Informal Financial Networks: Brokerage and the Financing of Commercial Properties

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Abstract

This paper examines a significant informal financial network in the U.S. by studying the role of professional property brokers in the commercial real estate market. We find that brokers provide a novel form of financial intermediation by forming informal relationships with banks, directing business to banks in exchange for preferential access to finance for their clients. Controlling for endogenous broker selection, hiring a broker strikingly increases the probability of obtaining a bank loan from 40 to 58 percent. Our results demonstrate that even in the U.S., with its well-developed capital markets, informal networks play an important role in controlling access to finance.

I. Introduction

This paper examines a significant informal financial network in the U.S. by studying the role of professional property brokers in the commercial real estate market. We find that brokers form informal relationships with banks, directing business to banks in exchange for preferential access to finance for their clients. Buyers and sellers must pay brokerage fees in order to enjoy the financing benefits arising from the close cooperation between brokers and banks. We find that hiring a broker raises the probability that a transaction will be financed with bank debt from 40 to 58 percent. Our results strongly support the theory that brokers and banks who transact repeatedly develop relationships and cooperate. Controlling for endogenous broker selection, we find that brokers provide their clients with better access to bank finance through these relationships. We also consider three alternate theories of broker intermediation: monitoring, certification, and endogenous broker selection and find that these theories cannot explain our findings.

This paper provides insights on theories of informal financial networks and on financial intermediation more broadly. Property brokers are commission-compensated agents who deal with multiple principals and assist them in securing finance. Investment bankers play a very similar role for large and medium-sized firms (Beatty and Ritter (1986)). In the small business finance market, lawyers, accountants, and consultants fulfill this function for their clients.[1] Informal networks are also very important in the venture capital market (Mason and Harrison (1997)). It is difficult, however, to document the nature and importance of informal financial networks. In this paper we show that property brokers form long-term relationships with banks and secure access to finance for their clients. We provide evidence on the importance of loyalty and longevity in broker-bank relationships.

Informal financial networks also play an important role in developing countries (Burkett (1988) and Cobham and Subramaniam (1998)). These networks typically perform functions carried out by banks and stock exchanges in more developed markets. Frequent interactions and the resulting development of reputational capital are at the core of these informal lending channels (Ville and Fleming (2000)). Our evidence shows that similar mechanisms are important in the commercial real estate brokerage market in the U.S.

[1] See, for example, *Business Week*, March 2, 1998, p.6 ENT.

In this paper we demonstrate the crucial role played by networks of brokers and banks in determining financing in the U.S. commercial real estate market. Despite the existence of a well-developed bank lending system, brokers with no formal contractual authority perform a critical task in arranging financing. The decentralized and essentially local character of broker networks parallels that of informal financial systems in developing markets. Similar informal communication arrangements are also important in the venture capital market (Mason and Harrison (1997)), and have historically played a broad role in the financing of small businesses (Godley and Ross (1996)). This study demonstrates that informal networks are relevant even in the presence of well-functioning capital markets and provides some evidence on the benefits enjoyed by those with access to these networks.

More generally, research on financial intermediation forms a central part of the theoretical literature in corporate finance. There are several reasons for considering the particular case of broker intermediation. First, broker intermediation is an important form of financial intermediation. Our study shows that brokers serve a central role in providing their clients with access to finance. Brokers intermediate between firms and the bank. This form of intermediation is different from that discussed in Diamond (1984) and Krasa and Villamil (1992). Second, the commercial real estate market is a large and important asset market.[2] It is therefore of significant economic interest to have theories that explain the role of intermediaries in commercial real estate. Finally, the commercial, as opposed to the residential, real estate brokerage industry has received very little attention in the literature (Yang, Trefzger, and Sherman (1997)), despite its size and importance.

Brokerage is an important agency activity, yet the economic function of brokers is not well understood. We analyze the role that brokers play in securing finance for transactions they facilitate, and thereby highlight an important brokerage function that is not well-emphasized in the theoretical literature on these agents. The literature on brokerage has stressed two main broker functions: reducing property time on the market (e.g., Knoll (1988) and Yang and Yavas (1995)) and increasing the realized sale price (e.g., Williams (1998)). Our data does not permit us to analyze the former, but we provide evidence on the latter. We find that hiring a list broker increases the realized sale price only negligibly. We display evidence, however, that brokers significantly improve access to

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

finance, suggesting a new and important role for brokers that has not been well-studied in the literature.

The central hypotheses tested in this paper arise from a theory of broker-bank cooperation. In the course of repeated interactions, brokers and banks may develop a relationship. A bank may agree to grant preferential access to finance to a broker's clients in exchange for the broker directing loan-seekers to the bank. Brokers can reward banks with future business, so banks will prioritize the loan applications of brokerage clients over the applications of buyers without brokers. This theory resembles Diamond (1984), although it is repeated interactions rather than information acquisition that is important here. Informal networks of brokers and banks develop as both parties build reputational capital and agree to cooperate.

Cooperation between a broker and a bank will take the following form. In equilibrium, the bank will approve loans from the broker's clients more frequently than it approves other loans, the broker will direct his clients to seek loans from the bank and the broker's clients will pay the broker for his services. The broker offers a bundle of services including marketing assistance and the financial access just described. For some buyers (e.g., impatient buyers with high discount factors) the value of these services exceeds the brokerage fee and they engage the broker. Other buyers elect not to pay for a broker.

We also consider three alternate theories of brokerage intermediation that predict an association between broker presence and the frequency of bank finance. The first alternate theory is that brokers monitor banks and acquire useful information about the ability and propensity of different banks to make loans. They then direct their clients to the bank that is likeliest to grant a loan. The second alternate theory is that broker certification of properties, and possibly borrowers, encourages 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)). The third alternate theory is that 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 seller finance, so buyers in brokered deals may be forced to seek bank finance more aggressively. The evidence for the alternative theories is rather weak and uncompelling.

Our data contain 36,678 commercial real estate transactions from across the U.S. over the period January 1, 1992 to March 30, 1999. Our sample includes detailed financing information as well as a large set of buyer, seller, broker, and property attributes. Sale price, income and expenses, and property type are also reported. The large size of our data set affords us substantial power, and the extent of property financing and property characteristic information allows for a detailed examination of this market. One contribution of this paper is that we employ the robust semiparametric estimators of Powell (1986) and Klein and Spady (1993), methods that are not yet in general use. The estimates generated by these techniques are regarded as conservative and reliable.

The following is a summary of our main findings. First, we find strong evidence that brokers increase the probability of bank finance dramatically (from 40 to 58 percent). 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 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 for their clients. 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 relationships, and that broker-bank networks have a strong effect in determining the availability of finance.

We demonstrate that providing access to finance is an important brokerage function. Property brokers bundle this financial intermediation service with other complementary services such as marketing the property. The difficulty of monitoring brokers' marketing activities makes a commission schedule the optimal form of broker compensation (Williams (1998)). Commissions are only paid contingent upon sale, so brokers have an interest in completing the transaction. This encourages them to help buyers find financing. Brokers have repeated interactions with banks and can typically influence buyers' choice of bank, so they are able to extract concessions from financial institutions in exchange for future business. Banks will thus favor the loan applications of brokers' customers. Broker-bank networks may enable less qualified borrowers in brokered deals to obtain a loan they would not receive without broker assistance.

