that follows, we work with the following basic variables. First, we have five variables that can be thought of as proxies for the nature of the relationship between the firm and its bank: (1) Distance is the number of miles between the firm and the bank branch or office from which the most recent loan was granted; (2) Impersonal Relationship is a dummy that equals one if the firm primarily communicates with the bank by phone or mail, and zero if the communication is face-to-face; (3) Relationship Length is the number of years that the bank has been providing services to the firm; (4) Single Lender is a dummy that equals one if the bank making the most recent loan is the firm's *only* (bank or non-bank) lender; and (5) Trade Credit Paid Late is the fraction of trade credit that the firm reports paying when it is past due. (The survey asks for the proportion of trade credit that is paid late on a scale from 1 to 5. For ease of interpretation, we recode this variable to be between zero and one.)

Next, there are six variables that capture bank and banking-market characteristics: (1) Bank Size is the assets of the firm's bank, expressed in billions of dollars; (2) Number of Branches in Market is the number of branches that the firm's bank has in the MSA or non-MSA rural county in which the firm is located; (3) Bank Age is the number of years the bank has been in existence; (4) Median Bank Size is the median assets across all banks (weighted by branches) in the firm's market; (5) Open Market is the fraction of the ten years prior to our sample period (i.e., 1983–1992) during which the firm's state was neither a unit banking nor limited branching state; and (6) Market Herfindahl is the banking-market Herfindahl index for this market (a measure of industry concentration). Bank Size will be the key right-hand-side variable of interest in most of our regressions, and both Median Bank Size and Open Market will be used as instruments for Bank Size.

Finally, there are eight variables that measure firm and contract characteristics: (1) Firm Size is the firm's assets, in millions of dollars; (2) Firm Age is the number of years the firm has been in existence; (3) Loan Amount is the size of the most recent loan, in millions; (4) Line of Credit is a dummy that takes on the value one if the most recent loan is a line of credit; (5) Loan Collateralized is a dummy that takes on the value one if the most recent loan is secured; (6) Checking Account is a dummy that takes on the value one if the firm also has a checking account with the bank that made its most recent loan; (7) Firm in MSA is a dummy that takes on the value one if the firm is located in an MSA; and (8) Records is a dummy that takes on the value one if the firm's respondent to the NSSBF survey said "yes" when asked if he or she had documentation such as financial statements or accounting records to help in answering the survey questions. (In what follows, we sometimes imprecisely refer to a "yes" answer to this question as indicating that a firm keeps formal records; it is more accurate to say that we only have a proxy for the existence of records—using records to answer the survey is likely to be highly correlated with having records in the first place, but it is not exactly the same thing.)

3.3. Summary statistics by bank size class

Table 1 presents summary statistics for many of the variables for both the full sample (in Panel A) and for subsamples based on bank size (in Panel B). Although

Table 1
Summary statistics Panel A: full sample

Panel A contains summary statistics for the variables used in all subsequent estimation. Distance is the distance between a firm and the bank branch or office it uses most often. Impersonal Relationship equals one if the firm interacts with its bank most often by phone or mail and zero if the interaction is in person. Relationship Length is the number of years the bank and the firm have been interacting (through lending, deposit, or service activities). Single Lender is a dummy variable that equals one if the firm has a single lender. Trade Credit Paid Late is the fraction of its trade credit the firm reports paying when it is past due. Bank Size is the assets of the bank from which the firm has its most recent loan. Number of Branches in Market is the number of branches which the *firm's bank* has in its market (MSA or county). Median Bank Size is the size of the median bank in the *firm's market* (MSA or county) weighted by branches. Open Market is the fraction of the previous ten years during which there were no restrictions on within-state branching in the firm's state. Firm Size is the assets of the firm. Loan Amount is the size of the most recent loan. Records is a dummy variable that equals one if the person answering the income statement and balance sheet questions for the firm had documentation such as financial statements or accounting records to help answer the questions. There are 1,131 observations in the sample.

Variable	Mean	Std Dev	25%	50%	75%
Lending methods					
Distance (miles)	26.053	136.992	1.000	3.000	10.000
Impersonal relation (1 = yes)	0.294	0.456	0.000	0.000	1.000
Relationship length (yrs)	8.750	7.508	3.000	6.000	12.000
Single lender (1 = yes)	0.499	0.500	0.000	0.000	1.000
Trade credit paid late	0.352	0.208	0.250	0.250	0.500
Bank characteristics					
Bank size ($B)	8.883	23.147	0.163	0.956	7.685
No. of branches in market	21.486	45.494	1.000	5.000	25.000
Bank age (years)	75.263	43.914	39.000	80.000	106.000
Median bank size ($b)	6.159	13.426	0.196	1.203	6.077
Open market	0.446	0.266	0.000	0.400	0.800
Firm characteristics					
Firm age (years)	14.842	8.865	8.000	13.000	22.000
Firm size ($m)	3.003	7.136	0.150	0.680	2.850

Table 1 (*continued*)

Variable	Mean	Std Dev	25%	50%	75%
Loan amount ($m)	1.001	3.750	0.030	0.125	0.600
Records (1 = yes)	0.570	0.495	0.000	1.000	1.000

Panel B: means by bank size

Panel B contains the means of selected variables across four categories of bank size (less than $100M, $100M-1B, $1B-10B, and over $10B in assets). Regressions estimating how the lending method variables depend upon bank size as well as on other firm and bank characteristics are contained in later tables.

Variable	<100M	100M-1B	1B-10B	10B+
Lending methods				
Distance (miles)	14.947	9.488	19.302	71.363
Impersonal relation (1 = yes)	0.168	0.216	0.375	0.406
Relationship length (yrs)	9.384	9.261	8.762	7.389
Single lender (1 = yes)	0.616	0.496	0.497	0.410
Trade credit paid late	0.325	0.374	0.340	0.349
Bank characteristics				
Bank size ($b)	0.058	0.386	4.346	36.167
No. of branches in market	1.442	5.158	24.140	60.487
Bank age (years)	49.111	67.858	86.543	92.679
Median bank size ($b)	2.765	4.401	5.304	12.964
Open market	0.305	0.413	0.497	0.544
Firm characteristics				
Firm age (years)	13.763	15.037	15.595	14.346
Firm size ($m)	0.704	1.752	3.860	5.695
Loan amount ($m)	0.180	0.375	1.198	2.402
Records (1 = yes)	0.474	0.562	0.576	0.654
Number of observations	190	379	328	234

the firms in our sample are small (fewer than 500 employees), we still see a significant range of firm and loan sizes.[2] The range of bank sizes is even larger, increasing from $163 million in assets at the 25th percentile of the distribution to $7.69 billion in assets at the 75th percentile. Although these banks are selected because a small firm has borrowed from them, they are not exclusively small banks. In fact, they appear to be somewhat larger than is typical in a comprehensive sample of banks. For example, the 25th percentile of bank assets in our sample corresponds to roughly the 80th percentile of the size distribution of *all* banks in 1993 as reported in Kashyap and Stein (2000).

