Informal Financial Networks: Theory and Evidence

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We develop a model of informal financial networks and present corroborating evidence by studying the role of property brokers in the U.S. commercial real estate market. Our model demonstrates that service intermediaries, who do not themselves supply loans, can facilitate their clients' access to finance through informal relationships with lenders. Empirically we find that, controlling for endogenous broker selection, hiring a broker strikingly increases the probability of obtaining bank finance. Our results demonstrate that even in the United States, with its well-developed capital markets, informal networks play an important role in controlling access to finance.

Research on financial intermediation forms a central part of the theoretical literature in corporate finance. Most of this research focuses on the role of formal financial intermediaries such as commercial banks [Diamond (1984)]. Yet in many economic settings, *informal* financial networks fulfill a critical function in determining access to credit. In the small and medium business finance market lawyers, accountants, insurance agents, consultants, suppliers, customers, and brokers often act as informal financial intermediaries.[1] In developing countries, informal networks of middlemen perform a vital role in the allocation of capital [Burkett (1988) and Cobham and Subramaniam (1998)].

Informal intermediaries are not themselves a source of finance, but they connect borrowers and lenders while providing other commercial services. Despite their pervasiveness and importance, there is little theoretical modeling of their function. It is also difficult to empirically document the nature and significance of informal financial networks. We provide a

We thank the Center for Research in Security Prices and the Dimensional Fund Advisors Research Fund for financial support. Special thanks to Michael Arabe, John Edkins, and Peggy McNamara as well as COMPS.com for providing the U.S. real estate data, and to Bob Figlio, Dave Ingeneri, and CAP Index, Inc., for providing the crime data. We are grateful to Stephen Cauley for his assistance and advice and we have benefited from suggestions and comments from David Barker, Doug Diamond, Eugene Fama, Joe Gyourko, Gordon Phillips, Matthew Spiegel, two anonymous referees, the editor, Maureen O'Hara, and seminar participants at the University of Illinois, University of Maryland, University of Minnesota, University of Chicago, Wharton, UCLA, the NBER Summer Institute on Asset Markets and Real Estate, the Board of Governors of the Federal Reserve, University of Minnesota, and especially Raghu Rajan.
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[1] See, for example, *Business Week*, March 2, 1998, p. 6 ENT.

The Review of Financial Studies Winter 2003 Vol. 16, No. 4, pp. 1007–1040, DOI: 10.1093/rfs/hhg025

theoretical model of informal financial networks and analyze the implications of this model for a unique dataset detailing brokerage activity in the U.S. commercial real estate market. Our empirical evidence is striking in that it demonstrates the importance of informal financial networks, even in the United States, a country with very well-developed capital markets.

Informal intermediaries fulfill a crucial function in markets in which borrowers seek financing relatively infrequently and have little opportunity to develop relationships with lenders themselves. Borrowers who can benefit from this form of cooperation include entrepreneurs seeking business loans, individuals in need of home mortgages, farmers looking for farm loans, and small corporations that require bank financing. The set of loan seekers who profit from the aid of informal intermediaries is wide.

We present a model of a general informal financial network that demonstrates that non-financial intermediaries, who participate in a market over the long-run, can facilitate their clients' access to loans. The central hypotheses tested in this article arise from our theory of cooperation between nonfinancial (or service) intermediaries and lenders. In our model, lenders cooperate with service intermediaries by expending effort to expedite the evaluation of loan applications made by the service intermediary's clients. This allows more transactions to be consummated, generating more fees for the service intermediary. In return, the service intermediary advises his clients to seek a loan from the lender. Borrowers without service intermediaries participate in the market only infrequently and cannot therefore promise future business to a lender. Lenders are thus unwilling to expedite the loan requests of borrowers when no service intermediary is present. Informal networks of service intermediaries and lenders develop as both parties build reputational capital and cooperate.

To test the implications of our theory, we apply the model to the large and significant commercial real estate market.[2] Here a natural service intermediary is the property broker, and the lender with whom he builds a relationship is a bank. Our study shows that brokers serve a central role in providing their clients with access to finance in this market. First, hiring a broker raises the probability that a transaction will be financed with bank debt from 40% to a striking 58%. Second, brokers tend to concentrate their deals among a small set of banks, and brokers whose business is most concentrated among a few banks (i.e., those with the closest ties to a specific set of banks) have the strongest positive influence on their clients' access to finance. Third, brokers and banks in longer relationships grant each other a larger share of their respective businesses. Fourth, brokers with longer histories have a particularly strong effect in increasing the probability of a bank loan for their clients. Finally, brokers who exhibit

[2] The value of outstanding commercial mortgages alone in the United States in 1999 was in excess of $1.3 trillion [Werner (2000)], and this figure does not include the value of commercial real estate equity.

more loyalty (in terms of consistently directing clients) to the bank improve access to finance for their clients by an even greater margin, while disloyal brokers actually decrease the likelihood of obtaining subsequent finance. These results are obtained by instrumenting brokerage activity and therefore do not depend on endogenous broker selection. These findings strongly suggest that brokers and banks develop informal networks that have a significant effect on the availability of finance.

We also consider three alternate theories of brokerage intermediation that would predict an association between broker presence and the frequency of bank finance. First, if brokers monitor banks and acquire useful information about the ability and propensity of different banks to make loans, they may then direct their clients to the bank that is likeliest to grant a loan. Second, brokers may certify properties, and possibly borrowers, encouraging banks to make loans in brokered transactions. This is similar to the certification role played by commercial and investment banks [Puri (1994, 1996)] and venture capitalists [Brav and Gompers (1997)]. Third, sellers who use brokers may do so because they are liquidity constrained and in need of a quick sale. Such sellers are unlikely to provide financing themselves, so buyers in brokered deals may be forced to seek bank financing more aggressively. The evidence for the alternative theories is rather weak and uncompelling.

The rest of the article is organized as follows. Section 1 presents a theory of informal financial intermediation based on cooperative relationships between nonfinancial intermediaries and lending institutions. Section 2 details the commercial real estate data used to examine informal lending channels and describes our econometric approach. Section 3 addresses the endogenous selection of brokers and identifies several instruments for brokerage activity. Section 4 conducts our empirical tests for broker-bank relationships and their influence on financial structure. Section 5 tests alternative theories of broker involvement and financial influence. Section 6 concludes.

1. Theory of Informal Financial Networks

We develop a theory of informal financial cooperation in a lending game. We consider four agents in this market: buyers who need to borrow funds, sellers, service intermediaries, and lenders. Lenders and long-run service intermediaries are long-run players who play every period in an infinitely repeated game. Sellers, buyers, and short-run service intermediaries are short-run players who each play only one period. There are $i > 1$ lenders and $j > 1$ long-run service intermediaries. The number of buyers and sellers is equal in every period t and is denoted by p_t, which may vary from period to period. The number of short-run service intermediaries in period t is given by ss_t, an exogenous variable that may also be time

varying. All players are risk neutral and discount the future using the discount factor $\delta \in (0, 1)$.

This simple game may be thought of as representing many different types of economic activities. For instance, in applying the game to the small business finance market, the buyer would be an entrepreneur seeking some initial capital to establish his firm, lawyers or accountants would act as service intermediaries and lenders would be banks, large financial institutions, or private outside equity sources such as angels. In other corporate settings, the buyer would be a firm seeking to purchase an asset, the lender would be a commercial bank, and the role of service intermediary may be played by a large customer or supplier of the buyer. Alternatively, this model could apply to a developing country in which the buyer is a small producer or farmer seeking to upgrade his physical capital. Private money lenders, rich individuals, and banks act as lenders and produce traders, or goods-conveying middlemen act as service intermediaries. In addition, the model can be used to describe real estate markets in which buyers may be firms or partnerships purchasing a commercial property or individuals purchasing a home, banks and insurance companies provide financing, and commercial or residential brokers function as service intermediaries. In the empirical section we will use our dataset on commercial property transactions and brokerage activity to test some of the implications of the theory we develop below. The model, however, extends beyond this market and may be applied to a number of settings.

Each service intermediary s, both long run and short run, generates $l_s \geq 1$ potential transactions each period, and each transaction involves a buyer and seller. For simplicity we will assume that there is only one service intermediary involved in every potential transaction. There are also l_{us} potential transactions that do not involve a service intermediary. Potential transactions are of either good or bad quality. The present value of the asset to the seller is $n > 0$. A good buyer possesses a short-duration opportunity to increase the value of the seller's asset to $(v + n)/\delta$ next period. A bad buyer will extract the value n from the asset for his personal benefit and leave the asset with a value of zero. Buyers know whether they are good or poor, but initially no one else is privy to this information.[3] A proportion $p \in (0, 1)$ of potential buyers are good. The precise allocation of bargaining power between the buyer and the seller is unimportant for our results. For simplicity we will assume that in all cases sellers play a completely passive role and that the buyer and seller agree to transfer the asset at a price n.

[3] A model in which the quality of the asset is observed only by sellers would be very similar. The main distinction is that in such a model buyers would regard a bank's rejection of their loan application as a negative signal discouraging purchase. A model in which buyers differ in their probability of success would also yield very similar results, as long as parameters are chosen such that all types of buyers benefit from undertaking a purchase. Details are available from the authors upon request.

The consummation of these agreements between buyers and sellers requires that the wealth-constrained buyers receive financing in the amount of $I \in (0, n)$, since buyers hold only $n - I > 0$ in cash. This financing may be obtained from a lender. All lenders are presumed to be individually capable of financing all projects. Since opportunities are of short durations, buyers only have time to seek a loan from one lender. In transactions involving a service intermediary, buyers will seek advice from their service intermediaries about which lender to approach. If the lender does not provide financing, the buyer may liquidate some of his long-term assets inefficiently to provide the required financing. This inefficient liquidation has a cost c to the buyer.