The rest of the paper is organized as follows. Section II describes a theory of broker financial intermediation based on informal relationships between brokers and lending institutions. Section III details our data set used to examine informal lending channels, highlighting the various forms of financing in commercial real estate markets and describing the characteristics of properties and market participants. This section also describes the methodology employed in the paper. Section IV addresses the endogenous selection of brokers and identifies several instruments for brokerage activity. These will be employed in our analysis of broker influence on financial structure. Section V conducts our empirical tests for broker-bank relationships and their influence on financial structure and Section VI tests alternative theories of broker involvement and financial influence. Finally, Section VII concludes.

II. Theory of Broker-Bank Cooperation

In this section we develop the theory of broker-bank cooperation that will be examined in our data set. We assume that banks receive deposits that they lend out to firms. Deposit arrivals and loan requests are both random, so in any given period banks may have either too much or too little cash on hand to lend. Capital surpluses are costly to banks in that they have to pay interest to their depositors on money that they cannot lend out. Banks have two types of customers, solitary buyers and buyers accompanied by brokers. Individual buyers engage in few and isolated transactions, while brokers complete multiple transactions each period. In deciding how to allocate its capital, a bank may choose to prioritize one type of buyer. If a bank grants a loan to a solitary buyer, the buyer cannot offer much future business to the bank simply because buyers do not make many purchases.[3] Brokers may counsel their clients on which banks to approach for loans. If a bank grants a loan to a buyer who has a broker, both the buyer and the broker benefit from the consummation of the deal (brokers only receive commissions for completed transactions). A broker will reward a bank that approves its customers' loans by advising its future customers to seek loans from the bank. This will benefit the bank in periods when it is experiencing a capital surplus.

[3]In our data set, most buyers and sellers appear only once, while brokers consummate multiple transactions. Over 64 percent of brokered deals were negotiated by brokers who completed at least 10 transactions, while less than 2.6 percent were completed by buyers involved in at least 10 transactions. Consequently, brokers have much more opportunity to develop relationships with banks.

Brokers and banks interact repeatedly over time and may develop a relationship. A bank may offer to prioritize the applications of a broker's customers in exchange for the broker's agreeing to direct mortgage-seeking buyers to the bank. If the bank cannot profit on a brokered loan (for example, a loan secured against a poor quality property), then it may decline the loan, but, in general, servicing brokers' customers offers the bank direct benefits from the loan business and indirect cooperative benefits in the form of future brokered business. Loans to solitary buyers offer only direct benefits. Let us consider the form of cooperation between a specific bank and broker. In equilibrium, the bank will approve loans from the broker's clients more frequently than it approves other loans, the broker will direct his clients to seek loans from the bank and the broker's clients will pay the broker for his services. The broker offers a bundle of services including marketing assistance and the financial advantage just described. For some buyers (e.g., impatient buyers with high discount factors) the value of these services exceeds the brokerage fee and they engage the broker. Other buyers elect not to pay for a broker.

The model described here is a form of relationship lending similar to that of Diamond (1991), though repeated interactions rather than informational considerations underly this explanation. The indirect form described of the cooperation, in which banks reward brokers for business by approving their clients' loan applications rather than through direct payments, skirts the moral hazard issues and legal restrictions associated with such payments.[4] As a result of these concerns, broker-bank relationships are usually informal, though some brokers and lenders have established formal joint ventures (Stahl (1993)).

Buyers seeking financing may also approach a second source of loans, the seller of the property. Sellers are less diversified than banks, and loans by sellers are inefficient from a diversification standpoint. Such loans must offer unattractive terms to compensate sellers for the idiosyncratic risk that they bear. As a result, such loans, known as vendor-to-buyer (VTB) loans, are less

[4]Brokers who receive referral fees from banks might be inclined to direct their clients to the banks with the highest fees, rather than the best loan terms. As a result, clients would disregard the advice of their brokers. In the cooperation model presented in this section, clients share in the benefit given by the bank (higher loan acceptance rates), and will therefore accept their broker's recommendation. From a legal perspective, formal relations between 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 brokers 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 explicitly exempted commercial loans from the RESPA provisions (*ABA Bank Compliance* 16.3, March, 1995).

attractive to buyers but may be used to complete transactions.[5]

If brokers and banks cooperate, then buyers in brokered deals should receive bank loans more often. Hence, this model makes the following prediction.

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

While brokered deals should receive financing more frequently, the size of the loans received is unclear. Smaller loans may be less attractive to buyers, but the broker is only concerned with completing the transaction. He would prefer that the bank make a small loan rather than none. For diversification purposes, banks will prefer to make many small loans rather than a few large loans, and a strong supply of brokerage business may make this possible. Moreover, the equilibrium implications for the size of the loan are ambiguous. If the effect of the relationship is to make the bank a priori less selective in considering applications in brokered deals, then the size of the loans in such deals may even be smaller than average. No clear prediction about loan size emerges from the model.

When a bank offers a loan to a broker's client, the broker will reciprocate by offering future transactions to the bank. If the bank offers a loan in a case when it is particularly desired by the broker, the broker will be expected to offer greater future compensation in the context of the cooperative relationship. As a result, the bank should be even likelier to offer cooperation when the broker especially needs it.

For instance, if a broker anticipates that seller financing will be difficult to obtain, it will be very important for him to negotiate bank financing for otherwise the deal might not be consummated. If a broker has a relationship with a bank, he will therefore seek to obtain bank financing particularly in those cases where seller financing might be unavailable.

Prediction 2. *The effect of broker presence in increasing the probability of a bank loan is particularly strong when there is no seller financing.*

If relationships between brokers and banks exist in this market, then a given broker's deals will be concentrated among a select few banks. If banks offer brokers special consideration arising from

[5] In private conversations, brokers explained that VTB finance was typically only preferred if the buyer could not secure bank finance. Nothaft and Westfall (1985) argue that seller finance in the residential real estate market is often used by buyers only until they find bank finance on better terms than those available when the transaction was completed.

repeated interactions, then brokers will direct their clients to a small group of lenders. Brokers will direct their clients toward the few banks with which they have a relationship, and these banks will in turn prioritize loans from clients of these brokers.

Prediction 3. *Brokers will concentrate their deals among a small number of banks.*

Furthermore, brokers having strong relationships with banks should increase the probability of their clients receiving a bank loan by an even greater amount than the average broker.

Prediction 4. *Brokers with strong bank relationships will have a larger effect on the granting of bank loans than the average broker.*

One common feature of relationships is that they strengthen over time, as the parties interact repeatedly and demonstrate their good faith. 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. As time passes and the relationship cements, the broker will do more business with the bank.

Prediction 5. *Brokers will direct a greater proportion of their clients to banks with whom they have longer relationships.*

A related prediction is that banks will complete more transactions with brokers with whom they have dealt for a longer period of time.