[2]The NSSBF does not use an equal-probability sample design but does include a weighting scheme that can be used to make the survey nationally representative. We choose not to employ the weights in the analysis presented here, since our hypotheses apply with equal force to all observations. However, we obtain very similar results if we run weighted versions of all our regressions.

As Panel B of Table 1 makes clear, there is a strong univariate correlation between bank size and many of the other variables. For example, mean loan size increases from $180,000 in the smallest class of banks (those with assets below $100 million) to $2.40 million in the largest size class (those with assets above $10 billion). Firm size increases similarly. The fraction of firms with financial records goes from 47.4% in the smallest class of banks to 65.4% in the largest class.

The aspects of lending relationships that we are interested in also vary across bank size classes in the manner predicted by the theory. The average distance between a firm and its bank rises from 14.9 miles for the smallest class of banks to 71.4 miles for the largest. Relatedly, the incidence of impersonal communication increases from 16.8% among the smallest banks to 40.6% among the largest banks. Mean relationship length is 9.4 years in the smallest class of banks, and 7.4 years in the largest class. The incidence of exclusive relationships is 61.6% among the smallest banks, and 41.0% among the largest banks.

3.4. The availability of small-bank branches in different markets

Our instrumenting strategy relies on being able to identify markets where there are substantial differences in the availability of small banks. To get a sense for the variation along this dimension, for each market in our sample, we calculate the fraction of branches that are owned by small banks, defined as those with assets of less than $100 million. This variable has a mean of 31%. Not surprisingly, its correlation with our median-bank-size instrument is very strong, at −0.75. Moreover, when we regress the former on the latter, we find that increasing median bank size by two standard deviations decreases the fraction of small-bank branches in a market by 23 percentage points, which looms large relative to the mean of 31%. Thus, movements in the median-bank-size instrument would seem to translate into economically large changes in the availability of small-bank branches. Even more vividly, the 15 markets with the fewest small-bank branches have literally *no* branches owned by banks with less than $100 million in assets, and hardly any (never more than 5%) branches owned by banks with less than $300 million in assets. It is also worth noting that these markets are of widely varying sizes—they range from small markets like Burlington, VT to middle-sized ones like Lancaster, PA to larger population centers like Honolulu, HI, Jersey City, NJ, and Cleveland, OH.

4. Regression results

4.1. The choice of bank

We start by asking what determines the size of the bank from which a firm borrows. In Column 1 of Table 2, we use ordinary least squares (OLS) to regress Ln(Bank Size) against the firm and contract characteristics: Ln(Firm Size), Ln(1 + Firm Age), Ln(Loan Amount), Line of Credit, Loan Collateralized, Checking Account, Firm in MSA, and Records. The regression also includes

Table 2
Determinants of bank size

The dependent variable is Ln(Bank Size). Bank Size is expressed in thousands of dollars and Firm Size and Loan Size are expressed in dollars before taking logs. Ln(Median Bank Size) is the log of the median bank assets in the *firm's market* (MSA or county) weighted by branches. Open Market is the fraction of the previous ten years during which there were no restrictions on within-state branching in the firm's state. We use Ln(Median Bank Size) and Open Market to instrument for Ln(Bank Size) in the models that follow. Each regression contains dummy variables for whether the loan is a line of credit, whether it is collateralized, and whether the firm has a checking account from the bank. Records is a dummy variable that equals one if the person answering the income statement and balance sheet questions for the firm had documentation such as financial statements or accounting records to help answer the questions. Each regression also includes dummies for the firm's industry (construction, retail, or services) and the year in which the loan was secured (1992–1994). The number of observations is 1,131. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Independent variables	Models	
	1: OLS	2: OLS
Bank and market characteristics		
Ln(median bank size)		0.222***
		(0.032)
Open market		0.438***
		(0.145)
Ln(1 + No. of branches)		0.594***
		(0.039)
Market Herfindahl		−0.226
		(0.541)
Ln(1 + bank age)		0.523***
		(0.051)
Firm and contract characteristics		
Ln(firm size)	0.125**	0.099**
	(0.051)	(0.040)
Ln(1 + firm age)	−0.172*	−0.224***
	(0.094)	(0.073)
Ln(loan amount)	0.277***	0.198***
	(0.051)	(0.040)
Line of credit (1 = yes)	0.197	0.110
	(0.141)	(0.110)
Loan collateralized (1 = yes)	−0.313**	−0.059
	(0.134)	(0.105)
Checking account (1 = yes)	−0.467**	−0.869***
	(0.210)	(0.166)
Firm in MSA (1 = yes)	1.220***	0.040
	(0.140)	(0.151)
Records (1 = yes)	0.240**	0.178*
	(0.121)	(0.094)
Adjusted R^2	0.218	0.526

dummies—not shown in the table—for the firm's industry (construction, retail, or services) as well as for the year in which the most recent loan was made.

As expected, bank size is strongly correlated with both the size of the firm in question and the size of the loan. If the size of the firm and the size of the loan both double, the regression tells us that bank assets increase by about 40%. But perhaps the most interesting result from this regression is the coefficient on Records, which is 0.240 and significant at the 5% level. Controlling for firm size, firms that have financial records borrow from banks that are roughly 24% larger. This is consistent with the idea that, all else equal, larger banks are at a comparative advantage in lending to firms for which hard information is more readily available.