The lenders evaluate all loan applications received in one of two ways. A standard evaluation will distinguish good buyers from bad ones, but requires so much time that only $q/p \in (0, 1)$ of all good transactions can be completed since some opportunities will disappear due to the passing of time. To conduct a standard evaluation, the lender must exert an unverifiable effort cost $e_0 < (qv/2)$. An expedited evaluation also distinguishes good and bad buyers, but does so quickly enough that all good opportunities may be exploited. An expedited evaluation requires an observable but unverifiable effort with cost $e_1 \in (e_0, pv/2)$ on the part of the lender.[4] It is not known in advance to any player whether an expedited evaluation will be required for any particular potential transaction. If the buyer is determined to be good by the lender and the opportunity is still available, the buyer and the lender bargain over the interest rate on the loan. In the bargaining game, the lender and the buyer both simultaneously propose a repayment next period for the loan of I today. If the proposed amounts are identical, then the loan is provided on the agreed terms. If the lender and buyer disagree, the loan is not provided. In the absence of lender financing, a buyer may elect to self-finance, which incurs an inefficient liquidation cost c that is distributed uniformly on the range $[v - \epsilon, v + \epsilon]$ (independently across service intermediaries), for $0 < \epsilon < v/2$. If the transaction is consummated, the service intermediary receives a fixed fee $0 < f < v/2$.

We make the following parametric assumptions. The lender will not approve loans without evaluating them:

$$p(v + n) + (1 - p)(0) < I. \tag{1}$$

Expedited evaluation is ex ante efficient:

$$(p - q)v \; > \; e_1 - e_0. \tag{2}$$

[4] A similar model would allow the bank to exert additional effort in the evaluation process if it wished to employ a more sensitive screening mechanism to ensure that the credit quality of marginal types is always determined and not left ambiguous. The bank may also expend additional effort to negotiate unexpected legal or regulatory roadblocks.

Expedited evaluation is not in the lender's short-term interest:

$$\frac{(p-q)v}{2} \; < \; e_1 - e_0. \tag{3}$$

We also presume that loan application and transaction information is private and is only available to buyers, sellers, service intermediaries, and lenders who participate in the particular transaction.

In our first result, we show that if the discount factor is sufficiently high, then cooperative dyadic relationships between lenders and long-run service intermediaries can emerge.

Result 1. *For sufficiently high $\delta < 1$, there is a subgame perfect equilibrium of the lending game in which*

(i) A set of $i_c > 0$ cooperative long-run service intermediaries follow a strategy of advising all their clients to request loans from one specific lender, where this lender may differ across intermediaries, as long as the intermediary has done so in every previous period and the lender has expedited all the loan requests ever made by its clients. Otherwise the intermediary follows a mixed strategy of recommending that his clients seek loans from every other lender with equal probability. A cooperative long-run service intermediary is said to be in a dyadic relationship with the given lender to which it directs all its customers. All short-run service intermediaries and $i_{nc} = i - i_c > 0$ noncooperative long-run service intermediaries play a mixed strategy of advising their buyers to seek a loan from each lender with equal probability.

(ii) All buyers follow the advice of their service intermediaries, and buyers in deals without a service intermediary follow a mixed strategy of applying for a loan from each lender with equal probability.

(iii) A lender in a dyadic relationship with a cooperative long-run service intermediary expedites all the loan requests made by the clients of this intermediary, and approves all loan requests from good buyers, as long as at least one client of the intermediary has approached the lender in each period, and the lender has expedited all the requests of the intermediary's clients. Otherwise the lender evaluates all the service intermediary's clients' loan requests in the standard manner and approves all loans requested by good buyers. All loan requests made by all other types of buyers are evaluated in the standard manner and approved if the buyer is good.

(iv) The outcome of the bargaining game between a lender and a good buyer is that the lender grants a loan in the amount of I that has a promised repayment in the next period of $(I + (v/2)/\delta)$. Good buyers who were turned down for a loan self-finance if $c \leq v$ if they

have no service intermediary and if $c \leq v - f$ *if they have a service intermediary*.

A proof is given in Appendix A.

In our second result, we show that lenders will not cooperate with any short-run player.

Result 2. *For no value of* δ *is there a Nash equilibrium of the lending game in which a lender provides an expedited evaluation of the application of a buyer without a service intermediary or of the application of a client of a short-run service intermediary*.

A proof is given in Appendix A.

The equilibrium described in Result 1 is robust to changes in the structure of the lending game that make more information public. The strategies described constitute an equilibrium in games in which transactions data is made available to all long-run players or, indeed, all players. The intuition underlying Result 2 that cooperation between lenders and short-run players is unlikely to emerge also holds under varying information structures, as long as some information such as the number of loan applications received by a lender remains private. In almost all settings this is likely to hold. For example, consider a model in which all historical transactions data is available to all players, but the number of loan applications received by a lender is private. If the variation in the number of applications is sufficiently large, then the information content of the public transactions data will be inadequate to sustain cooperation between lenders and short-run players [Kandori (1992)]. Equilibria in which lenders and long-run service intermediaries cooperate will, however, continue to exist.

This model focuses on the service intermediary's role in aiding his clients in securing loans, but service intermediaries also perform other services such as marketing assistance, consulting, legal advice, etc., and it is often these other services that the client is primarily interested in obtaining. For some buyers (e.g., impatient buyers with low discount factors) the value of these services exceeds the service intermediation fee and they engage the service intermediary. Other buyers elect not to pay for a service intermediary. The indirect form of the cooperation, in which lenders reward service intermediaries for business by expediting their clients' loan applications rather than through direct payments, skirts the moral hazard issues and legal restrictions associated with such payments.[5] As a result of these concerns, service intermediary-lender relationships are usually informal, though some service intermediaries and lenders have established formal joint ventures [Stahl (1993)].

[5] Service intermediaries who receive referral fees from lenders might be inclined to direct their clients to the lenders with the highest fees rather than the best loan terms. As a result, clients would disregard the advice

1.1 An application to commercial real estate

We will now develop implications from the theory for our commercial real estate data in order to test its implications. Here we can view the service intermediaries as brokers and the lenders as banks. We will presume that Result 1 describes the equilibrium. Good buyers who do not use brokers receive bank loans with probability q/p. Those who do not receive bank loans self-finance with probability 1/2. This implies that of nonbrokered completed transactions, a fraction $2q/(q+p)$ receive bank financing. Since banks expedite the loan applications of the clients of cooperative long-run brokers, all completed transactions of these buyers receive bank loans. The good clients of brokers who do not cooperate with a bank (whether short run or long run), receive bank financing with probability q/p. Those who do not receive bank loans self-finance with probability $(\max\{\epsilon - f, 0\})/(2\epsilon)$, which implies that $(2q\epsilon)/(q(2\epsilon - \max\{\epsilon - f, 0\}) + p(\max\{\epsilon - f, 0\}))$ of the completed transactions of these buyers receive bank finance. The inequalities

$$1 \geq \frac{2q\epsilon}{q(2\epsilon - \max\{\epsilon - f, 0\}) + p(\max\{\epsilon - f, 0\})} > \frac{2q}{q+p} \qquad (4)$$

provide us with our first prediction.

Prediction 1. *Brokered deals are more likely to receive new bank financing.*

The clients of brokers in cooperative relationships with banks receive expedited evaluations of their loans which leads to more approvals. Clients of brokers who do not have cooperative relationships do not enjoy preferential access to loans, but they are less willing to self-finance than buyers in nonbrokered transactions, since they must pay a broker's commission in addition to engaging in costly self-financing. As a result, buyers with noncooperating brokers are also more likely to use bank finance in completed transactions than buyers without brokers.

In the equilibrium described in Result 1, cooperating brokers send all their clients to one specific bank. Cooperation is dependent upon the bank's ability to verify each period that the broker is sending it at least one buyer. We argue informally that cooperation may be possible with more than one bank, though cooperation can only be maintained with a

of their service intermediaries. In the cooperation model presented in this section, clients share in the benefit given by the lender (higher loan acceptance rates), and will therefore accept their service intermediary's recommendation. From a legal perspective, formal relations between lenders and certain service intermediaries are often prohibited. For example, in the real estate market, lenders and brokers are governed by the ambiguous Real Estate Settlement Procedures Act (RESPA) of 1974. RESPA was interpreted to prohibit lenders from paying fees to service intermediaries in exchange for commercial loan business. Certain formal partnerships between brokers and lenders were permitted. Regulatory changes enacted in 1994 by the Department of Housing and Urban Development (HUD) explicitly exempted commercial loans from the RESPA provisions (*ABA Bank Compliance* 16.3, March 1995).

small number of banks, as it requires repeated interactions and brokers only have a limited number of clients. We extend this intuition to generate Prediction 2.

Prediction 2. *Brokers will concentrate their deals among a small number of banks.*

In the equilibrium in Result 1, there are both cooperating and noncooperating brokers. Only cooperating brokers increase their clients' probability of receiving a bank loan. Cooperating brokers will have a long history of dealing with one bank.

Prediction 3. *Brokers with long bank relationships will have a larger effect on the granting of bank loans than the average broker.*

Brokers who have dealt with a bank for multiple periods are likely to be cooperating banks who will send all their clients to the same bank in the future, as well. The empirical analog for this is that brokers and banks with long relationships should be expected to do more business with each other than with agents with whom they have short relationships.

Prediction 4. *Brokers will direct a greater proportion of their clients to banks with which they have longer relationships.*

In the equilibrium described above, short-run brokers do not develop cooperative relationships with banks. Result 2 shows that it is very hard for such cooperation to arise in equilibrium. Only long-run brokers cooperate with banks and raise their clients' loan approval rates. The formal model distinguishes only between long-run and short-run brokers, but the general intuition is that brokers who have been in the market longer are more likely to participate in cooperative relationships.