Prediction 6. *Banks will offer more loans to the clients of brokers with whom they have longer relationships.*

Brokers with long histories of transactions will have had the opportunity to develop well-established relationships with banks. These brokers should thus be better able to secure financing for their clients.

Prediction 7. *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.*

Given the assistance provided by the broker through his relationship with the bank, if the buyer fails to receive bank financing in a brokered deal, then this sends a particularly negative signal about his creditworthiness. Consequently, the seller, who must offer residual financing to complete the deal, will scale back the size of his loan. This provides another prediction from this model.

Prediction 8. *When the buyer does not receive bank financing, the size of VTB loans will be smaller in brokered deals than in non-brokered 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.

Prediction 9. *Brokered deals are more likely to receive assumed mortgage financing.*

III. Data and Methodology

A. The U.S. Commercial Real Estate Market

Our sample consists of 36,678 commercial real estate transactions drawn from across the U.S. over the period January 1, 1992 to March 30, 1999. The data are obtained from COMPS.com, a leading provider of commercial real estate sales data in the U.S., and contain detailed financing information as well as a large set of buyer, seller, broker, and property attributes.[6] 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. COMPS attempts to comprehensively capture property sales across all regions within the states, rather than focus exclusively on the largest metropolitan areas. Defining the "city center" as the largest city or cities in each state,[7] Table I reports that fewer than half of all transactions occur in

[6]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.

[7]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

city centers. Various property types are also covered by COMPS. We group properties into three mutually exclusive types: apartments (defined as multi-family dwellings, apartment complexes, condominiums, and townhouses), vacant land, and commercial and industrial buildings, comprising about 35 percent, 18 percent, and 47 percent of property sales, respectively.

A.1 Property Characteristics

Table I reports summary statistics on the U.S. commercial real estate market. We report statistics for all properties, for properties inside and outside city centers, for the smallest and largest half of property sales, and for apartments, land, and commercial and industrial buildings separately. Panel A contains general information about the properties. The mean age of all properties is 35.5 years, with older properties residing in cities (42.5 years) and younger properties located outside of major cities (29 years). 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)[8] are scheduled for immediate development. Approximately 6.3 percent of property sales are scheduled for development, with a much higher fraction (16.3 percent) for vacant land deals. More development occurs outside of major cities and among larger deals. Panel A also reports the capitalization rate (cap rate) on the properties, which is defined as net operating income divided by the sale price. The average property earns 9.35 cents in income per dollar of value. This ratio is slightly higher for apartments.

COMPS also provides eight digit latitude and longitude coordinates of the property's location. From these, we construct a crime score index for each property location using crime data from CAP Index, Inc., who provide crime scores (risk of personal and property crimes) for location descriptions as fine as eight digit latitude and longitude coordinates within the U.S. Since eight digit latitude and longitude coordinates are precise to within 10 meters, this level of refinement corresponds to a *property specific* crime score which makes the data quite useful. Hence, properties on the same city block can and often do have different crime scores. CAP Index, Inc. computes the crime score index for a particular location by combining geographic, population, economic, and education data with

period.

[8]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.

local police, victim, and loss reports.[9] 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 1 means that the likelihood of a particular crime being committed is the same in the location as the county average. Scores greater than 1 imply an above-average crime risk, and scores less than 1 indicate below-average crime risk. Crime scores range from 0.1 to 20. CAP Index, Inc. scores the seven crimes listed in the FBI's Uniform Crime Reports (UCR) as Part 1 Offenses. These are homicide, rape, robbery, aggravated assault, burglary, larceny, and motor vehicle theft. These crimes are classified into two categories: Crimes against persons (homicide, rape, robbery, aggravated assault), and crimes against property (burglary, larceny, motor vehicle theft).[10] For brevity, and due to the high correlation among the various personal crime measures as well as among the various property crime measures, we employ the homicide rate as our 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 paper are robust to several other crime score measures. Panel A of Table I indicates that the properties in our sample are almost twice as likely to be the scene of a crime than the county average. Not surprisingly, properties in major cities have higher crime levels, and vacant land is subject to slightly lower crime rates.

A.2 Market Participants

Another interesting aspect of our data set is the detailed information provided about market participants. COMPS provides the location (city and state) of the buyer and seller, which we match with latitude and longitude coordinates provided by the *Geographic Names Digital Gazetteer*, published by the U.S. Geological Survey. 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). Buyers are on average 194 kilometers away from the property, while sellers are located more than 255 kilometers away. The respective median distances, however, are approximately the same for buyers and sellers (38 versus 43 kilometers), indicating that distances are highly skewed. Furthermore, we also group market

[9]The demographic data on population, income, and education levels are derived from the Census Bureau, which reports these statistics for each of over 100,000 census tracts in the U.S. 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.

[10]For more details on the construction and composition of the CAP Index, Inc. crime database, see Garmaise and Moskowitz (2000b).

participants more coarsely by state. Only 11.8 percent and 16.3 percent of buyers and sellers, respectively, reside in a different state from the property. The distance between market participants and the property decreases significantly for the smallest deals. These statistics indicate that the commercial real estate market is highly localized, as noted in Garmaise and Moskowitz (2000a).

In addition to buyer and seller location, our data contain information on the use of professional brokers 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 finance for their clients in order to do so. Brokers participate in more than 65 percent of property sales in our database. As Table I Panel B indicates, the use of brokers is far more common for the sale of apartment complexes and far less common for vacant land deals. Finally, in a small number of cases the broker acts as a principal rather than an agent, buying (3.2 percent of the time) or selling (2.7 percent of the time) the property on his own account. It is clear from Table I that broker involvement is pervasive in the commercial real estate market. What role do they serve in this market and how economically important is their function? We attempt to answer these questions by examining the role of brokers, focusing particularly on their influence on client financial access and their impact on financial structure in this market.

A.3 Financial Structure

A main goal of this paper is to understand financing patterns in the commercial real estate market, and how they are related to brokerage activity. Our data set 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 (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. Bank financing is generally cheaper than VTB loans due to the illiquidity and lack of diversification of sellers. VTB financing is often subordinate to bank debt and is generally the residual loan used to complete the deal.

Panel C of Table I contains information about property financing. The average sale price of the properties is just under \$2.4 million, ranging from \$20,000 to \$734 million over the sample period, with a median sale price of \$618,000. Approximately 5 percent of buyers assume an existing mortgage on the property, which typically comprises 67 percent of the purchase price when present. More than 52 percent of buyers obtain a new mortgage, comprising 73 percent of the price when this form of financing is used. Perhaps one of the most interesting features of the commercial real estate market is the extent of VTB financing. VTB financing is used in nearly 19 percent of cases, comprising almost 60 percent of the purchase price when used, and is typically junior to bank loans.