One objection to this conclusion is that the Records variable could be endogenous. In particular, some firms might go to larger banks (for whatever reason) that then encourage record-keeping, so that the causality flows from bank size to records, rather than the other way around. Although it is hard to completely rule out this possibility—and given the story we have in mind, it is not clear that we would want to—we can make a partial attempt, as follows. If bank size drives record-keeping, then the correlation between bank size and records ought to be less pronounced for borrowers whose relationship to the bank is new, since the bank has not yet had time to really influence their behavior. However, this turns out not to be the case. We re-run the regression in Column 1 of Table 2, adding an interaction term given by the product of the Records variable and a dummy for whether the relationship is less than two years old (not shown). The interaction term is significantly positive, suggesting that, if anything, the correlation between bank size and records is *more* pronounced for newer relationships.

As discussed above, in our subsequent regressions we will use Ln(Bank Size) as an explanatory variable, and we will employ Ln(Median Bank Size) and Open Market as instruments for Ln(Bank Size). In Column 2 of Table 2, we display the first-stage regression that underlies this instrumenting procedure. In particular, we keep Ln(Bank Size) on the left, and add to the specification of Column 1 the following bank and banking-market variables: Ln(Median Bank Size), Open Market, Ln(1 + Number of Branches), Ln(1 + Bank Age), and Market Herfindahl. All of the right-hand-side variables in Column 2 of Table 2 will be controls in future regressions, except Ln(Median Bank Size) and Open Market, which will serve as the instruments for Ln(Bank Size). The main point to draw from this regression is that both Ln(Median Bank Size) and Open Market appear sufficiently correlated with Ln(Bank Size) to be viable instruments. They attract economically large coefficients and are highly statistically significant, with t-stats of 6.9 and 3.0, respectively.

4.2. The distance between firms and their banks

Table 3 examines the link between bank size and distance. In Column 1, we run an OLS regression in which the dependent variable is Ln(1 + Distance). The explanatory variables include the bank and banking-market characteristics Ln(Bank Size), Ln(1 + Number of Branches), Ln(1 + Bank Age), and Market Herfindahl, as well as the firm and contract characteristics Ln(Firm Size), Ln(1 + Firm Age),

Table 3
Distance between the firm and its bank

The dependent variable is the log of one plus the distance (in miles) between the firm and the bank branch or office that it uses most often. Ln(Bank Size) is the log of bank assets. Bank Size is expressed in thousands of dollars and Firm Size and Loan Size are expressed in dollars before taking logs. In Column 2, we report instrumental-variable estimates where the instruments for Ln(Bank Size) are Ln(Median Bank Size), the log of the median assets of banks in the area where the firm is located, and Open Market, the fraction of the previous ten years during which there were no restrictions on within-state branching in the firm's state. The number of branches in the market includes only branches of the bank from which the firm borrows. Each regression contains dummy variables for whether the loan is a line of credit, whether it is collateralized, and whether the firm has a checking account from the bank. Records is a dummy variable that equals one if the person answering the income statement and balance sheet questions for the firm had documentation such as financial statements or accounting records to help answer the questions. Each regression also includes dummies for the firm's industry (construction, retail, or services) and the year in which the loan was secured (1992–1994). The number of observations is 1,131. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Independent variables	Models	
	1: OLS	2: IV
Bank and market characteristics		
Ln(bank size)	0.184***	0.296***
	(0.021)	(0.078)
Ln(1 + No. of branches)	−0.385***	−0.467***
	(0.031)	(0.063)
Market Herfindahl	−0.352	−0.455
	(0.392)	(0.403)
Ln(1 + bank age)	0.002	−0.049
	(0.038)	(0.052)
Firm and contract characteristics		
Ln(firm size)	0.028	0.018
	(0.030)	(0.031)
Ln(1 + firm age)	−0.216***	−0.189***
	(0.054)	(0.058)
Ln(loan amount)	0.076**	0.049
	(0.030)	(0.035)
Line of credit (1 = yes)	0.121	0.107
	(0.082)	(0.083)
Loan collateralized (1 = yes)	0.049	0.066
	(0.078)	(0.079)
Checking account (1 = yes)	−0.870***	−0.758***
	(0.125)	(0.147)
Firm in MSA (1 = yes)	0.255**	0.200*
	(0.105)	(0.112)
Records (1 = yes)	−0.026	−0.046
	(0.070)	(0.072)
Adjusted R^2	0.269	0.235

Ln(Loan Amount), Line of Credit, Loan Collateralized, Checking Account, Firm in MSA, and Records. In Column 2, we run the same basic regression by IV, using Ln(Median Bank Size) and Open Market as instruments for Ln(Bank Size). These regressions, and all those that follow, also include suppressed dummies for the firm's industry and the year the most recent loan was made.

Consistent with our theoretical prediction, firms that are customers of larger banks borrow at substantially greater distances. Both the OLS and the IV coefficients are statistically significant at the 1% level, and the IV coefficient is larger in magnitude, 0.296 versus 0.184. According to the IV estimate, increasing bank size from \$163 million in assets (the 25th percentile) to \$7.69 billion in assets (the 75th percentile) raises the predicted distance between a firm and its lender by 114%.

It is also worth briefly discussing some of the other controls in the regression and their importance. First, and not surprisingly, we find that the number of branches that the firm's lender has in the market is an important determinant of distance. Since larger banks naturally have more branches than small banks, it is especially important that we control for the number of branches in our tests. What the regression is then telling us is that the distance between a firm and its bank is positively related to *the size of the bank outside of the firm's local market*. In other words, if the bank adds branches outside of the firm's market, distance increases, but if the bank adds branches inside the firm's market, distance decreases, for the obvious mechanical reasons. We have verified this statement by re-running the basic OLS and IV regressions in Table 3, replacing Ln(Bank Size) with the log of one plus the number of branches that the bank has *outside* the market in question. In both cases, the coefficient on this variable is also positive and strongly significant.

We also find that older firms tend to be closer to their banks. At first, this seems puzzling because older firms might be expected to have better-established reputations (Diamond 1991), which should facilitate borrowing at a distance. The answer to the puzzle could be that firm age proxies for when the relationship was started. Petersen and Rajan (2002) and Hannan (2003) find that the distance between firms and their banks has been growing over time, partly because of the greater availability of hard information. So older firms could be closer to their banks because they started their relationships at a time when little hard public information was available about them. Finally, firms that have checking accounts with their banks are also closer to them. This replicates a finding in Petersen and Rajan (2002), and may be explained by the greater necessity of making physical trips to the bank with which one has a checking account.