Prediction 5. *Brokers who have participated in the market for a longer period of time will have a larger effect on the granting of bank loans than the average broker.*

Buyers seeking financing may also approach a second source of loans, the seller of the property. Sellers are less diversified than banks, making loans by sellers less efficient. Such loans must offer unattractive terms to compensate sellers for the idiosyncratic risk they bear. As a result, such loans, known as vendor-to-buyer (VTB) loans, are less attractive to buyers but may be used to complete transactions.[6]

[6] In private conversations, brokers explained that VTB finance was typically only proffered if the buyer could not secure bank finance. Nothaft and Westfall (1985) argue that seller finance in the residential real

We may incorporate VTB loans into the model by assuming that some sellers are liquidity constrained and apply a discount factor $\beta < \delta$ to next period's cash flows. If the buyer has been rejected by a bank, he may seek seller financing. Since the seller cannot evaluate the buyer and has a low discount factor, he will demand a high interest rate, but for I sufficiently low (i.e., when the buyer provides most of the sales price in cash) and for $(p - q)/(1 - q)$ sufficiently large (i.e., many good buyers are rejected by banks), there are equilibria in which the seller provides finance. A buyer who has a broker is likelier to have been rejected by the bank because he is a bad type. A seller will be willing to offer less financing to such a buyer. That is, only for smaller values of I will sellers finance buyers with brokers in equilibrium.

Prediction 6. *When the buyer does not receive bank financing, the size of VTB loans will be smaller in brokered deals than in nonbrokered deals.*

Finally, since banks must typically approve the assumption of an existing mortgage on a property by a new buyer, broker-bank relationships should also encourage banks to permit the assumption of old mortgages. This will only apply if the broker happens to have a relationship with the bank holding the previous mortgage on the property. It may be the case, however, that the seller will choose his broker with this criterion in mind, or that the seller will receive a broker recommendation from his bank. In both these cases, a broker-bank relationship is possible and will improve the probability that loan assumption will be permitted, in analogy with the model of new bank loans given earlier.

Prediction 7. *Brokered deals are more likely to receive assumed mortgage financing.*

Ideally we would test the conditional prediction that brokered deals are more likely to receive assumed mortgage financing when the broker and the bank have a prior relationship. It is not possible, however, to test the conditional prediction. A screen on prior bank-broker relationships will exclude all cases in which there is no new or assumed loan. (If there is no loan, then there is no bank and hence no bank-broker relationship.) This would leave us with brokers present only in transactions with new or assumed loans, and any regression would therefore exaggerate brokers' influence in aiding their clients to get assumed mortgage financing.

It is the case, however, that conditional on no bank-broker relationship, brokered deals should be equally likely to receive assumed mortgage

estate market is often used by buyers only until they find bank finance on better terms than those available when the transaction was completed. Zinn (1991–1992) and Wilder (1995) indicate that seller financing is used as a last resort in commercial real estate. Garmaise and Moskowitz (2004) provide evidence that seller financing is not used to reduce information asymmetries.

financing. This implies that brokered deals are *unconditionally* more likely to receive assumed mortgage financing, as long as *some* broker-bank relationships exist. The unconditional regression we run is therefore an appropriate (though weaker) test.

2. Data and Methodology

2.1 The U.S. commercial real estate market

Our sample consists of commercial real estate transactions drawn from across the U.S. over the period January 1, 1992, to March 30, 1999, from COMPS.com, a leading provider of commercial real estate sales data.[7] Of the 36,678 commercial real estate transactions reported over our sample period, 22,642 met our initial data requirements (i.e., recorded sale price, financing data, identities of principals, property location, and information on broker activity). The data span 11 states: California, Nevada, Oregon, Massachusetts, Maryland, Virginia, Texas, Georgia, New York, Illinois, and Colorado, as well as the District of Columbia. We define the "city center" as the largest city or cities in each state.[8]

Table 1 reports summary statistics on the U.S. commercial real estate market. Various property types are covered by COMPS. We group properties into three mutually exclusive types: apartments (defined as multifamily dwellings, apartment complexes, condominiums, and townhouses), vacant land, and commercial and industrial buildings. We further identify properties with imminent planned development by assuming that purchasing development firms plan to develop the property in the immediate future. In addition, we presume that properties that are zoned "PUD" (planned unit development)[9] are scheduled for immediate development. Panel A also reports the capitalization rate (cap rate) on the properties, which is defined as net operating income divided by the sale price.

COMPS also provides eight-digit latitude and longitude coordinates of the property's location. From these, we construct characteristics of the local market in which each property resides. For instance, a crime score index for each property location is provided using crime data from CAP Index, Inc. Eight-digit latitude and longitude coordinates are precise to

[7] COMPS collects data on commercial real estate transactions by contacting buyers, sellers, and brokers, and then confirms their reports with each of these parties. The COMPS data are considered very accurate in the industry, and provide information on sale prices, income and expenses, financing data, property types, and buyer, seller, and broker details.

[8] The city centers for each state are defined as follows: CA–Los Angeles and San Francisco; NV–Las Vegas; OR–Portland; MA–Boston; MD–Baltimore and DC area; VA–DC area; TX–Austin and Dallas; GA–Atlanta; NY–New York city; IL–Chicago; CO–Denver. San Diego, CA and Houston, TX were not covered by COMPS over the sample period.

[9] Planned unit development is a zoning designation for property which waives standard zoning requirements and permits the adoption of a set of site-specific development standards.

Table 1
Summary statistics of the U.S. commercial real estate market

	All	City center	Non city	Small deals	Large deals	Apt.	Land	C&I
Panel A: Property characteristics								
No of Sales	22,642	10,815	11,827	11,325	11,317	7,924	4,134	10,584
Age[a]	35.48	42.49	28.85	39.85	31.19	37.78	0	33.63
Development	6.33%	4.74%	7.78%	5.40%	7.26%	3.50%	16.30%	4.70%
Cap. rate[a]	9.35%	9.58%	9.12%	9.16%	9.53%	10.01%	7.59%	8.26%
Personal crime rate	1.52	1.69	1.36	1.62	1.41	1.50	1.48	1.55
Property crime rate	1.92	2.37	1.50	1.99	1.85	2.04	1.60	1.94
Panel B: Market participants								
Buyer distance (median)	193.62	198.72	188.96	113.35	273.95	170.42	203.87	206.04
	(38.47)	(39.90)	(37.76)	(35.80)	(41.86)	(36.46)	(37.40)	(40.57)
Buyer out of state	11.84%	11.84%	11.84%	6.38%	17.29%	8.99%	15.43%	12.56%
Seller distance (median)	255.34	248.79	261.32	195.94	314.77	221.01	231.37	290.17
	(42.87)	(43.60)	(42.34)	(40.65)	(45.45)	(40.41)	(41.55)	(44.94)
Seller out of state	16.34%	16.26%	16.41%	12.10%	20.58%	11.75%	18.05%	19.15%
Broker present	65.23%	67.07%	63.55%	63.65%	66.82%	76.81%	46.71%	63.38%
Buyer is broker	3.22%	4.04%	2.46%	3.25%	3.18%	4.47%	3.48%	2.14%
Seller is broker	2.69%	3.26%	2.17%	2.68%	2.70%	2.73%	3.68%	2.28%
Panel C: Financial structure								
Sale price ($,000)	$2,386	$2,814	$1,995	$355	$4,419	$1,843	$1,491	$3,134
New mortgages frequency	52.16%	53.74%	50.71%	52.54%	51.77%	68.95%	25.11%	49.85%
New mortagages/Price	72.59%	70.94%	75.18%	76.57%	72.21%	75.60%	71.51%	71.16%
Vendor-to-buyer frequency	18.80%	19.47%	18.18%	23.21%	14.39%	17.66%	17.59%	20.00%
Vendor-to-buyer/Price	59.54%	60.64%	58.15%	63.27%	58.68%	50.72%	70.92%	61.17%
Assm. mortgages frequency	5.32%	5.71%	4.96%	5.03%	5.60%	9.59%	1.28%	3.65%
Assm. mortgages/Price	67.37%	69.42%	65.26%	72.23%	67.11%	70.61%	74.53%	64.10%
Loan-to-Value	72.57%	71.19%	74.62%	78.04%	71.99%	74.94%	73.60%	71.10%

Descriptive statistics on COMPS commercial real estate transactions over the period January 1, 1992, to March 30, 1999, are reported. Panel A reports general characteristics of the properties in the database, including the average capitalization rate (defined as net operating income divided by sales price) and local (county) crime index scores for crimes against property and persons, obtained from CAP Index, Inc. Panel B reports information on participation in the commercial real estate market, including the mean and median distance buyers and sellers are from the property, as well as the percentage of sales that employed a broker and where a broker bought or sold on his own behalf. Panel C contains financing information on the real estate transactions. The three types of financing are vendor-to-buyer (VTB), assumed mortgage, and new mortgage. Both the frequency of each type of financing, and the percentage of the sale price each type of financing comprises when it is used are reported. In addition, the sum of all financing used as a fraction of the sale price is reported (total loan/value). All statistics are reported for the whole sample, for transactions within and outside of the largest metropolitan areas (city center — defined as the largest city or cities in each state), for the smallest and largest half of deals, and for apartments (Apt.), vacant land (Land), and commercial and industrial buildings (C&I) separately.