There is little difference between city and non-city transactions in terms of financing choice. Smaller deals use a greater proportion of VTB financing, and vacant land transactions employ bank debt far less frequently than apartment or commercial and industrial building sales. When a bank loan is used in a land deal, however, it typically comprises the same fraction of the sale price as it does for apartments and commercial buildings. In this paper, we examine both the frequency and magnitude of each form of financing, and are careful to distinguish between these two features of the data. Brokerage theories make distinct predictions about the probability of a financial instrument being used as well as the amount of the loan contract. We will show how brokerage activity affects these two aspects of financial structure. Summing all of the debt on each property as a fraction of its sale price, the average loan to value ratio is 72.6 percent across all properties (value-weighted), with only marginal differences across property types. Therefore, the most significant variation exhibited across property types is in the type of debt contract used. In this respect, vendor and bank financing may be considered substitutes.

Finally, Garmaise and Moskowitz (2000a) document that there are no significant sample selection issues associated with the COMPS data, with one notable exception. States that recognize land trusts (these are Illinois and Virginia in our study) have much smaller reported VTB financing relative to bank financing. In a land trust, the owner of real property conveys it to a trust administered by a bank. The owner owns the beneficial interest in the trust and instructs the bank to act on its behalf. Hence, in our data set, when the seller of a land trust provides financing, it is recorded as bank financing, since the bank technically owns the property. Consequently, VTB loans will be understated and new bank loans will be overstated in states where land trusts are recognized. However, we include state dummy variables in all of our regressions to account for this and other potentially confounding effects at the state level.

B. Methodology

Because of the unique nature of our financing variables and recent econometric developments, we run robust semiparametric regression models in our analysis that overcome some of the problems noted in parametric estimators. 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. Our data are also severely censored; in many cases more than 80 percent of a financing variable's data points have a value of zero. Ordinary least squares is inappropriate for data censored in this way and adjusted estimators must be used. We analyze the censored financing data using both the Klein and Spady (1993) binary response model and the truncated regression model of Powell (1986). The appendix details these two regression specifications.[11] These two forms of analysis describe two distinct aspects of the data. The binary response model provides information on the factors determining the frequency of various forms of financing, while the truncated regression indicates which variables increase the magnitude of the types of financing when they are present. The descriptive statistics in Table I 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. In addition, censored estimators such as Powell's (1984) CLAD model are not identified for our data set because of its unusually high degree of censoring.

In addition to these robust estimators, for both the binary response and truncated regressions, we employ the methodology of Fama and MacBeth (1973) to compute robust standard errors on our coefficient estimates. Specifically, we run the regressions for each year separately and report the time-series average of the coefficient estimates along with their associated time-series t-statistics. The Fama-MacBeth methodology accounts for potential cross-correlations in the residuals by run-

[11] The binary response model of Klein and Spady (1993) is a robust semiparametric single index model that allows the error term to be unspecified. The truncated regression of Powell (1986) is a robust semiparametric estimator that is consistent and asymptotically normal under the assumption that the error terms, conditional on the regressors, are symmetrically distributed and unimodal. For further details about these robust regression models and their advantages, see the appendix, as well as Klein and Spady (1993), Powell (1986), and Garmaise and Moskowitz (2000a).

ning regressions separately for each year. This 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. An advantage of the Fama-MacBeth procedure is that it does not require a constant panel of firms and the standard errors of the average slope coefficients allow for whatever drives the precision of these estimates.[12]

IV. Broker Activity and its Influence on Bank Financing

A. Instrumenting Brokerage Activity

We begin by analyzing the conditions under which brokers are used. The goals of this analysis are twofold. First, 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. That is, since the choice of employing a broker in a deal is an endogenous decision, there may be unobservable attributes that determine the broker's presence and are correlated with the financial decision. We control for this using instrumental variables. Second, brokerage is an important aspect of the commercial real estate market, and it is useful to understand which buyer, seller, and property attributes are associated with the hiring of brokers.

We analyze the choice of hiring a broker by regressing the presence of various types 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 a dummy variable indicating if the buyer is not a corporation, seller and buyer distance from the property, a dummy indicating whether the property is slated for immediate development, the property's age, dummies for property type (apartment and vacant land), a dummy for properties located in major cities (City-center), the crime rate score for crimes against property, and the log of the sale price. State dummies are also included as regressors, but their coefficient estimates are omitted from the table for brevity. The Klein and Spady (1993) binary response model requires setting one of the regression coefficients to a constant for scale normalization. We set the coefficient on log(Price) to 1 for scale normalization based on logit regression results that indicated a negative

[12] For an example and discussion of the Fama-MacBeth methodology applied to a binary response model, see Fama and French (2000). In addition, they report that Fama-MacBeth standard errors are more than 2 to 5 times larger than those obtained from a pooled time-series cross-sectional panel regression that ignores residual cross-correlation.

and statistically significant coefficient estimate on log(Price) (for further details on this model, see Klein and Spady (1993) and Garmaise and Moskowitz (2000a)).

In addition to the control variables, which may be related to both broker presence and financial choice, we employ five instruments for brokerage activity that we expect to be unrelated to financial structure, except through their effect on broker presence. These instruments are added to the previously described regressors to predict the presence of a broker. The first instrument, *Radius*, measures the population density of the local area in which the property resides. The population density radius is defined as the minimum of the radius which encompasses 100,000 people and 3 miles (this data is 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, however, the personal crime rate should not affect the form of financing (loan officers need not repeatedly visit the property). Since crime rates are also measured relative to the local county average, this instrument is really 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 variable measures the cross-sectional price variance in the local market and indicates the extent of local property quality heterogeneity. Brokers specialize in marketing properties of a specific type and quality and can be expected to avoid districts with a wide diversity of varying properties. 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

[13]The "national" brokers are the 12 largest national commercial real estate firms in our data base. 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.

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 (this measure also excludes the property itself). This index is defined for property j as

$$Herf_j = \sum_{k \in K^j} \left(\frac{\$Brok_{j,k}}{\sum_{k \in K^j} \$Brok_{j,k}} \right)^2, \tag{1}$$

$$\$Brok_{j,k} = \sum_{i \in N^{(j,k)}} \$P_i \tag{2}$$

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 one-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.

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

B. Broker Influence on Obtaining Bank Debt

Using these instruments to generate exogenous variation in the presence of a broker, we examine whether broker presence influences the probability of obtaining a new bank loan or the size of the loan. Panel B reports the results from a regression of the frequency of bank financing on the instrumented measure of brokerage activity plus a set of control variables for property, buyer, and seller characteristics. The regressions are run for each year separately under the Klein and Spady (1993) binary response model and the time-series average of the coefficient estimates along with their associated time-series t-statistics are reported in the style of Fama and MacBeth (1973). Panel C reports regressions under Powell's (1986) truncated model, where the sample is truncated to only those observations for which bank financing is used. The dependent variable is the size of the loan as a fraction of the sale price. These regressions determine the relation between brokerage activity and the size of the loan. Again, the regressions are run separately for each year and the time-series average of the coefficient estimates and time-series t-statistics are reported in the style of Fama and MacBeth (1973). Both our theoretical predictions and our subsequent analysis illustrate the importance of examining the frequency of loan type separately from the size of the loan.