A couple of other points deserve mention. The literature on bank consolidation has raised the question of whether banking mergers disrupt relationships, especially those that rely on soft information. Thus, when we find that larger banks are more likely to lend at a distance, we want to be sure that our bank size result is not due only to the effect of mergers. To test this, we re-run our basic specification, adding two controls for bank mergers (in regressions not reported in the tables). These variables are individually insignificant and make no material difference to our principal conclusions. In a similar spirit, we also add more controls for bank health and firm risk; again our results are qualitatively unaffected.[3]

4.3. The mode of conducting business: personal vs. impersonal

In Table 4, we investigate the link between bank size and the mode of communication. The right-hand-side variables are exactly the same as in Table 3, and the left-hand-side variable is now Impersonal Relationship. Also, given the dichotomous nature of the Impersonal Relationship variable, we run the regressions by logit, instead of by OLS (though our results are virtually identical if we use OLS). In Column 1, we use Ln(Bank Size) directly in the logit regression, and in Column 2 we instrument for Ln(Bank Size) by replacing it with its fitted value from the first-stage regression in Column 2 of Table 2.

Both the ordinary logit and the IV version yield strong, statistically significant estimates for the influence of bank size on the mode of communication, though as before the IV estimate is noticeably bigger. Based on the IV coefficient, an increase in bank size from the 25th to the 75th percentile raises the probability of impersonal communication from 15% to 38%. As with distance, the number of branches that the firm's bank has in the local market also affects the way in which the firm and the bank interact. In this case, having more in-market branches leads to significantly less impersonal communication, as would be expected.

Impersonal communication and physical distance are clearly related—it is more difficult to visit a distant bank in person. As a more stringent test, we can ask if bank size affects the mode of communication even after controlling for distance. In an unreported regression, we find that when we add Ln(1 + Distance) to the right-hand side of the IV specification, the coefficient on Ln(Bank Size) drops from 0.324 to 0.160. Although this still represents an economically interesting magnitude, the point estimate is no longer statistically significant. In the un-instrumented logit specification, adding Ln(1 + Distance) drops the coefficient on Ln(Bank Size) from 0.196 to 0.096, but in this case the coefficient remains significant at the 10% level.

With respect to firm characteristics, we find strong evidence that larger firms are more likely to communicate impersonally with their bankers, which is not surprising. At the same time, controlling for size, we find that older firms are *less likely* to communicate impersonally. This is at least in part driven by the earlier finding that older firms are physically closer to their banks. There may also be a vintage effect at work, whereby managers of older firms started off their careers interacting with their bankers face-to-face and have not changed their ways, even as the technology of

[3]As added bank controls, we include dummy variables for each of the following: whether a bank was the surviving bank in a merger in the last three years; whether the bank changed top-tier holding companies in the last three years; whether the bank's equity to asset ratio was in the bottom 10% of our sample; and whether the bank's ratio of non-performing loans to all loans was in the top 10% of our sample. As added firm-risk controls, we include the firm's leverage ratio and dummies for whether, over the past three years, any of the following have occurred: the owner has been 60 or more days delinquent on personal obligations; the firm has been 60 or more days delinquent; or a judgment was rendered against the owner.

Table 4
Impersonal communication between the firm and its bank

The dependent variable is a dummy that equals one if the bank and firm communicate impersonally (by phone or mail) and zero if they communicate in person. A logit model was estimated. Ln(Bank Size) is the log of bank assets. Bank Size is expressed in thousands of dollars and Firm Size and Loan Size are expressed in dollars before taking logs. In Column 2, we report instrumental-variable estimates where Ln(Bank Size) is replaced with its predicted value based on Ln(Median Bank Size), the log of the median assets of banks in the area where the firm is located, and Open Market, the fraction of the previous ten years during which there were no restrictions on within-state branching in the firm's state (see Table 2, Column 2). The number of branches in the market includes only branches of the bank from which the firm borrows. Each regression contains dummy variables for whether the loan is a line of credit, whether it is collateralized, and whether the firm has a checking account from the bank. Records is a dummy variable that equals one if the person answering the income statement and balance sheet questions for the firm had documentation such as financial statements or accounting records to help answer the questions. Each regression also includes dummies for the firm's industry (construction, retail, or services) and the year in which the loan was secured (1992–1994). The number of observations is 1,131. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Independent variables	Models	
	1: logit	2: logit/IV
Bank and market characteristics		
Ln(bank size)	0.196***	0.324**
	(0.046)	(0.165)
Ln(1 + No. of branches)	−0.267***	−0.365***
	(0.064)	(0.131)
Market Herfindahl	−0.808	−0.883
	(0.907)	(0.916)
Ln(1 + bank age)	−0.132	−0.179
	(0.082)	(0.108)
Firm and contract characteristics		
Ln(firm size)	0.259***	0.248***
	(0.070)	(0.070)
Ln(1 + firm age)	−0.329***	−0.290**
	(0.119)	(0.124)
Ln(loan amount)	0.082	0.049
	(0.066)	(0.075)
Line of credit (1 = yes)	0.659***	0.642***
	(0.191)	(0.190)
Loan collateralized (1 = yes)	0.215	0.245
	(0.170)	(0.170)
Checking account (1 = yes)	−1.128***	−0.982***
	(0.266)	(0.302)
Firm in MSA (1 = yes)	0.687***	0.608**
	(0.245)	(0.255)
Records (1 = yes)	−0.109	−0.115
	(0.153)	(0.154)
Pseudo R^2	0.179	0.168

banking has evolved. We also find that firms that have checking accounts with the bank are more inclined to meet with their banker face-to-face.

4.4. The effect of bank size on relationship length and exclusivity

Table 5 looks at the effect of bank size on relationship length. The structure is identical to that of Table 3, except that the dependent variable is now Ln(1 + Relationship Length). Relationships are significantly shorter when the firm borrows from a larger bank. According to the IV specification in Column 2 of Table 5, an increase in bank size from the 25th to the 75th percentile cuts the predicted length of a relationship almost in half, shrinking it from 8.8 to 4.5 years.