[a] Averages are computed only among those properties containing age and capitalization rate information.

within 10 meters, and CAP Index, Inc. provides crime rate data for this level of refinement. Thus we obtain a *property-specific* crime score.[10] The crime scores measure the probability that a certain crime will be committed in a given location relative to national and local (county) levels of crime. For example, a local crime score of one means that the likelihood of a particular crime being committed is the same in the location as the county average. For brevity, and due to the high correlation among the various crime measures, we employ the homicide rate as a measure of personal crime risk and the larceny rate for property crime risk. The correlation between these two crime scores is less than 0.50, and results in the article are robust to several other crime score measures.

2.1.1 Market participants. Another interesting aspect of our dataset is the detailed information provided about market participants. COMPS provides the location (city and state) of the buyer and seller. Using the latitude and longitude coordinates of each market participant and the property, we compute the actual distance (in kilometers) between these two locations using the arclength formula in Coval and Moskowitz (1999). Our data also contain information on the use of professional brokers (service intermediaries) in the deals. In many cases, the seller hires a broker to list and market the property. It is also common for a second broker, the sale broker, to participate in the transaction by hearing about the listing and finding a potential buyer. In some cases both functions are performed by the same broker. Upon sale of the property, the seller pays the commission to *both* brokers (typically split evenly between them). In any case, brokers are uniformly interested in completing the transaction (and hence receiving their commission) and therefore may be interested in obtaining financing for their clients in order to do so.

Brokers participate in more than 65% of property sales in our database. In a small number of cases the broker acts as a principal rather than an agent, buying (3.2% of the time) or selling (2.7% of the time) the property on his own account. In these cases, the broker is not acting as a service intermediary and therefore we must control for these few occurrences in our empirical analysis. It is clear from Table 1 that broker involvement is pervasive in the commercial real estate market.

2.1.2 Financial structure. We wish to understand financing patterns in the commercial real estate market and how they are related to brokerage

[10] CAP Index, Inc. computes the crime score index for a particular location by combining geographic, population, economic, and education data with local police, victim, and loss reports. The demographic data on population, income, and education levels are derived from the Census Bureau, which reports these statistics for each of more than 100,000 census tracts in the United States. The census tracts typically cover several square block areas within cities and slightly larger areas in more remote locations. For example, Cook County, Illinois, contains 1,352 census tracts.

activity. Our dataset contains detailed financing information for each property transaction. Four types of financing appear in the data. Buyers either use cash, receive financing from the seller (known as vendor-to-buyer or VTB financing), assume an existing mortgage on the property, or obtain a new mortgage from a bank. In many cases, some combination of these financing types is used. While generally little equity financing is used in real estate transactions, COMPS does not track the presence of equity and essentially treats it as cash. Our tests primarily focus on the three other types of financing and the choice between seller and bank financing. VTB loans, while typically junior to bank loans, are not short-term "bridge" financing used to expedite the deal. The maturity of VTB loans is often as long as (or longer than) the maturity of bank loans. Panel C of Table 1 contains information about property financing. In this article, we examine both the frequency and magnitude of each form of financing. We will show how brokerage activity affects these two aspects of financial structure.

2.2 Econometric methodology

The financing variables that serve as dependent variables in our regression models are nonnegative; buyers do not, for example, take out mortgages in a negative amount. In addition, some of our financing variables, such as seller financing, occur less than 20% of the time. These features of the data must be taken into account in our econometric analysis. Ordinary least squares is inappropriate for data censored in this way and adjusted estimators must be used. We analyze the form of financing from two distinct aspects of the data: the frequency of the form of financing and the magnitude of the form of financing when it is present. The descriptive statistics in Table 1 demonstrate that our variables of interest often have a different impact on the frequency and magnitude of a given form of financing. We therefore do not conduct censored regressions [such as Tobit or Powell's (1984) censored least absolute deviation (CLAD) model] in this paper because they combine both types of information into a single model, obscuring this important distinction.

Because of the unique nature of our financing variables, we employ a probit model (binary response) to determine the frequency of the financial contract and the truncated regression model of Cragg (1971) to determine the magnitude of the type of financing when it is present.[11]

[11] We have also employed more robust semiparametric estimators that allow for more general distributions of the error term than the normal. These estimators are the Klein and Spady (1993) binary response model, which allows the error term to be unspecified, and the Powell (1986) truncated regression model, which assumes that the error terms, conditional on the regressors, are symmetrically distributed and unimodal. Since the results from these models were qualitatively similar and generated the same conclusions in the article, we only report the probit and Cragg (1971) estimation results for brevity. Results from the semiparametric estimators are available at http://gsbwww.uchicago.edu/fac/tobias.moskowitz/research/ and from the NBER Working Paper Series website.

We employ the methodology of Fama and MacBeth (1973) to compute robust standard errors on our coefficient estimates. Specifically, we run cross-sectional regressions for each year separately and report the time-series average of the coefficient estimates and use the time-series standard errors of the average slopes to draw inferences. The procedure is the same as running a panel (pooled time-series cross section) regression that weights years equally and allows the constant, slope coefficients, and variable means to change across years. The Fama–MacBeth methodology is a convenient way to account for potential cross-correlations in the residuals and heteroscedasticity, producing robust standard errors that allow for whatever drives the precision of the coefficient estimates.[12]

3. Broker Activity and its Influence on Bank Financing

3.1 Instrumenting brokerage activity

We begin by analyzing the conditions under which brokers are used. In order to account for endogenous selection of brokers by certain types of buyers and sellers, we seek to identify exogenous predictors of brokerage activity that are otherwise unrelated to financial choice for use in instrumental variable regressions. We analyze the choice of hiring a broker by regressing the presence of brokers on property, buyer, and seller characteristics. The dependent variable is one if a broker is present in the deal (acting as an agent, not as a principal) and zero otherwise. The independent variables include both control variables and instruments.

We employ five instruments for brokerage activity that we expect to be unrelated to financial structure, except through their effect on broker presence. The first instrument, *Radius*, measures the population density of the local area in which the property resides, defined as the minimum of the radius which encompasses 100,000 people and 3 miles (obtained from Cap Index, Inc.). We expect more densely populated areas (i.e., those with low *Radius* measures) to have a higher likelihood of broker presence, since brokerage, which involves the physical showing of properties, is likely more cost efficient in these regions.

The second instrument is the *personal* crime score for the property's location. The risk of personal harm or death likely deters broker participation, since they must visit and display the property frequently. Controlling for the property crime rate as well as city-center location, the personal crime rate should not affect the form of financing (loan officers

[12] The Fama–MacBeth procedure does not take into account autocorrelation, but can be easily modified to do so. Our slope estimates exhibit very little autocorrelation, hence an additional adjustment is not necessary. For an example and discussion of the Fama–MacBeth methodology applied to a binary response model, see Fama and French (2001), who report that Fama–MacBeth standard errors are more than two to five times larger than those obtained from simple panel regressions.

need not repeatedly visit the property). Since crime rates are also measured relative to the local county average, this instrument is the orthogonal component of the murder rate once the property crime rate and local crime rates have been accounted for.

The third instrument, σ_{local}, is the standard deviation of capitalization rates of all sales within a 10 mile radius of the property, excluding the property itself. This cross-sectional scaled price variance of the local market indicates the extent of local property quality heterogeneity. Brokers specialize in marketing properties of a specific type and quality and may be expected to avoid more heterogeneous districts. Note the σ_{local} measure differs for each property and, because it excludes the property itself from the calculation, it is not mechanically related to the sale price.

The fourth instrument is the dollar-weighted fraction of brokered deals within a 10 mile radius conducted by a national broker (excluding the property itself).[13] This variable measures the degree to which brokers have penetrated the local market, since national brokers tend to dominate young, remote markets and only over time do smaller, regional brokers emerge. The smaller this fraction, the more developed the local brokerage networks and therefore the higher the likelihood of employing a broker.

Finally, the last instrument we employ is the dollar-weighted Herfindahl index of brokerage activity within a 10 mile radius of the property (excluding the property itself). This index is defined for property j as

$$Herf_j = \sum_{k \in K^j} \left(\frac{\$Brok_{j,k}}{\sum_{k \in K^j} \$Brok_{j,k}} \right)^2, \tag{5}$$

$$\$Brok_{j,k} = \sum_{i \in N^{(j,k)}} \$P_i \tag{6}$$

where $N^{(j,k)}$ is the set of properties within 10 miles of property j (excluding the property itself) which were brokered by broker k, $\$P_i$ is the sale price of property i, and K^j is the set of distinct brokers who brokered a property within a 10 mile radius of property j. If a deal is brokered by two brokers, each is given half credit for the sale. The Herfindahl variable measures the competitiveness of the local brokerage industry. More competitive broker markets (i.e., those with lower Herfindahl measures) should have lower broker commissions and better broker services. Hence broker hiring should be more prevalent in these markets.

Panel A of Table 2 demonstrates that the instruments are successful in predicting brokerage activity. An F-test that the instruments should be

[13] The "national" brokers are the 12 largest national commercial real estate firms. These are Century 21, Coldwell Banker, Colliers International, Cushman and Wakefield Inc., The Galbreath Company, Grubb and Ellis Company, Koll Real Estate Group, Insignia/ESG, Marcus and Millichap Real Estate Investment Brokerage Company, REMAX, The Staubach Company, and Trammell Crow Company.