C. Do Brokers Influence the Frequency of Bank Financing?

Table II Panel B reports Fama-MacBeth 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 the Klein and Spady (1993) binary response model, in which the dependent variable is one if bank financing is used in the deal and zero otherwise. The regressions are conducted 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 in non-brokered transactions is 40 percent, in contrast to a 58 percent probability of a bank loan in the presence of a broker. (These probabilities are calculated at the median values of the exogenous variables.) The imputed increase in probability of obtaining bank debt from hiring a broker is thus a striking 18 percentage points, indicating an economically important impact from broker presence. 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. But, in Section VI, we will present and test alternative theories regarding

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

[15]In addition to producing robust standard errors that account for cross-correlations in the residuals, the Fama-MacBeth procedure, because it simply takes the time-series average of the coefficient estimates, implicitly produces standard errors that reflect the fact that the broker variables were estimated from the first-stage regression. Because the instrumented broker variables are themselves estimates, this will result in more variable slope coefficient estimates in the second stage regression, which will be accounted for in the Fama-MacBeth procedure by producing larger time-series standard errors of those slope estimates.

broker financial intermediation. Our conclusion, however, will be that it is these informal financial networks that play the key role in determining commercial real estate capital structure.

We also examine the influence of brokers on the probability of new bank financing when no seller financing is provided. Under the broker-bank cooperation theory, brokers would exploit their relationships with banks most strongly when other forms of financing are unattainable (Prediction 2). As Table II demonstrates, the effect of broker presence on new bank financing is three times stronger when no seller financing is present. Hence, the relative advantage of brokers is particularly strong in these cases, supporting this model.

D. Do Brokers Influence the Magnitude of Financing?

Table II Panel C 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 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 Powell's (1986) truncated model, in which the sample is first truncated to only those observations with a positive dependent variable. The results demonstrate a negative but fairly insignificant relation between the size of new bank loans and the presence of a broker. This is consistent with the broker-bank cooperation theory, which does not make an unambiguous prediction about loan size.

Finally, Panel D of Table II employs the non-instrumented endogenous broker variables in the bank financing regressions for comparison. The coefficients on the instrumented and non-instrumented broker variables are highly significant and similar in magnitude in the probability of bank financing regression, indicating that broker selection may not confound the likelihood of bank debt. However, in the truncated regression for the magnitude of the loan, the instrumented broker variable generates a much weaker relation between loan size and broker presence than the non-instrumented variable. This signifies both that broker selection may be important in this market, and that our instruments address the endogenous selection. We will revisit the potential influence of broker selection in Section VI.

V. Testing Broker-Bank Relationships and Their Influence on Financial Structure

The previous regressions highlight an important role for brokers in increasing the likelihood of obtaining bank debt. While this result may be consistent with many theories of broker financial intermediation, we will argue in this section that brokers develop informal relationships with banks, which leads to their influence on property financing. In this section, we test directly whether brokers and banks have relationships and how this influences financial structure in the commercial real estate market.

A. Do Brokers Have Relationships with Banks?

A.1 Broker-Bank Concentration

If relationships between brokers and banks exist, then a given broker's deals should be concentrated among a small selection of banks. Prediction 3 states that if relationships are important, then brokers will concentrate their deals 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,

$$BankHerf_k = \sum_{b \in B^k} \left(\frac{\#Deals_{k,b}}{\sum\limits_{b \in B^k} \#Deals_{k,b}} \right)^2, \tag{3}$$

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,

$$BankShare_k = \max_{\{b \in B^k\}} \left(\frac{\#Deals_{k,b}}{\sum\limits_{b \in B^k} \#Deals_{k,b}} \right). \tag{4}$$

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 non-brokered properties to reflect these characteristics. Specifically, for each property brokered by broker k that receives bank financing, we consider the set of non-brokered 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, supporting the broker-bank network hypothesis. To test for broker-bank concentration, we compute the difference between the true and matched sample concentration measures for each broker and average the differences across all brokers. If brokers do not concentrate their deals among certain banks in an unusual way, then this difference will be statistically indistinguishable from zero.

Table III reports this average difference across all brokers for both the Herfindahl and share concentration measures. The average $BankHerf$ measure across brokers is slightly greater than 12 percent, while the Herfindahl measure of the matched sample is only 6.16 percent, resulting in a 6 percentage point difference that is statistically significant at less than the 0.5 percent level (t-statistic = 3.47). Likewise, the average $BankShare$ measure (21.89 percent) is 8.29 percent higher than the matched sample (13.60 percent) with a strong t-statistic of 4.08. This indicates strongly that brokers tend to concentrate their business among a few banks, supporting Prediction 3 and the existence of broker-bank networks.

Prediction 4 states that brokers with strong bank relationships will exert a larger influence on the granting of loans than the average broker. To test this implication, we repeat the two-stage binary response regression from Table II of the probability of new bank financing on a set of control variables and the instrumented broker variable. In addition, we add an interaction term between the instrumented broker variable and whether the broker has strong ties with banks. As a measure of strong 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 stronger bank ties improve the likelihood of obtaining bank financing more than other brokers. The broker presence variables are again instrumented to control for the endogenous selection of brokers.

As Table III indicates, brokers with strong bank ties (high concentration measures) increase the probability of obtaining bank debt significantly more than other brokers do. This is consistent with Prediction 4 and suggests that the concentration measure represents the strength of broker-bank ties. Repeating this regression using the $BankShare$ measures to compute a concentration dummy which equals one if a broker's $BankShare$ is greater than his matched sample, we find the same result. Brokers who concentrate their deals among fewer banks, and thus likely have stronger ties with these banks, further improve their clients' probability of obtaining bank debt.

A.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 long 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. Specifically, 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, then the fraction of the broker's deals devoted to a particular bank should increase over time. Prediction 5 states that the share of a broker's deals devoted to the bank will increase with the longevity of its relationship with the bank. To test this, we regress the share of the broker's deals involving a particular bank after 1997 on the length of their relationship (number of years since their first deal), measured *prior* to 1997. Table III 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. Relationships, however, should work both ways. That is, not only should the broker's business become more concentrated over time among certain banks, but also 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 III documents a strong positive correlation, consistent with Prediction 6.[16]

Finally, if broker-bank relationships are important and if longevity helps capture the strength

[16]Standard errors are computed using White's (1982) consistent error covariance estimator.

of such relationships, then we should see an even more significant impact on financial structure from brokers with longer bank relationships (Prediction 7). To test this, we regress the probability of obtaining a new bank mortgage on the instrumented broker presence variable plus an interaction term between the broker's age and the instrumented broker measure. To ensure that we do not bias the outcome, the dependent variable only contains transactions after 1997, while the broker longevity measure is estimated prior to 1997. The independent variables also include the buyer, seller, and property controls used previously plus state fixed effects. The regression is run under the Klein and Spady (1993) binary response model in the style of Fama and MacBeth (1973). As Table III indicates, the interaction term is highly significant and in fact eliminates the significance of the broker variable itself. Thus, brokers with long histories who have cultivated bank relationships greatly improve the likelihood of obtaining bank debt for their clients, while young brokers, who have not established these relationships, do not increase the probability of bank financing significantly.