It should be noted that the estimated coefficient on Ln(Bank Size) is nearly three times higher in Column 2, where we use IV, as compared to Column 1, where we use OLS. Indeed, the theory suggests that it ought to be particularly important to deal with the endogeneity of bank size here, since firms might be more prone to switch to small banks—thereby setting the relationship-length clock back to zero—if they get into trouble and become the sort of "difficult" credits for which soft information is especially important. This would obviously make it hard to find an OLS association between small banks and longstanding relationships.

Table 6 analyzes the exclusivity of banking relationships, putting Single Lender on the left-hand side of the regressions. As in Table 4, the regressions are run with logit, given the dichotomous nature of the dependent variable. According to the IV specification, the effect of bank size on exclusivity is extremely strong: an increase in bank size from the 25th to the 75th percentile reduces the probability of an exclusive relationship by almost 50 percentage points, from 74% to 27%.

Again, we see the importance of instrumenting, as the coefficient on Ln(Bank Size) goes from –0.096 in the ordinary logit to –0.526 in the instrumented version. And again, this makes perfect sense in light of the theory. Petersen and Rajan (1994) show that troubled firms are more likely to have multiple relationships—presumably as they cast around for someone willing to accommodate their needs—and our theory suggests that troubled firms should also be more prone to match with small banks. Hence we would expect the non-instrumented coefficient to be significantly biased towards zero.

At this juncture, it might be useful to ask whether the effects of bank size on distance and on the mode of interaction work only indirectly through the kind of relationship (long and exclusive with small banks, short and non-exclusive with large banks), or whether there is also a direct effect. One way to test this is to include both Ln(1 + Relationship Length) and Single Lender as additional controls in the regressions of Tables 3 and 4, where the dependent variables are Ln(1 + Distance) and Impersonal Relationship, respectively. In both cases, the coefficients on Ln(Bank Size) continue to be strongly statistically significant and only slightly diminished in magnitude, suggesting that bank size indeed has an important independent effect.

Table 5
Relationship length between the firm and its bank

The dependent variable is log of one plus the length of the relationship between the firm and its bank (in years). Ln(Bank Size) is the log of bank assets. Bank Size is expressed in thousands of dollars and Firm Size and Loan Size are expressed in dollars before taking logs. In Column 2, we report instrumental-variable estimates where the instruments for Ln(Bank Size) are Ln(Median Bank Size), the log of the median assets of banks in the area where the firm is located, and Open Market, the fraction of the previous ten years during which there were no restrictions on within-state branching in the firm's state. The number of branches in the market includes only branches of the bank from which the firm borrows. Each regression contains dummy variables for whether the loan is a line of credit, whether it is collateralized, and whether the firm has a checking account from the bank. Records is a dummy variable that equals one if the person answering the income statement and balance sheet questions for the firm had documentation such as financial statements or accounting records to help answer the questions. Each regression also includes dummies for the firm's industry (construction, retail, or services) and the year in which the loan was secured (1992–1994). The number of observations is 1,131. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Independent variables	Models	
	1: OLS	2: IV
Bank and market characteristics		
Ln(bank size)	−0.048***	−0.150***
	(0.012)	(0.044)
Ln(1 + No. of branches)	0.051***	0.125**
	(0.017)	(0.035)
Market Herfindahl	0.313	0.408*
	(0.215)	(0.225)
Ln(1 + bank age)	0.108***	0.155***
	(0.021)	(0.029)
Firm and contract characteristics		
Ln(firm size)	0.022	0.031*
	(0.016)	(0.017)
Ln(1 + firm age)	0.607***	0.582***
	(0.030)	(0.032)
Ln(loan amount)	−0.045***	−0.020
	(0.016)	(0.020)
Line of credit (1 = yes)	0.000	0.012
	(0.045)	(0.046)
Loan collateralized (1 = yes)	−0.056	−0.072
	(0.043)	(0.044)
Checking account (1 = yes)	0.446***	0.343***
	(0.068)	(0.082)
Firm in MSA (1 = yes)	−0.165***	−0.115**
	(0.057)	(0.063)
Records (1 = yes)	−0.049	−0.031
	(0.038)	(0.040)
Adjusted R^2	0.366	0.348

Table 6
Exclusive relationship between the firm and its bank

The dependent variable is a dummy that equals one if the bank is the firm's only lender, and zero otherwise. A logit model is estimated. Ln(Bank Size) is the log of bank assets. Bank Size is expressed in thousands of dollars and Firm Size and Loan Size are expressed in dollars before taking logs. In Column 2, we report instrumental-variable estimates where Ln(Bank Size) is replaced with its predicted value based on Ln(Median Bank Size), the log of the median assets of banks in the area where the firm is located, and Open Market, the fraction of the previous ten years during which there were no restrictions on within-state branching in the firm's state (see Table 2, Column 2). The number of branches in the market includes only branches of the bank from which the firm borrows. Each regression contains dummy variables for whether the loan is a line of credit, whether it is collateralized, and whether the firm has a checking account from the bank. Records is a dummy variable that equals one if the person answering the income statement and balance sheet questions for the firm had documentation such as financial statements or accounting records to help answer the questions. Each regression also includes dummies for the firm's industry (construction, retail, or services) and the year in which the loan was secured (1992–1994). The number of observations is 1,131. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Independent variables	Models	
	1: logit	2: logit/IV
Bank and market characteristics		
Ln(bank size)	−0.096**	−0.526***
	(0.040)	(0.144)
Ln(1 + No. of branches)	0.075	0.388***
	(0.057)	(0.116)
Market Herfindahl	−0.637	−0.242
	(0.721)	(0.732)
Ln(1 + bank age)	0.115	0.308**
	(0.071)	(0.095)
Firm and contract characteristics		
Ln(firm size)	−0.318***	−0.283***
	(0.057)	(0.058)
Ln(1 + firm age)	0.246**	0.143
	(0.102)	(0.107)
Ln(loan amount)	0.112**	0.219***
	(0.056)	(0.065)
Line of credit (1 = yes)	−0.078	−0.027
	(0.150)	(0.152)
Loan collateralized (1 = yes)	−0.351**	−0.149***
	(0.142)	(0.145)
Checking account (1 = yes)	0.517**	0.087
	(0.235)	(0.271)
Firm in MSA (1 = yes)	−0.098	0.110
	(0.192)	(0.204)
Records (1 = yes)	−0.120	−0.044
	(0.128)	(0.131)
Pseudo R^2	0.062	0.067

4.5. Bank size and credit availability

Thus far, we have argued that soft information is likely to be important in evaluating the creditworthiness of small firms, and that small banks have a comparative advantage in acquiring and acting on such soft information, which is why they can form stronger relationships with the firms in our sample. But do these stronger relationships translate into more financing? In other words, do they have meaningful real effects?