Table 2
Predicting brokerage activity and its influence on obtaining bank financing

	Panel A: First-stage broker instrumented regression				
Dependent variable	Population radius	Personal crime	σ_{local}	\$ National/ \$ Brokered	Broker Herfindahl
Broker presence (*t*-statistic)	0.037 (0.75)	−0.383** (−2.63)	−0.113* (−1.79)	−1.493* (−1.88)	−3.995** (−2.80)

	Second-stage new bank mortgage financing			
	Panel B: Prob.(newm)		**Panel C: Size**(newm/price)	
Regression model:	Probit		Cragg (1971)	
Noncorporate buyer	0.042 (0.82)	0.084** (2.02)	−0.003 (−0.73)	−0.004 (−1.21)
Seller distance	−0.003** (−2.27)	−0.004** (−2.06)	0.001 (1.53)	0.001 (1.35)
Buyer distance	−0.016** (−4.02)	−0.017** (−3.79)	0.001 (0.49)	0.001* (1.70)
Development	−0.039 (−1.02)	−0.036 (−1.17)	0.001 (0.00)	0.008 (1.53)
Age	−0.001** (−2.13)	−0.001 (−1.49)	0.001 (−1.38)	0.001 (−0.38)
Land	−0.703** (−6.98)	−0.780** (−7.51)	−0.029 (−1.48)	−0.016 (−0.86)
Apartment	0.339** (7.92)	0.385** (7.68)	0.029** (3.15)	0.014** (3.03)
City center	0.016 (1.16)	0.034** (3.33)	−0.001 (−0.20)	−0.003 (−1.04)
Property crime	0.004 (0.42)	0.001 (−0.01)	0.001 (0.92)	0.003** (2.69)
Broker (instr.)	0.757** (3.26)		−0.124* (−1.67)	
Broker		0.380** (16.07)		−0.010** (−6.40)
Log(price)	−0.017 (−1.08)	−0.019** (−2.51)	−0.006** (−2.83)	−0.008** (−6.70)

Panel A reports the first-stage regression coefficients on several exogenous instruments used to identify brokerage activity: radius = minimum mile radius that encompasses 100,000 people or 3 miles, personal crime rate (homicide), variance of capitalization rate of properties within a 10 mile radius (excluding the property itself), the dollar fraction of brokered deals conducted by a national broker within 10 miles, and the Herfindahl index of brokerage activity within 10 miles. Additional regressors include a dummy for noncorporate buyers, seller and buyer distance, dummies for development, property type, and city center, the local property crime rate (larceny rate), and log of the sale price. Panel B reports results from the second-stage probit model regressions of the probability of new bank financing (newm) on the instrumented and noninstrumented broker variable. Panel C reports results from the second-stage Cragg (1971) truncated regressions of the magnitude of new bank financing (dollar amount divided by sale price), truncated to only those observations where the dependent variable is positive, on instrumented and noninstrumented brokerage activity. The time-series average of the coefficient estimates over the period January 1, 1992, to March 30, 1999, and their associated *t*-statistics (in parentheses) are calculated in the style of Fama and MacBeth (1973). All regressions include a constant and state dummies, which are omitted from the table for brevity.

**,* Significant at the 5% and 10% levels, respectively.

excluded from the regression is clearly rejected (at less than the 0.5% level). Broker presence increases significantly when personal crime risk is low and when the local broker market is more competitive. Brokerage activity is negatively related to local property quality heterogeneity and is decreasing in the fraction of nationally brokered deals.

3.2 Do brokers influence the frequency of bank financing?

Panel B of Table 2 reports regressions of the probability of obtaining bank financing on the instrumented measures of brokerage activity and the set of control variables. The regressions are conducted using a two-stage procedure. In the first stage, the presence of a broker is estimated using the instruments and controls from panel A under a linear probability model.[14] In the second stage, the fitted (predicted) values from the first regression are used as explanatory variables in the probability of financing regression. The second-stage regression is estimated under a probit model. Both the first- and second-stage regressions are estimated year by year in the style of Fama and MacBeth (1973).[15]

The results demonstrate a significant and influential role for brokers on the frequency of bank debt employed in the deal. The instrumented broker measure exhibits substantial explanatory power for the probability of obtaining bank financing, supporting the use of the selected instruments. The estimated probability of a bank loan increases from 34% in nonbrokered transactions to a striking 63% when a broker is present, indicating an economically important impact. Employing the more robust Klein and Spady (1993) semiparametric estimation generates an increase in the probability of bank financing from 40% to 58% when a broker is present. These results are consistent with the broker-bank cooperation theory, which predicts a higher frequency of new bank loans (Prediction 1). Of course, there may be many reasons why brokers seem to influence the likelihood of bank financing. We will argue in this and the next section that this influence arises from informal broker-bank relationships. In Section 5 we will present and test alternative theories regarding this result. Our conclusion, however, will be that informal financial networks play the key role in determining capital structure in this market.[16]

3.3 Do brokers influence the magnitude of financing?

Panel C of Table 2 reports Fama–MacBeth regressions of the magnitude of new bank financing on a set of control variables as well as the instrumented measure of brokerage activity. The regression procedure is as above except

[14] This procedure is recommended by Angrist (2000).

[15] Although the Fama–MacBeth procedure produces robust standard errors by allowing anything that results in more variable slope coefficient estimates to determine the standard errors, it does not account for the fact that the broker variable was estimated in the first-stage regression. Fama and French (2002) employ a similar two-stage regression procedure using the Fama–MacBeth approach. The robust standard errors produced by the Fama–MacBeth approach are two to five times larger than those from a simple panel regression. The adjustment to standard errors from taking into account estimation error in the first stage is typically small.

[16] In an interesting recent development, the Federal Reserve and Treasury Department proposed that banks be permitted to offer real estate brokerage services (see, e.g., *The Wall Street Journal*, January 25, 2001, p. A2). A regulatory change of this kind would likely disrupt the broker-bank cooperation we find, as banks would presumably favor their in-house brokerage firms.

that the dependent variable in the second-stage regression is the size of the loan type, expressed as a fraction of the sale price. The second stage regression is run under Cragg's (1971) truncated model. The results demonstrate a weak negative relation between the size of new bank loans and the presence of a broker. While the informal relationship theory makes no prediction about loan size, alternative theories in Section 5 make specific predictions about the loan amount, which we will revisit later.

Finally, Table 2 also reports the results for the noninstrumented endogenous broker variables in the bank financing regressions for comparison. The coefficients on the instrumented and noninstrumented broker variables are highly significant for the probability of bank financing, indicating that broker selection may not confound the likelihood of bank debt. In the truncated regression for the magnitude of the loan, the size of the coefficient on the instrumented broker variable is larger in absolute terms, but is only marginally reliably different from zero, while the noninstrumented broker variable is significantly negative. This suggests that broker selection may be important in this market, and that our instruments help address the endogenous selection. We will revisit the potential influence of endogenous broker selection in Section 5.

4. Testing Broker-Bank Relationships and their Influence on Financial Structure

4.1 Do brokers have relationships with banks?

4.1.1 Broker-bank concentration. If relationships between brokers and banks exist, then Prediction 2 states that a given broker's deals should be concentrated among a few banks. To test this implication, we calculate two measures of broker concentration in banks. The first is the bank Herfindahl index for each broker, defined for broker k as,

$$BankHerf_k = \sum_{b \in B^k} \left(\frac{\#Deals_{k,b}}{\sum_{b \in B^k} \#Deals_{k,b}} \right)^2, \tag{7}$$

where B^k is the set of banks that made loans to clients of broker k, and $\#Deals_{k,b}$ is the number of deals brokered by broker k that involved a loan from bank b. The second broker-bank concentration measure is the largest share of brokered deals involving bank debt that were completed by any one bank. For broker k this is defined as,

$$BankShare_k = \max_{\{b \in B^k\}} \left(\frac{\#Deals_{k,b}}{\sum_{b \in B^k} \#Deals_{k,b}} \right). \tag{8}$$

In order to determine whether brokers concentrate deals among certain banks, we compare the *BankHerf* and *BankShare* concentration measures for a particular broker to similar measures on a matched sample of deals

that were *not* brokered. Since the location of the property, its type, and its size (price) may influence both the likelihood that it is brokered as well as the likelihood that bank financing is received, we form the matched sample of nonbrokered properties to reflect these characteristics. Specifically, for each property brokered by broker k that receives bank financing, we consider the set of nonbrokered properties that also receive bank debt, are within 10 miles of the brokered property, and are of the same type (e.g., apartment, land, or commercial and industrial building). The property in this set closest in size to the brokered property is selected as the match. We compute the bank Herfindahl and bank share measures on this matched sample of firms, as above. To be conservative and to produce a meaningful measure of concentration, we focus on brokers having at least 20 deals in our database. This covers roughly 80% of all brokered transactions. Broker-bank concentration measures higher than those of the matched sample provide evidence that brokers concentrate their deals among fewer banks than non-relationship-driven bank selection would suggest.

The average *BankHerf* measure across brokers is slightly more than 12% while the Herfindahl measure of the matched sample is only 6.16%—a 6 percentage point difference that is statistically significant at less than the 0.5% level (t-statistic = 3.47). Likewise, the average *BankShare* measure (21.89%) is 8.29% higher than the matched sample (13.60%) with a t-statistic of 4.08. This indicates that brokers tend to concentrate their business among a few banks, supporting Prediction 2 and the existence of broker-bank networks.

However, there could be many reasons why brokers concentrate their deals among a few banks. For instance, transaction costs could produce the same outcome. To help distinguish our theory, Prediction 3 states that brokers with long bank relationships will exert a larger influence on the granting of loans than the average broker. This should not be true if the motivation is to reduce transaction costs. To test this implication, we add to the two-stage probit regression from Table 2 an interaction term between the instrumented broker variable and whether the broker has long ties with certain banks. As a measure of broker-bank relations, we define a concentration dummy variable equal to one if the broker's *BankHerf* measure is greater than its matched sample measure, and zero otherwise. This variable is multiplied by the instrumented broker presence variable to indicate whether brokers with more concentrated bank ties improve the likelihood of obtaining bank financing more than other brokers.