The accumulated evidence in Table III indicates that brokers develop relationships with banks and that certain brokers (those with stronger bank relations) improve financial access for their clients by an even greater margin. This establishes the importance of broker-bank networks and demonstrates that cultivating relationships with banks is a valuable service provided by brokers for their clients.

VI. 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. In this section we will consider three alternate theories of broker intermediation. The first theory is that 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. A second possibility is that 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. Specifically, liquidity-constrained sellers, anxious to complete a sale quickly, may be more likely to hire brokers and are less likely to provide seller finance.

A. Advisory Services

The first alternate theory argues that brokers monitor the loan-granting policies of various banks and encourage buyers to seek loans from the bank that can process a given loan with the highest probability. In this sense, brokers may provide a financial advisory service to buyers. Through their 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 non-brokered deals. Hence, this model, like the relationship model, predicts that brokers increase the probability of obtaining bank financing (Prediction 1). As for the cooperation theory, however, the size of loans in brokered deals is not unambiguously predicted by this model.

The advisory service theory differs from the cooperation theory in several 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.

Prediction A1. *If brokers provide advisory services, then brokers will distribute their deals among a large number of banks.*

If certain banks become more competitive and offer better rates and easier credit, then their market share should increase. If brokers provide advisory services, then brokers should direct their clients to these banks. In other words, brokered business should be relatively fickle and should be expected to flow towards the banks whose market shares are most increasing. Period-to-period brokered transaction volumes will vary greatly with total bank loan volumes. If brokers and banks have long-term relationships, however, then brokerage business should be fairly steady and unwavering. Cooperation between banks and brokers should dampen short-term fluctuations in the loan business. Brokers will be loyal in consistently directing business to the same banks. As a result, the elasticity of a bank's brokerage business with respect to its total loan business should be less than one.

Prediction A2. *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 to find financing. If brokers and banks form relationships, then banks will only reward loyal brokers. In this case, clients of loyal brokers will be most advantaged in seeking bank loans.

Prediction A3. *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 finance.*

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. Once a bank begins to offer more competitive terms and looser credit, many brokers will direct their clients to this bank. 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 will the same bank.

Prediction A4. *If brokers provide advisory services, brokers from different firms will herd in directing their clients to the same banks.*

Prediction A1 does not seem to be borne out by the data, as brokers are highly concentrated in a few banks and, moreover, the most concentrated brokers improve the probability of bank financing by the greatest margin. These findings appear inconsistent with the information/advisory services theory. We also test this theory directly, however, by examining the other three predictions of this model.

A.1 Herding by Brokers into Banks

As a direct test of the information/advisory service theory, we analyze whether brokers herd among banks. If information about bank loan policies drives broker selection of banks, then herding should be prevalent among brokers, as suggested by Prediction A4. To test this, we compute the following measure of herding by brokers in each bank. For bank b, the herding measure is,

$$Herd_b = \left| \frac{\sum_{k \in K} \#Deals_{k,b}}{\#Deals_b} - \frac{\sum_{b \in B} \sum_{k \in K} \#Deals_{k,b}}{\sum_{b \in B} \#Deals_b} \right| - E(|\cdot|) \tag{5}$$

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 banks 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. The herding measure in equation (5) 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.[17]

Table IV reports the level of herding by brokers in banks. The average herding measure is 0.022 and is statistically greater than zero. Thus, there does appear to be some herding by brokers in banks, but it is not economically significant. This level of herding may be interpreted in the following way. 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; a bank to which brokers are not herding will transact two fewer brokered deals out of a hundred total deals. 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 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, we find that herding is non-existent 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.

[17]The simulation details are provided in Wermers (1999) and are also available upon request.

A.2 Broker Loyalty to Banks

To better distinguish between the advisory services or information theory and our conjecture about informal broker-bank relationships, we examine how loyal brokers are to the banks they have dealt with. Prediction A2 states that brokers will continue to send business to the banks they have relationships with, even when the bank's total volume declines for any reason. In other words, if brokers have relationships with banks, we should see loyalty among brokered deals with banks. Conversely, if information about bank loan granting policies drives the relation between broker involvement and financial structure, then we would expect brokers to be disloyal to banks. That is, when new information arrives about the bank, brokers will shift their business accordingly to reflect that information. Hence, broker business directed to the bank should be very sensitive to changes in the bank's loan policies or share of the market. If relationships exist, however, then brokers will be less sensitive to changes in the bank's business, and broker business directed to the bank will be sticky.

To test these conjectures, 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

$$Elasticity_{k,b} = \frac{\%\Delta\theta_{k,b}}{\%\Delta\omega_b} = \frac{\left(\frac{\theta_{k,b}^{>1997}-\theta_{k,b}^{\leq 1997}}{\theta_{k,b}^{\leq 1997}}\right)}{\left(\frac{\omega_b^{>1997}-\omega_b^{\leq 1997}}{\omega_b^{\leq 1997}}\right)} \tag{6}$$

$$\theta_{k,b} = \frac{\#Deals_{k,b}}{\#Deals_k} \tag{7}$$

$$\omega_b = \frac{\#Deals_b}{\sum\limits_{b\in B}\#Deals_b} \tag{8}$$

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. Alternatively, this measure can be viewed as the coefficient from a regression of $\%\Delta\theta_{k,b}$ on $\%\Delta\omega_b$. An elasticity less than 1 indicates that the broker's share devoted to the bank is less sensitive than the market's fickleness toward that bank (e.g., the broker is more loyal to the bank than the market). An elasticity of equal to or greater than 1 suggests the broker is equally or more sensitive than the market. We designate this a disloyal relationship.

Table IV reports that the average elasticity measure across all broker-bank relationships is statistically no different from 1. This suggests either brokers are not loyal or perhaps that some brokers are loyal and some are not, resulting in an average elasticity of 1. Moreover, brokers may have informal relationships with some banks but not others, resulting in some loyal partnerships and some disloyal interactions. 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 IV 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 1. 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. If brokers have better information about bank loan policies, then disloyalty (an indicator of new information about banks) should increase the probability of obtaining bank debt, according to Prediction A3. The relationship or cooperative theory, however, makes exactly the opposite prediction. If relationships are important in this market, then loyal brokers will greatly improve the probability of receiving bank financing and disloyalty should reduce the likelihood of garnering bank debt.

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 1) and disloyalty (elasticity greater than 1) 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. The regressions are run under the Klein and Spady (1993) model in the style of Fama and MacBeth (1973) and include all of the buyer, seller, and property controls, as well as state dummies, used previously. These coefficient estimates are not reported for brevity.

As Table IV 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 explains the relation between brokerage activity and financial structure.

B. 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 non-brokered pool. The presence of a broker should therefore encourage bank finance. More formally,

Prediction B1. *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 B1 is consistent with the data, the size of bank loans is marginally *negatively* affected by the presence of a broker. 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 models, this model makes a prediction about the price of the property. Broker certification reduces the information discount associated with selling a property and should therefore lead to higher average prices.