The problem in measuring the availability of credit is that we cannot simply look at the amount of debt on a firm's balance sheet, for that will reflect both demand and supply considerations. But we can use an alternative approach, following Petersen and Rajan (1994). The idea is that if banks (or any other intermediaries) limit the credit extended to a firm, the firm will be forced to borrow from a more expensive source. Holding investment opportunities constant, the amount borrowed from the more expensive sources should measure the degree of credit rationing by banks.

Petersen and Rajan (1994, 1995) point to stretched trade credit as an extremely costly marginal source of finance, and argue that the fractional share of a firm's trade credit that is paid late provides a reliable measure of the extent to which the firm is rationed. Older and larger firms, which are presumably less constrained by banks, pay less of their trade credit late. Similarly, firms that have long-term relationships with their banks also pay less of their trade credit late.

In Table 7, we repeat our basic specification, putting Trade Credit Paid Late on the left-hand side. Given that this variable is bounded between zero and one, we run the regressions with a two-sided Tobit procedure. (Again, however, we get essentially identical results—both with and without instrumenting—if we use ordinary least squares instead of Tobit.) It should also be noted that the number of observations in Table 7 is reduced from 1,131 to 546, because we do not have the trade-credit data for all of the firms in our sample.

It is in these regressions that instrumenting for bank size is most important. The coefficient on Ln(Bank Size) is small and statistically insignificant in Column 1, when we enter it directly in the regression. But when we instrument for it in Column 2 with Ln(Median Bank Size), the coefficient becomes statistically significant and economically large. In particular, the IV estimate implies that an increase in bank size from the 25th percentile to the 75th percentile raises the fraction of trade credit that is paid late by 17 percentage points, from 26% to 43%. The bottom line is that firms that are forced to borrow from large banks appear to be substantially more credit constrained than those that can borrow from small banks.

When we test formally whether bank size is exogenous in this model, we reject the hypothesis, with a *p*-value of 0.06. This is seen in the Hausman (1978) test in Column 3 of Table 7. The sign of the bias, however, is again interesting. The endogenous portion of bank size (i.e., the residual from the first-stage regression in Column 2 of Table 2) is *negatively* correlated with Trade Credit Paid Late. To the extent that they can choose, firms that are more prone to being credit rationed pair up with smaller banks. This endogenous pattern of firm-bank matching fits with both the theory and all of the other evidence that we have documented so far. Given that small banks are

Table 7
Fraction of trade credit paid late

The dependent variable is the fraction of trade credit the firm pays late. A tobit model is estimated. Ln(Bank Size) is the log of bank assets. Bank Size is expressed in thousands of dollars and Firm Size and Loan Size are expressed in dollars before taking logs. In Column 2, we report instrumental-variable estimates where Ln(Bank Size) is replaced with its predicted value based on Ln(Median Bank Size), the log of the median assets of banks in the area where the firm is located, and Open Market, the fraction of the previous ten years during which there were no restrictions on within-state branching in the firm's state (see Table 2, Column 2). The number of branches in the market includes only branches of the bank from which the firm borrows. Each regression contains dummy variables for whether the loan is a line of credit, whether it is collateralized, and whether the firm has a checking account from the bank. Records is a dummy variable that equals one if the respondent to the survey had documentation to help answer the questions. Bank Size Residual is the residual from the first-stage bank-size regression (Table 2, Column 2) and is used to conduct a test of whether bank size is exogenous. Each regression also includes dummies for the firm's industry (construction, retail, or services) and the year in which the loan was secured (1992–1994). The number of observations is 546. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Independent variables	Models		
	1: tobit	2: tobit/IV	3: tobit
Bank and market characteristics			
Ln(bank size)	0.006	0.044**	0.044**
	(0.006)	(0.021)	(0.021)
Ln(1 + No. of branches)	−0.017**	−0.044***	−0.044***
	(0.008)	(0.017)	(0.017)
Market Herfindahl	0.024	−0.016	−0.016
	(0.112)	(0.114)	(0.114)
Ln(1 + bank age)	0.007	−0.010	−0.010
	(0.010)	(0.014)	(0.014)
Bank size residual (Hausman test)			−0.041*
			(0.023)
Firm and contract characteristics			
Ln(firm size)	−0.002	−0.005	−0.005
	(0.009)	(0.009)	(0.009)
Ln(1 + firm age)	0.022	0.032**	0.032**
	(0.015)	(0.016)	(0.016)
Ln(loan amount)	−0.008	−0.017*	−0.017*
	(0.009)	(0.010)	(0.010)
Line of credit (1 = yes)	0.003	0.000	0.000
	(0.023)	(0.023)	(0.023)
Loan collateralized (1 = yes)	0.042*	0.050**	0.050**
	(0.022)	(0.022)	(0.022)
Checking account (1 = yes)	−0.003	0.036	0.036
	(0.039)	(0.045)	(0.045)
Firm in MSA (1 = yes)	0.066**	0.047	0.047
	(0.030)	(0.031)	(0.031)
Records (1 = yes)	0.028	0.022	0.022
	(0.020)	(0.020)	(0.020)
Log likelihood	12.425	14.090	14.180

better at building relationships based on soft personal information, we should expect firms that are having a hard time raising finance to be especially likely to turn to small banks for help.

Our results for trade credit are especially noteworthy, in the following sense. Some of our other findings—particularly those for distance and the mode of communication—can be seen as consistent with the hypothesis that, because they can better spread fixed costs, big banks use a strictly dominant technology (credit scoring), which in turn gives them an absolute advantage over smaller banks when it comes to small-business lending. But this hypothesis implies that big banks should do *better* at the task of relaxing credit constraints, which is the opposite of what we see in the data.