As Table 3 indicates, brokers with high concentration measures increase the probability of obtaining bank debt significantly more than other brokers. This is consistent with Prediction 3 if the concentration measure represents the extent of broker-bank ties. Repeating this regression using a concentration dummy that equals one if a broker's *BankShare* is greater than his matched sample, we find the same result. While these results are

Table 3
Broker-bank relationships and their impact on capital structure

	Bank concentration measures		
	Brokered transactions	Nonbrokered transactions	Difference (*t*-statistic)
BankHerf	12.06	6.16	5.89**
			(3.47)
BankShare	21.89	13.60	8.29**
			(4.08)

	Broker-bank longevity measures		
	Dependent variable	Share of broker's deals directed to the bank	Share of the bank's deals done by the broker
Longevity of relationship in years (*t*-statistic)		0.0036**	0.0568**
		(3.15)	(14.98)

	Impact on capital structure Probit model (Fama–Macbeth regressions)		
Dependent variable	Prob.(newm)	Prob.(newm)	Prob.(newm)
Broker (instr.)	1.128**	0.867**	1.029**
	(4.31)	(4.17)	(4.41)
Broker (instr.) × concentration (*Herf*)	0.360**		
	(10.95)		
Broker (instr.) × concentration (*share*)		0.364**	
		(13.45)	
Broker (instr.) × broker longevity			0.020**
			(3.06)

The concentration of brokered deals among banks is reported using two concentration measures: (1) the Herfindahl index of each broker among banks and (2) the maximum share of a broker's deals devoted to a bank. These measures are also computed for a matched sample of nonbrokered deals and their average differences (*t*-statistics in parentheses) are reported. Also reported is the elasticity of the broker's share devoted to a particular bank with respect to the longevity of the relationship between the broker and the bank. This is measured by regressing the broker's share of deals sent to the bank (measured from 1997 to 1999) on the age of the earliest deal the broker had with that bank (measured prior to 1997). This regression is repeated for the bank's share of deals conducted by the broker as the dependent variable. Also reported are results from the two-stage probit model regressions of the probability of new bank financing on instrumented brokerage activity and broker-bank concentration and longevity measures. All regressions include a constant, property, buyer, and seller characteristics, and state dummies, which are not reported for brevity. The time-series average of the coefficient estimates and their associated *t*-statistics (in parentheses) are calculated in the style of Fama and MacBeth (1973).

**,* Significant at the 5% and 10% levels, respectively.

consistent with an informal network, they could also be consistent with an information story where brokers simply use a few good banks. However, as we will see in the next section, not all brokers are using the *same* banks. Each broker concentrates his business among a few banks, but these banks differ across brokers. This is inconsistent with an information story, but is compelling for our relationship theory.

4.1.2 Broker-bank longevity. In addition to concentrating their deals among a select few banks, brokers will have greater influence on banks with which they have a longer relationship. As a measure of the longevity of the relationship between the broker and the bank, we find the earliest date when each broker-bank pair completed their first deal together and

calculate from this the age of their relationship at the time of each subsequent deal. We compute the age of each relationship using only those deals taking place prior to 1997 and then apply these measures to a sample of transactions after 1997.

If brokers and banks develop informal relationships over time, the fraction of the broker's deals devoted to a particular bank should increase over time (Prediction 4). Table 3 indicates strongly that the longer the prior relationship with the bank, the more business the broker sends to the bank. This is consistent with the development of informal networks. We also expect that the share of the *bank's* deals should be more concentrated among a select few brokers over time. Regressing the share of each bank's deals involving each broker on the longevity of their relationship, Table 3 documents a strong positive correlation.[17]

Finally, if broker-bank relationships are important and if longevity helps capture the strength of such relationships, then we should see an even more significant impact on financial structure from brokers with longer bank relationships (Prediction 5). To test this, we examine the interaction between the broker's age and the instrumented broker variable on the probability of obtaining a new bank mortgage. Again, the dependent variable only contains transactions after 1997, while the broker longevity measure is estimated prior to 1997. (In other words, this is an out-of-sample test). As Table 3 indicates, the interaction term is highly significant. Thus brokers with long histories, who have cultivated bank relationships, greatly improve the future likelihood of obtaining bank debt for their clients.

5. Alternative Theories of Brokerage

While the evidence for informal broker-bank relationships is quite strong, it may be that the results can be explained by other theories of brokerage. First, brokers may monitor the loan policies of banks and direct or advise their customers to seek loans from the bank most likely to provide financing. Second, brokers may certify the quality of properties and the creditworthiness of borrowers to lending institutions. Finally, despite our efforts to control for endogeneity, the endogenous selection of brokers by certain types of sellers may contribute to the observed relation between brokerage activity and financing.

5.1 Advisory services

The first alternate theory argues that brokers monitor the loan-granting policies of various banks and advise buyers to seek loans from the bank that can process a given loan with the highest probability. Through their

[17] Standard errors are computed using White's (1980) consistent error covariance estimator.

involvement with many deals, brokers obtain information about various bank lending policies and practices, and convey this information to their clients. Buyers in brokered transactions should therefore be more likely to receive bank finance. It may also be the case that banks recognize this fact and prioritize the processing of loans in brokered deals over loans in nonbrokered deals. Hence this model, like the relationship model, predicts that brokers increase the probability of obtaining bank financing.

The advisory service theory differs from the cooperation theory in several key respects. First, if brokers are searching across the universe of banks for the bank most likely to grant their client a loan, we would expect brokers to have dealings with a large number of banks, particularly if the bank with the loosest lending policy changes over time. For example, the model in Section 1 could be altered so that in each period banks offer loans with different probabilities. Brokers would direct their clients to the bank with the highest probability of granting a loan. In this model, brokered business would be relatively fickle and should be expected to flow toward the banks whose market shares are most increasing. Period-to-period brokered transaction volumes will vary greatly with total bank loan volumes.

On the other hand, if brokers and banks have long-term relationships, then brokerage business should be fairly steady and loyal to the same banks. In the equilibrium described in Result 1, cooperating brokers always send all their clients to the same bank. As a result, the elasticity of a bank's brokerage business with respect to its total loan business should be less than one. This leads to the following prediction.

Prediction 8. *If brokers provide advisory services, then the elasticity of a bank's brokerage business with respect to its total loan business will be greater than one. If banks and brokers cooperate, then this elasticity will be less than one.*

We define brokers with elasticities less than one to be loyal. If brokers provide advisory services, then disloyal brokers, who presumably possess and exploit current market condition information, should be the most helpful in assisting their clients with finding financing. If brokers and banks form relationships, then banks will only reward loyal brokers. In the equilibrium outlined in Result 1, only cooperating brokers are loyal and improve bank loan approval.

Prediction 9. *If brokers provide advisory services, then disloyal brokers will most improve their clients' probability of receiving a bank loan. If banks and brokers cooperate, then loyal brokers will most improve their clients' ability to secure bank financing.*

If brokers make use of information to direct their clients to the source of financing that is currently most obliging, then brokerage clients should be expected to exhibit herding in their choice of banks. To the extent that

brokers have useful information on the best banks to approach for a loan, this information must be correlated. As new information arrives about certain banks, brokers and their clients will systematically flock to banks with the most attractive loan policies and away from those with unattractive ones. If brokers have relationships with banks, however, brokerage business will be fairly stable, and there is no reason to think all brokers will have relationships with the same bank.

Prediction 10. *If brokers provide advisory services, brokers from different firms will herd in directing their clients to the same banks.*

5.1.1 Herding by brokers into banks. If information about bank loan policies drives broker selection of banks, then herding should be prevalent among brokers, as suggested by Prediction 10. To test this, we compute the following measure of herding by brokers in each bank. For bank b, the herding measure is,

$$Herd_b = \left| \frac{\sum_{k \in K} \#Deals_{k,b}}{\#Deals_b} - \frac{\sum_{b \in B} \sum_{k \in K} \#Deals_{k,b}}{\sum_{b \in B} \#Deals_b} \right| - E(|\cdot|), \qquad (9)$$

where K is the number of brokers and B the number of banks in this market. This measure is the absolute value of the difference between the share of bank b's deals that are brokered and the share of all bank financed deals that are brokered. The term $E(|\cdot|)$ is an adjustment factor for the mean of this absolute difference to allow for random variation around the expected proportion of brokered deals under the null hypothesis of independent broker decisions on which bank to direct their clients.[18]

Table 4 reports the level of herding by brokers in banks. The average herding measure is 0.022. This level of herding implies that on average a bank to which brokers herd will transact two more brokered deals out of a hundred total deals than would be expected under random variation. This is not particularly compelling, given that on average 65 deals out of a hundred are brokered. Herding is not generating a significant deviation from that average on a bank-by-bank basis.

It may be, however, that certain banks are herded into more than others. In particular, larger banks, for which information is more readily available, may have more herding, while small banks, for which information

[18] The herding measure in Equation (9) is of the same flavor as those used by Lakonishok, Shleifer, and Vishny (1992) and Wermers (1999) to address stock herding in the money management industry. We follow both of these studies by computing the adjustment factor using simulations under a binomial distribution for each bank employing the actual proportion of brokered deals as the parameter in the simulations. The simulation details are provided in Wermers (1999) and are also available upon request.