Prediction B2. *Properties sold through the agency of a broker will receive higher average prices.*

C. Broker Selection

Finally, 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. 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 C1. *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 C2. *Properties sold through the agency of a broker will receive lower average prices.*

Most of our findings are not consistent with either of these last two theories. For instance, the fact that certain types of brokers (loyal, greater longevity, and more concentrated) have a greater impact on financial access than others is unlikely related to the creditworthiness of the buyer or property (to be consistent with certification) or the type of seller who might hire a broker (to be consistent with selection). Nevertheless, we attempt to examine the predictions of these last two theories directly by testing broker's influence on other forms of financing and on market prices. This will also provide additional tests on the strength of the relationship hypothesis.

D. 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. We examine the presence and magnitude of vendor (VTB) financing, VTB financing when no bank financing is present, and the probability of assuming an existing mortgage.[18] Once again, we instrument brokerage activity and compute estimates in the style of Fama and MacBeth (1973). As Table V reports, exogenous broker presence has little influence on either the presence or size of VTB financing. Conditional on no bank financing being present, the frequency of VTB increases but the size of the loan granted decreases. Finally, the probability of assuming an existing mortgage also increases with broker presence. This is consistent with a relationship theory (Prediction 9) but is not predicted by any other theory.

[18] The size of an existing mortgage obviously cannot be chosen.

E. Broker Selection and the Influence on Sale Prices

Finally, we examine whether brokers influence the market prices of commercial properties. Table VI reports the results of Fama-MacBeth regressions of property capitalization rates on the various instrumented measures of brokerage activity and control variables. The same two stage procedure is conducted, in which the second stage is estimated via least squares, since cap rates are neither censored nor truncated. As Table VI indicates, there is virtually no effect on price from brokerage activity. This generally negative result is striking, given that increasing the sale price is one of the primary brokerage functions described in the literature. Neither the cooperation nor advising theories make predictions about brokers influencing prices. The certification story, however, predicts that brokered deals will have higher prices (Prediction B2) while the endogenous selection of brokers by liquidity-constrained sellers predicts that brokered deals have lower prices (Prediction C2).

As a direct test of broker selection, we also report the cap rate and probability of VTB financing regressions using the non-instrumented 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 C1 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 VI, however, this relation disappears. Thus, broker selection does appear to be important in this market, but our use of instruments seems to account for the endogenous selection.

Table AI summarizes the theoretical predictions from the cooperative relationship theory as well as the three alternative brokerage intermediation theories (e.g., advisory services, certification, and selection) and records whether each of these predictions were verified in the data. As clearly summarized in the table, the evidence seems to overwhelmingly favor the cooperative broker-bank relationship theory. Furthermore, while the endogenous selection of brokers is present in the data, our use of instrumental variables in identifying broker presence seems to overcome this endogeneity.

VII. Conclusion

In this paper we analyze patterns of financing in the commercial real estate market and find that informal broker-bank networks play a significant role in determining access to finance. We show that 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. Our results do not provide support for the theory that brokers only provide buyers with information on promising loan sources, rather than preferential access. There is little evidence that broker certification is important in the commercial property financing market. We also find that broker presence has little effect on price.

This paper argues that an integral part of brokerage services is the provision of access to finance. This access is provided along with other brokerage functions such as seeking potential buyers. Complementarities arise between these services because the broker receives his fee only if the transaction is completed. This often requires that the buyer obtain finance. Brokers provide a form of novel financial intermediation that differs from that typically studied in the literature.

This bundling of financial access with other services has several analogues in other areas of finance. Investment bankers frequently offer their clients advice on firm restructurings and corporate policy, and also facilitate their clients' access to the capital markets. Lawyers provide professional services to their small business clients and may also aid them in finding private equity or bank loan capital. An accountant may serve as a client's connection to a local angel network. In all these cases, intermediaries who have multiple principals as clients can aquire reputations and achieve cooperation with sources of financing. In many instances, the importance of the outside advisor is difficult to measure, partly because he may be performing multiple functions, but this paper demonstrates that informal connections can be critical in providing access to finance.

The results of the paper indicate that informal broker-bank relationships have a significant influence on the ability of buyers to obtain loans, even in well-functioning and highly-developed capital markets. These relationships, cultivated in the course of repeated interactions, are one of the most important determinants of financial structure in U.S. commercial real estate markets. Our paper suggests a role for informal networks in controlling access to finance that has not been well-analyzed in the theoretical literature.

Appendix

This section describes and motivates the econometric methodologies used in the paper.

A. Semiparametric Binary Response Model

First, we consider only the presence or absence of the dependent variable. For example, we set $y_n = 1$ if a positive amount of VTB financing is used in the nth deal, and we set $y_n = 0$ if no VTB is used in the deal. We then consider a binary response model of the following form

$$\begin{aligned} y_n^* &= \beta' x_n + u_n \\ y_n &= 1 \text{ if } y_n^* \geq 0 \\ y_n &= 0 \text{ otherwise} \end{aligned} \tag{A1}$$

where x_n is a $q \times 1$ vector of explanatory variables, β is a $q \times 1$ vector of parameters, u_n is a random error term and $n = 1, ..., N$. Although a probit or logit model may be used to estimate this system, several simulation studies have shown that both of these models may be radically biased when the error distribution is not normal or logistic, respectively (see Gerfin (1996) for a general discussion of these studies). Economic theory does not propose any particular distribution for the error term. It is therefore better to estimate (A1) using the semiparametric single-index model of Klein and Spady (1993), which allows the error distribution to be unspecified. This model presumes that

$$P(y_n = 1|x_n) = F(\beta' x_n), \tag{A2}$$

where F is an unknown function whose range is contained in $[0, 1]$. The term $\beta' x_n$ is referred to as the index.[19] The intercept component of β is subsumed in F and is therefore not estimated. This model accommodates any form of heteroscedasticity that is consistent with (A2). The estimator of β is the argument that maximizes the quasi-log-likelihood function

$$logL_N(b) = \sum_{n=1}^{N} \left[y_n logF_N(b' x_n) + (1 - y_n) log(1 - F_N(b' x_n)) \right], \tag{A3}$$

where F_N is a nonparametric kernel estimate of F. We follow Klein and Spady (1993) and set F_N in equation (A3) equal to a nonparametric kernel estimate of F. We use the adaptive local smoothing

[19] See Horowitz (1998) for a general discussion of single-index models.