4.6. Banks vs. bank holding companies: whose size matters?

Any bank in our sample can be either a stand-alone bank, or part of a multi-bank holding company. The measure of bank size that we have been using throughout *does not* include the assets of other banks that are part of the same holding company. Moreover, 65% of our sample firms borrow from banks that are part of holding companies.

To examine the effects of holding-company structure, we try including an additional variable in all of our regressions: the log of assets of the *other* banks in the multi-bank holding company, if any exist. (This variation is not reported in the tables.) Interestingly, we find that, keeping the assets of the firm's own bank constant, the size of the rest of the holding company does not have a meaningful effect on any of the outcomes—i.e., distance, the mode of communication, the length and exclusivity of relationships, and the extent of credit constraints. Even in the few specifications where the size of the rest of the holding company yields a statistically significant coefficient, this coefficient is an order of magnitude smaller than that for the size of the firm's own bank. Similar results emerge if we instead add to our baseline specifications either: (i) a multi-bank holding-company dummy; or (ii) this dummy along with its interaction with the size of the firm's bank. In all cases, the coefficients on own bank size remain essentially unchanged, and the holding-company variables contribute little additional explanatory power.

These patterns can be thought of as supportive of Stein (2002). As argued in Section 2, Stein's control-rights-based model suggests that if decisions within the holding company can be credibly decentralized to the bank level, then the size of the holding company outside of the specific bank in question should not matter much. The evidence can also be rationalized within the explicit-incentives framework of Brickley et al. (2003). At first glance, one might interpret their theory as predicting that it is primarily the size of the holding company that ought to matter, since share ownership by individual loan officers is likely to be negatively related to holding-company size. However, there are other reasons why explicit incentives might be a function of the size of the bank rather than of the holding company. For example, individual bank subsidiaries within holding companies produce their own audited financial statements, which, as described by Blackwell et al. (1994), can facilitate the provision of a variety of performance-based incentives at the bank level (e.g., profit-linked bonuses, promotions, or terminations). And given the existence of such bank-level incentives, standard free-riding arguments might suggest that they would optimally be higher-powered when the bank in question is smaller.

While the distinction between the size of the bank vs. the size of the holding company might not allow us to cleanly separate the theories of Stein (2002) and Brickley et al. (2003), it is more helpful in cutting against other interpretations of some of our results. As noted above, one might argue that our findings for variables like distance simply reflect an *absolute advantage* of big banks. Perhaps credit scoring—and the associated tendency to lend at a greater distance—is just a better technology for lending, but only big banks can afford to use it because it involves substantial fixed costs. However, if this were the case, we would expect the size of the holding company to be the most significant determinant of distance, since the cost of a credit-scoring system can presumably be spread across an entire holding company.

4.7. Robustness: instrumenting with only the state-level regulatory variable

As noted above, it is possible to question the validity of one of our instruments, Ln(Median Bank Size): one can hypothesize that some markets have certain attributes that tend to attract both banks of a certain size and firms with particular characteristics. (One of the most obvious such attributes is population; however, when we replace the MSA dummy in all of our regressions with a log-population control, nothing changes.) So as an alternative, we try dropping Ln(Median Bank Size) and using the state-level regulatory variable Open Market as our only instrument.

On the one hand, Open Market is sufficiently correlated with Ln(Bank Size) that it would appear to be a workable instrument on its own—the univariate correlation between the two variables is 0.227. On the other hand, it is a weaker instrument than Ln(Median Bank Size), which has a correlation of 0.490 with Ln(Bank Size). Thus, this approach, while more conservative, also sacrifices considerable power.

Comfortingly, the results using Open Market as the only instrument are generally very close to those obtained with the two instruments together.[4] Moreover, if we adopt the identifying assumption that Open Market is exogenous, we can for each of our left-hand-side variables conduct a specification test of the hypothesis that Ln(Median Bank Size) is exogenous as well. This hypothesis is never rejected, which lends more support to the notion that Ln(Median Bank Size) is a legitimate instrument.

[4]In the Distance regression, we report in Table 3 an IV coefficient of 0.296 on Ln(Bank Size); this coefficient changes to 0.362 when we use Open Market as our only instrument. With Impersonal Relationship, the IV coefficient on Ln(Bank Size) goes from 0.324 to 0.207, with Relationship Length it goes from –0.150 to –0.189, with Single Lender it goes from –0.526 to –0.485, and with Trade Credit Paid Late it goes from 0.044 to 0.028. In spite of the increased standard errors, the estimates for Distance, Relationship Length, and Single Lender continue to be highly statistically significant (with p-values of 0.002, 0.002, and 0.017 respectively). The estimates for Impersonal Relationship and Trade Credit Paid Late, however, are no longer significant.

5. Connection to the banking literature

There is a large literature on banks' lending practices. Although we cannot provide a full survey of this work, we can sketch some of its broad contours, in an effort to show how our findings fit in. A first category of research has employed regulatory data on banks (such as the Call Reports and the Summary of Deposits used in this paper), *without* being able to match these data to information on the small businesses doing the borrowing. These studies typically find that large banks allocate far lower proportions of their assets to small-business loans than do small banks (e.g., Berger et al., 1995), and that ratios of small-business loans to assets tend to decline after large banks are involved in mergers and acquisitions (e.g., Peek and Rosengren, 1998; Strahan and Weston, 1996, 1998; Berger et al., 1998; Sapienza, 2002). Brickley et al. (2003) document that rural banking offices are more likely to be owned by small banks. Although small-business loans and rural locations are potentially correlated with soft information, these papers do not establish the link between bank size and soft information directly.

A second category of work has examined data on small businesses (such as the NSSBF survey that we use) but, again, without being able to match these data to information on the banks doing the lending. These studies find that stronger bank-borrower relationships are generally associated with better treatment for borrowers, in terms of lower interest rates and reduced collateral requirements (Berger and Udell, 1995), increased credit availability (Petersen and Rajan, 1994, 1995; Cole, 1998), and greater protection against interest rate shocks (Berlin and Mester, 1998). While all of these results help make the case that the soft information embedded in a banking relationship is valuable, none of them speak to the question of what kind of bank is best able to generate and act on soft information.