Table 4
Broker herding, loyalty, and its impact on capital structure

	Bank herding measures		
	All banks	Small banks (<10 deals)	Large banks (≥10 deals)
Broker herding into banks	0.0222**	0.0064	0.0584**
Different from zero (*t*-statistic)	(6.08)	(1.32)	(14.89)
	Broker-bank loyalty measures		
	All brokers	Small deals (<$10 million)	Large deals (≥$10 million)
Elasticity of business	1.08	0.80**	1.38*
Different from one (*t*-statistic)	(0.77)	(−2.56)	(1.78)
	Impact of loyalty on capital structure Probit model (Fama–MacBeth regressions)		
Dependent variable	Prob.(newm)	Prob.(newm)	Prob.(newm)	Prob.(newm)
Broker(instr.)	1.208**	0.995**	1.021**	0.945**
	(3.33)	(4.12)	(6.06)	(3.97)
Broker(instr.) × loyalty(#)	0.266**	0.026**		
	(7.97)	(2.51)		
Broker(instr.) × disloyalty(#)		−0.019**		
		(−2.61)		
Broker(instr.) × loyalty($)			0.214**	0.042**
			(3.81)	(2.69)
Broker(instr.) × disloyalty($)				−0.025**
				(−4.35)

The loyalty of brokered deals among banks is measured as the elasticity of the change in a broker's share of business with a bank with respect to the change in the bank's share of the commercial real estate loan market. The change in the share of broker business devoted to each bank is measured both by number of transactions (loyalty(#)) and dollar volume (loyalty($)). Herding by brokers in certain banks is measured as the absolute value of the difference between the fraction of a bank's deals that are brokered and the fraction of all bank deals that are brokered, minus the expected value of this absolute difference, which is simulated under a binomial distribution. Average loyalty and herding measures are reported across brokers and banks, respectively (*t*-statistics in parentheses). These measures are also reported separately for brokers with less than and greater than $10 million in transaction volume, and for banks with less than and greater than 10 deals. Also reported are results from two-stage probit regressions of the probability of new bank financing on instrumented brokerage activity and broker-bank loyalty, defined as a dummy variable equal to one if the broker's elasticity measure is less than one. We also report results for the interaction between broker presence and disloyalty (i.e., broker elasticity greater than one). All regressions include a constant, property, buyer, and seller characteristics, and state dummies, which are not reported for brevity. The time-series average of the coefficient estimates and their associated *t*-statistics (in parentheses) are calculated in the style of Fama and MacBeth (1973).

**,* Significant at the 5% and 10% levels, respectively.

may be limited, may not. In addition, as Peek and Rosengren (1996) discover, lending relationships tend to exist most strongly among small banks and smaller market participants. Hence, we would expect low or zero herding among small banks. Recomputing the herding measures for large (i.e., at least 10 deals) and small banks separately, we find that herding is nonexistent among small banks, but is quite strong among the largest banks. This suggests that an information theory may only be relevant among large banks and deals, whereas relationships may be most important among small deals.

5.1.2 Broker loyalty to banks. To better distinguish between the advisory services theory and the theory of informal broker-bank relationships, we examine how loyal brokers are to the banks with which they have dealt. We compute the elasticity of the change in the broker's business directed to the bank with respect to the change in the bank's share of the commercial real estate loan market. The latter captures various factors affecting changes in the way the bank conducts business. More formally, for each broker-bank pair, we compute

$$Elasticity_{k,b} = \frac{\%\Delta\theta_{k,b}}{\%\Delta\omega_b} = \frac{\left(\theta_{k,b}^{>1997} - \theta_{k,b}^{\leq 1997}\right) \Big/ \theta_{k,b}^{\leq 1997}}{\left(\omega_b^{>1997} - \omega_b^{\leq 1997}\right) \Big/ \omega_b^{\leq 1997}} \tag{10}$$

$$\theta_{k,b} = \frac{\#Deals_{k,b}}{\#Deals_k} \tag{11}$$

$$\omega_b = \frac{\#Deals_b}{\sum_{b \in B} \#Deals_b}, \tag{12}$$

where $\%\Delta\theta_{k,b}$ is the percentage change in broker k's share of deals devoted to bank b and $\%\Delta\omega_b$ is the percentage change in bank b's share of the market. Changes are estimated by splitting the sample before and after January 1, 1997. An elasticity less than one indicates that the broker's share devoted to the bank is less sensitive than the market's fickleness toward that bank (i.e., the broker is more loyal to the bank than the market). An elasticity of equal to or greater than one suggests the broker is equally or more sensitive than the market. We designate this a disloyal relationship.

Table 4 reports that the average elasticity measure across all broker-bank relationships is statistically no different from one, which does not lend particular support to either the advisory services or relationship theories (Prediction 8). This suggests either brokers are not loyal or perhaps that some brokers are loyal and some are not, resulting in an average elasticity of one. To test this, we split the sample into the smallest (less than \$10 million) and largest deals. Relationships are more likely exhibited among smaller deals. Table 4 documents that this is indeed the case, as the average elasticity among this group is 0.80 and statistically less than 1 at the 1% significance level. Large deals, on the other hand, exhibit an elasticity greater than one. These findings mirror those found on herding and suggest that informal relationships exist, but are primarily concentrated among the smaller deals, where such relationships are likely most needed and most valuable. Among the larger deals, disloyalty and herding occur, suggesting that information issues may be more pertinent among the largest deals.

Although some relationships may be loyal and some disloyal, and some brokers may be systematically loyal or disloyal, the important question is whether loyalty or disloyalty improves the probability of receiving financing (Prediction 9). To test the impact of loyalty on financial structure, we identify brokers as being loyal or disloyal via their average elasticity measure across the banks they deal with. Dummy variables for loyalty (elasticity less than one) and disloyalty (elasticity greater than one) are created and interacted with the instrumented broker presence variable to be employed as regressors in the binary response regression of the probability of new mortgage financing. Once again, the loyalty measures are calculated using data prior to 1997 and applied to property transactions after 1997, thus avoiding any overlapping sample biases.

As Table 4 reports, loyal brokers significantly improve the likelihood of receiving a bank loan, while disloyal brokers significantly decrease the probability of obtaining bank debt. This is compelling evidence that broker loyalty is important, and strongly supports the hypothesis of informal broker-bank networks pervading this market and influencing capital structure. For robustness, we also repeat these regressions using a broker loyalty measure derived from the dollar volume of broker deals directed to the bank as opposed to the number of transactions. The regressions generate an even stronger impact on financial structure from broker loyalty and negative effect from disloyalty. This is again compelling evidence that informal relationships *not* information/advisory services explain the relation between brokerage activity and financial structure.

5.2 Certification

The second alternate theory we investigate argues that brokers serve a certification role similar to that of venture capitalists [Brav and Gompers (1997)] or commercial and investment banks [Puri (1994) and Lizzeri (1999)]. The analogy to investment bankers is particularly close, since typically neither brokers nor investment bankers have significant equity stakes in the assets they certify. Broker certification will result in brokered transactions receiving loans more frequently and receiving larger loans, as the certified pool is of higher quality than the nonbrokered pool. The presence of a broker should therefore encourage bank finance. More formally, we have Prediction 11.

Prediction 11. *Brokered deals are more likely to receive bank financing, and the size of bank loans will be greater for brokered deals.*

Although the first part of Prediction 11 is consistent with the data, the size of bank loans is *negatively* affected by the presence of a broker. The noninstrumented broker variable has a strong negative impact on loan size, while the instrumented broker variable is marginally negative. This is

inconsistent with a certification story. In addition, the results on broker concentration in banks, broker-bank longevity, and broker loyalty do not seem related at all to a certification story.

Unlike the first two theories, the certification story makes a prediction about the price of the property. Broker certification will reduce the information discount associated with selling a property and should therefore lead to higher average prices.

Prediction 12. *Properties sold through the agency of a broker will receive higher average prices.*

5.3. Broker selection

Finally, despite our efforts to control for endogenous broker selection via instrumental variables, the third alternate theory is that brokers are hired by liquidity-constrained sellers. Knoll (1988) and Yang and Yavas (1995) document that the average time on the market is lower for brokered properties [also see Williams (1998)]. Therefore, sellers who are liquidity constrained may be willing to pay the brokerage commission in exchange for a more rapid sale. Such sellers, however, will be very reluctant to provide VTB financing.

Prediction 13. *Brokered deals will exhibit less VTB financing.*

Liquidity constrained sellers will also be willing to accept lower prices in exchange for much needed current cash flows.

Prediction 14. *Properties sold through the agency of a broker will receive lower average prices.*

Although most of our findings are not consistent with either of these last two theories, we attempt to examine their predictions directly by testing broker's influence on other forms of financing and on market prices.

5.4 Do brokers influence other forms of financing?

Using the two-stage binary response and truncated regressions, we evaluate whether broker presence influences the frequency and magnitude of other forms of financing. As panel A of Table 5 reports, exogenous broker presence has a negative and statistically insignificant effect on the presence of VTB financing, and decreases slightly its size. Moreover, conditional on no bank financing being present, the frequency of VTB increases, and the size of the loan granted decreases significantly, consistent with our relationship model (Prediction 6). Finally, the probability of assuming an existing mortgage increases strongly with broker presence. This is also

Table 5
Do brokers influence other forms of financing and the sale price?

	Panel A: Other forms of financing Binary response probability of (Probit)				Truncated size of [Cragg (1971)]		**Panel B: Sale price** (Least squares)	
	VTB	VTB[a]	Assm	VTB	*VTB/Price*	*VTB[a]/Price*	Cap. rate	Cap. rate
Noncorp. buyer	0.152**	0.363**	0.120**	0.111**	−0.019	−0.004	−0.346**	−0.348**
	(7.89)	(4.65)	(3.30)	(4.43)	(−0.58)	(−0.22)	(−2.35)	(−10.34)
Seller distance	0.001	−0.014**	−0.010**	−0.002	0.003**	0.001*	0.011	0.009**
	(1.31)	(−3.31)	(−3.85)	(−1.28)	(2.72)	(1.90)	(1.53)	(2.17)
Buyer distance	−0.018**	−0.056**	0.002	−0.017**	−0.012**	−0.002	−0.006	−0.007**
	(−8.84)	(−3.59)	(0.70)	(−7.47)	(−4.12)	(−1.52)	(−0.87)	(−2.46)
Development	−0.111**	−0.094	0.012	−0.027	0.012	−0.050**	−0.225	−0.278**
	(−2.18)	(−1.01)	(0.21)	(−0.86)	(0.32)	(−3.67)	(−1.24)	(−2.42)
Age	0.004**	0.006**	0.001	0.005**	0.001**	0.001**	0.002**	0.002**
	(4.58)	(2.77)	(1.53)	(4.46)	(1.98)	(2.44)	(2.25)	(1.98)
Land	−0.367**	−4.580*	−0.276**	−0.433**	−0.045**	−0.091**	−0.124	−0.212
	(−2.02)	(−1.81)	(−3.20)	(−2.36)	(−2.68)	(−4.64)	(−0.42)	(−1.46)
Apartment	−0.089**	−0.025	0.228**	−0.150**	−0.147**	0.049**	−0.299*	−0.246**
	(−2.69)	(−0.41)	(5.16)	(−4.31)	(−5.50)	(4.76)	(−1.66)	(−3.30)
City center	0.008	−0.030	−0.071**	−0.004	−0.045**	−0.006	0.029	−0.018
	(0.48)	(−0.38)	(−2.18)	(−0.37)	(−3.06)	(−0.84)	(0.46)	(−0.29)
Property crime	0.003	0.043*	−0.003	0.010**	0.010*	0.008**	0.167**	0.198**
	(0.42)	(1.65)	(−0.54)	(2.03)	(1.78)	(6.44)	(4.17)	(4.55)
Broker(instr.)	−0.281	1.600**	1.433**		−0.267*	−0.450**	0.494	
	(−1.54)	(2.72)	(5.09)		(−1.66)	(−5.89)	(0.26)	
Broker				−0.224**				0.421**
				(−8.30)				(6.05)
Log(price)	−0.165**	−0.268**	0.081**	−0.190**	−0.036**	−0.015**	−0.144	−0.089**
	(−12.02)	(−7.92)	(3.86)	(−16.64)	(−5.12)	(−3.65)	(−1.58)	(−2.03)

Panel A reports results from the two-stage binary response (probit model) and truncated regressions [Cragg (1971) model] of the probability and magnitude of various forms of financing on instrumented brokerage activity. Three sets of dependent variables are used: vendor-to-buyer financing (VTB), VTB financing conditional on no bank financing being present (VTB[a]), and the assumption of an existing mortgage (Assm). Panel B reports results from the two-stage least squares regressions of capitalization rates (Cap. rate), defined as net operating income on the property divided by the sale price, on instrumented brokerage activity. The VTB and Cap. rate regressions are repeated using the noninstrumented broker presence variable. All regressions include a constant and state dummies, which are omitted from the table for brevity. The time-series average of the coefficient estimates and their associated *t*-statistics (in parentheses) are calculated in the style of Fama and MacBeth (1973).

[a] All property sales that do not employ any form of bank financing.

**,* Significant at the 5% and 10% levels, respectively.

consistent with the relationship theory (Prediction 7), but is not predicted by any other theory.

5.5 Broker selection and the influence on sale prices

Finally, we examine whether brokers influence the market prices of commercial properties. As panel B of Table 5 indicates, there is virtually no effect on price from brokerage activity once endogenous broker selection is taken into account. This generally negative result is striking, given that increasing the sale price is one of the primary brokerage effects described in the literature. The certification theory predicts that brokered deals will have higher prices (Prediction 12) while the endogenous selection of brokers by liquidity-constrained sellers predicts that brokered deals have lower prices (Prediction 14).

We also report the cap rate and probability of VTB financing regressions using the noninstrumented broker presence variable. Comparing the endogenous broker variable results with those employing the instruments, we see evidence of broker selection. The presence of brokers is consistently related to lower-priced properties, but accounting for endogenous broker selection with the instruments, there is no significant broker influence on price. Hence the relation between brokerage activity and price appears to be entirely driven by the type of sellers who choose brokers. The results are inconsistent with the broker certification theory, however. Equally compelling is the negative effect of broker presence on the probability of vendor financing when no endogenous selection is taken into account. Prediction 13 states that brokered deals will exhibit less VTB financing if liquidity constrained sellers tend to hire brokers. When employing the instrumented broker variable in Table 5, however, this relation is no longer significant. Thus broker selection does appear to be important in this market, but our use of instruments seems to account for the endogenous selection.

6. Conclusion

In this article we present a model of informal financial networks and substantiate the model's main predictions in an empirical study of patterns of financing in the U.S. commercial real estate market. We find that informal networks play a significant role in determining access to finance. Our model provides a formal analysis of the financial role of service intermediaries in markets in which borrowers seek loans infrequently and are therefore unable to establish cooperation with lenders. In our empirical analysis, we show that property broker involvement strongly increases the probability that bank debt will be granted. Broker-bank relationships are found to be the most significant feature of the market, and other theories of intermediation perform less well in explaining the data.

The informal financial intermediation described in this article is of significant importance in many settings, but it has not received sustained theoretical or empirical attention in the literature. In the small business market, lawyers provide professional services to their clients and may also aid them in finding private equity or bank loan capital. An accountant or consultant may serve as a client's connection to a local angel network. Small firms often receive guidance in seeking financing from suppliers or customers. In developing countries, various middlemen direct producers and farmers to sources of finance. This article analyzes the role of informal intermediaries and demonstrates that they can be critical in providing access to finance. The results of the article indicate that informal financial networks can have a powerful influence on credit markets and hence on real economic activity, even in highly developed economies such as the United States.

Appendix: Proof of Results

A.1 Result 1

Proof. Consider the strategies described in the statement of the result. We will show that no deviation is optimal in any subgame of the lending game. Short-term service intermediaries and buyers in deals without a service intermediary know that all lenders will handle their applications in the standard manner and bargain over the interest rate in the same (time invariant) way. They are therefore indifferent to the choice of lender.

Long-run noncooperative service intermediaries face a similar choice. Since no change in its strategy will alter the current or future behavior of any lender, a service intermediary is indifferent between all lenders. Long-run cooperative service intermediaries in a dyadic relationship raise their clients' probability of receiving expedited evaluation (and hence raise the probability that the service intermediary will receive its fee) by sending all their clients to the lender with whom they have a relationship. This strategy also guarantees that the service intermediary's future clients will have access to expedited evaluation. All other lenders will always provide the service intermediary's clients with standard evaluation, irrespective of the service intermediary's current or future advice. If the lender with which the service intermediary shares a dyadic relationship has defected in the past by not offering one of the service intermediary's clients expedited evaluation, then the lender will never offer any of the service intermediary's clients expedited evaluation in the future, and the service intermediary is just as well off by recommending other lenders to its clients. Clients of service intermediaries in a cooperative dyadic relationship benefit from an expedited evaluation when they follow their service intermediary's advice. All other buyers are indifferent about taking their service intermediary's recommendation.

Next, we consider the strategies of lenders. Given a loan request from a buyer who is not a client of a service intermediary with whom the lender has a dyadic relationship, the lender's choice of standard or expedited evaluation will not affect any future payoffs; short-run players select lenders randomly and the recommendations of long-run service intermediaries with whom the lender does not have a dyadic relationship are not affected by the lender's current decision. Equation (3) guarantees that the lender prefers to offer these applicants standard evaluation.

Now let us consider the lender's decision whether or not to expedite the loan requests of the clients of a service intermediary with whom the lender has a dyadic relationship. We will consider only the profits arising from the lender's relationship with the service intermediary,

since all other profits are unaffected. Suppose the service intermediary has $\hat{l}_s$ clients this period, all of whom he directs to the bank. If the lender evaluates even one of the clients' applications in the standard manner, it will receive no future clients from the service intermediary. Since evaluating applications in the expedited way is costly in the short run, if the lender elects to evaluate at least one of the applications in the standard manner, it does best to evaluate them all in the standard manner, for which it will receive

$$\hat{l}_s\left(-e_0 + \frac{qv}{2}\right). \tag{13}$$

If the lender evaluates all the applications in an expedited manner and follows its proposed equilibrium strategy, it expects that it will receive at least one application per period from this service intermediary (since $l_s \geq 1$ in every period), so its payoff is at least

$$\hat{l}_s\left(-e_1 + \frac{pv}{2}\right) + \frac{\delta(-e_1 + pv/2)}{1-\delta}. \tag{14}$$

For $\delta \to 1$, the second term in Equation (14) rises to infinity, showing that for δ sufficiently high, the lender will cooperate and expedite all the service intermediary's clients' requests.

Given that both buyers and lenders propose a repayment of $(I + v/2)/\delta$, their strategies in the bargaining part of the game are also optimal. Since self-financing leaves the buyer with $v - c \leq \epsilon < v/2$ (exclusive of service intermediary fees), lender financing is always preferable to self-financing. Good buyers who are rejected by a lender will self-finance if their residual $v - c$ exceeds zero if they have no service intermediary or if it exceeds f if they have a service intermediary. This establishes that the described profile of strategies does constitute a subgame perfect equilibrium.

A.2 Result 2

Proof. Let us consider a candidate equilibrium in which the lender provides an expedited evaluation of the application of a player of either of the two types described in the statement of the result. Suppose the lender changes its strategy by not providing this player with an expedited evaluation. Equation (3) shows that the lender will strictly improve its payoff in the current period. Furthermore, since the lender's decision is not observed by any player who plays in a future period, the strategies of all such players cannot condition on the lender's action this period. This implies that the lender's future payoffs in all periods are unaffected. This shows that a deviation is profitable, so the candidate equilibrium is not an equilibrium.

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