Finally, a handful of studies have used regulatory data on banks that *are* matched to their small-business borrowers, as in this paper. It has been found that large banks more often lend to larger, older, more financially secure firms (Haynes et al., 1999), and to firms that borrow from multiple banks (Berger et al., 2001).[5] Also, large banks charge relatively low interest rates and have low collateral requirements for small-business loans (Berger and Udell, 1996; Berger et al., 2003). All of these pieces of evidence fit with the idea that, within the general class of small-business loans, large banks systematically try to pick off the largest, safest, and easiest-to-evaluate credits. But it seems fair to say that none of them gets at the underlying mechanism that creates this pattern of behavior.

To our knowledge, only one previous paper has tried to directly examine how lending practices themselves differ between large and small banks. Cole et al. (2004) use survey data to look at the loan approval process across banks of different sizes. They find that for large banks (over \$1 billion in assets), approvals are based primarily on standard criteria obtained from financial statements—a so-called "cookie cutter" approach. In contrast, hard financial numbers have less explanatory

[5]Ongena and Smith (2001) find that large banks have longer relationships with firms, in contrast to our results. However, they use data on larger public firms that have access to other forms of external finance.

power (in an R^2 sense) for the approval decisions of small banks. This is consistent with small banks basing their decisions more heavily on soft information. It also ties in nicely with our results, which—though they are based on an entirely different set of variables and econometric procedures—suggest the same basic conclusions.

Black and Strahan (2002) find that the rate of creation of new businesses goes up in U.S. states that liberalize their banking laws, even while the share of small banks declines. While one might interpret this finding as evidence that small banks are not "special," there are other effects of liberalization. For example, competition increases, which is likely to increase both the number and efficiency of banks of all sizes, and hence to be beneficial for any given size distribution of banks. So it is hard to draw sharp conclusions from their work about whether small banks are particularly good at small-business lending. And conversely, none of our results should be taken to imply that the net effect of liberalization is negative. A similar point can be made about Jayaratne and Wolken (1999), who find that small firms are not more credit constrained in markets where large banks have a bigger fractional share—such markets could simply have a greater overall availability of nearby bank branches of any kind.

Finally, it is worth mentioning a recent paper that examines some of the same themes in the context of a different type of financial intermediation. Chen et al. (2005) show that small mutual funds tend to outperform large ones, particularly when it comes to investing in small-cap stocks that are located close by—i.e., stocks for which soft-information acquisition is likely to be most relevant. And in a striking parallel with our work, they find that it is the size of the *fund*, and not the size of the *fund family*, that matters for performance. Indeed, all else equal, funds belonging to large families actually perform better than those belonging to small families. As with our results for banks vs. holding companies, this would seem to suggest that decentralization of decision-making authority can have meaningful real effects.

6. Conclusions

While there has been much theoretical work by economists on the Coasian topic of organizations and their boundaries, there has been far less empirical work. A particularly under-explored set of empirical issues has to do with the ways in which an organization's form affects its ability to carry out different types of functions. The goal of this paper has been to take some first steps towards addressing these issues.

Our analysis is based on the premise that in small organizations, the center of decision-making authority is likely to be close to the point of information collection. According to Stein (2002), this creates strong incentives for soft-information production in small organizations. In contrast, large organizations have a tougher time providing incentives for their employees to produce soft information, although they tend to do well with respect to the creation of hard information. Large organizations also benefit from having broader internal capital markets—i.e., conditional on having acquired some hard information, they have more scope for actively reallocating resources based on this information. The bottom line is that one might expect small organizations to have a comparative advantage over large ones in activities that require the processing of a lot of soft information, and for the reverse to be true in activities that rely mostly on hard information.

In an effort to test this theory, we examine how banks of different sizes approach the task of small-business lending. We find that large banks lend primarily to larger firms with good accounting records, while small banks lend to more difficult credits. We also find that correcting for the endogeneity of the bank-firm match, large banks lend at a greater distance, interact more impersonally with their borrowers, have shorter and less exclusive relationships, and are not as effective at alleviating credit constraints. These effects are both statistically significant and economically large in magnitude, and they are all consistent with the hypothesis that small banks have a comparative advantage in lending based on soft information.

From a policy perspective, our results suggest that bank consolidation may raise meaningful concerns for small firms. Moreover, the key issue might be not so much about banks having market power in the traditional Herfindahl-index sense but rather, the degree to which firms have choice over the size of the bank they do business with. For it is when they have no choice and therefore have to borrow from large banks that our sample firms appear most prone to being credit constrained.

A similar policy-related observation can be made about the appeal to developing countries of encouraging entry by large multinational banks. Having foreign banking giants set up shop in a developing economy no doubt has a number of significant benefits. For example, they are probably more likely to be stable and financially sound. They might also be less likely to engage in the sort of corrupt related-lending practices documented by LaPorta et al. (2003). Without denying the importance of these factors, our analysis points to a potential tradeoff. If large foreign banks substantially crowd out smaller domestic ones, the supply of loans to informationally opaque small businesses could be negatively affected.

Finally, our results suggest that the standard practice in many countries of setting up large bureaucratic organizations to provide subsidized credit to small businesses (or alternatively, of forcing large banks to do so), might not be very effective. It might make more sense to target subsidies through smaller financial intermediaries, who can better incorporate soft information into their credit decisions.

While our analysis has focused on the banking industry, there are reasons to believe that the conclusions could generalize to a variety of other settings. Small-business lending is not unique in its reliance on soft information. Other relationship-based activities such as investment banking, consulting, and law also make heavy use of soft information. So too do certain kinds of research and new product development. Even some governmental activities, such as law enforcement, may require the creation and efficient use of substantial amounts of soft information. Our results suggest that, in all of these cases, organizational structure might play a crucial role in determining how effectively the job at hand is carried out. It would be instructive to study some of these other activities in detail, to see if this hypothesis is borne out more broadly in the data.

We have also found preliminary evidence—from the holding-company-level data—that seems to indicate that credible decentralization of decision-making can offset the effects of raw organizational size. This raises the possibility that a large organization might, at least to a degree, be able to enjoy the best of both worlds if it sets up an internal structure that achieves the right level of decentralization. Again, this is a conjecture that would greatly benefit from further empirical investigation.

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