estimator and define the kernel function to be $K(v) = (3/22)(1(-1/5)v^2 + (7/625)v^4)1(|v| \leq 5)$. The term F_N is estimated in two steps. In the first step, we define

$$G_N(v_i, \beta) = \frac{\sum_{j=1}^{N} \frac{y_j}{h_P} K\left(\frac{v_i - \beta' x_j}{h_P}\right)}{\sum_{j=1}^{N} \frac{y_j}{h_P} K\left(\frac{v_i - \beta' x_j}{h_P}\right) + \sum_{j=1}^{N} \frac{1-y_j}{h_P} K\left(\frac{v_i - \beta' x_j}{h_P}\right)}, \tag{A4}$$

where h_P is the pilot window size. The estimate of F_N is not very sensitive to the choice of h_P; we set $h_P = 1.5$. The function G_N serves as a preliminary estimate of the density function. In the second stage we define $l_{yj} = G_N(\beta' x_j, \beta)$ and set m equal to the geometric mean of the l_{yj}. We then set $L_{yj} = \left(\frac{l_{yj}}{m}\right)^{(-\frac{1}{2})}$. We define $h_{Nj} = (h_N)(\hat{\sigma}_{y_j}(\beta))(L_{yj})$, where $\hat{\sigma}_{y_j}(\beta)$ is the sample standard deviation of $\beta' x$ conditional on y_j and h_N is the window size. We set $h_N = N^{(-\frac{1}{7.98})}$, which satisfies Klein and Spady's condition for window sizes. We then define

$$F_N(v_i, \beta) = \frac{\sum_{j=1}^{N} \frac{y_j}{h_{Nj}} K\left(\frac{v_i - \beta' x_j}{h_{Nj}}\right)}{\sum_{j=1}^{N} \frac{y_j}{h_{Nj}} K\left(\frac{v_i - \beta' x_j}{h_{Nj}}\right) + \sum_{j=1}^{N} \frac{1-y_j}{h_{Nj}} K\left(\frac{v_i - \beta' x_j}{h_{Nj}}\right)}. \tag{A5}$$

Following Horowitz (1993) and Gerfin (1996), we do not use trimming to downweight extreme observations as is required by the theory, since trimming appears to have a very minor effect in applications.

As is standard in binary response models (including probit), β can only be identified up to a scale normalization which is typically achieved by setting one coefficient equal to one. Klein and Spady (1993) show that the estimator of β is consistent and asymptotically normal. This estimator performed well in simulations studied by Klein and Spady (1993) and in Gerfin's (1996) labor market application.

B. Truncated Regression Model

Our second mode of analysis is to consider only those data points (y_n^*, x_n) for which $y_n^* > 0$. That is, only data points with a positive amount of the dependent variable are considered, while data points for which $y_n^* \leq 0$ are discarded. A truncated regression model applies to this restricted sample. Formally,

$$y_n = \beta' x_n + v_n, \tag{A6}$$

where v_n has the conditional distribution of u_n given $u_n > -\beta' x_n$. Powell (1986) proposes a symmetrically truncated least squares estimator of this model that is consistent and asymptotically normal under the assumption that the error terms u_n, conditional on x_n, are symmetrically distributed and unimodal. The errors are permitted to be subject to heteroscedasticity of an unknown form. The estimator of β is defined to be the minimizer of

$$R_N(b) = \sum_{n=1}^{N} \left(y_n - max\{\frac{y_n}{2}, b'x_n\} \right)^2 .$$

For the financing regressions, we will presume that the total financing cannot exceed one hundred percent of the sale price. The correct model is therefore given by

$$y_n = min\{\beta' x_n + v_n, 1\}. \tag{A7}$$

The upper limit of 100 percent financing does not bind in most of our regressions. In cases where the upper limit does bind, however, we use Powell's (1986) censored and truncated estimator. This estimator of β is defined to be the minimizer of

$$\begin{aligned} Q_N(b) \quad &= \quad \sum_{n=1}^{N} 1(b'x_n < \frac{1}{2}) \left(y_n - max\{\frac{y_n}{2}, b'x_n\} \right)^2 \\ &+ \quad \sum_{n=1}^{N} 1(b'x_n \geq \frac{1}{2}) \left(y_n - min\{\frac{y_n + 1}{2}, b'x_n\} \right)^2 \\ &+ \quad \sum_{n=1}^{N} 1(b'x_n > \frac{1 + y_n}{2}) \left(\frac{(y_n - 1)^2}{4} (-min\{0, b'x_n - 1\})^2 \right), \end{aligned}$$

where $1(B)$ denotes the indicator function of the event B.

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Table I:
The U.S. Commercial Real Estate Market (1992-1999)

Descriptive statistics on the COMPS commercial real estate transactions from the U.S. over the period January 1, 1992 to March 30, 1999 are reported below. Panel A reports general characteristics of the properties in the database, reporting the number of sales, average age of the property, percentage of properties planned for development (Dev.), average capitalization rate (defined as net operating income divided by sales price), and local (county) crime index scores for crimes against property and person, obtained from CAP Index, Inc. Panel B reports information on participation in the commercial real estate market, reporting the mean and median distance buyers are from the property, percentage of buyers from out of state, mean and median distance sellers are from the property, percentage of sellers from out of state, 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. The mean sale price is reported and the frequency of each type of financing is reported as a percentage of the total number of transactions, as well as the percentage of the sale price each type of financing comprises when it is used. In addition, the sum of all financing used as a fraction of the sale price is reported (total loan/value). Both general statistics and financing information 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 (Comm. & Ind.) separately.

	All	City Center	Non City	Small Deals	Large Deals	Apt.	Land	Comm.& Ind.
Panel A: Property Characteristics								
# Sales	22,642	10,815	11,827	11,325	11,317	7,924	4,134	10,584
Age†	35.48	42.49	28.85	39.85	31.19	37.78	35.65	33.63
Development	6.33%	4.74%	7.78%	5.40%	7.26%	3.50%	16.30%	4.70%
Cap. Rate†	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	193.62	198.72	188.96	113.35	273.95	170.42	203.87	206.04
(median)	(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	255.34	248.79	261.32	195.94	314.77	221.01	231.37	290.17
(median)	(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 Mortgage (freq. %)	52.16%	53.74%	50.71%	52.54%	51.77%	68.95%	25.11%	49.85%
New Mortgage (% Price)	72.59%	70.94%	75.18%	76.57%	72.21%	75.60%	71.51%	71.16%
Vendor-to-Buyer (freq. %)	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. Mortgage (freq. %)	5.32%	5.71%	4.96%	5.03%	5.60%	9.59%	1.28%	3.65%
Assm. Mortgage (% Price)	67.37%	69.42%	65.26%	72.23%	67.11%	70.61%	74.53%	64.10%
Loan-to-Value ratio	72.57%	71.19%	74.62%	78.04%	71.99%	74.94%	73.60%	71.10%

† Averages are computed only among those properties containing age and capitalization rate information.

Table II:
Predicting Brokerage Activity and its Influence on Obtaining Bank Financing

The presence of a broker is regressed on property, buyer, and seller characteristics over the period January 1, 1992 to March 30, 1999. Included among the regressors are several exogenous instruments used to identify brokerage activity. These are: the population density radius of the local market, defined as the minimum of the mile radius which encompasses 100,000 people or 3 miles, a crime index score for crimes against persons (homicide rate), obtained from Cap Index, Inc., the capitalization rate or scaled price variance of the local market (for all properties within a 10 mile radius, excluding the property itself), the dollar fraction of brokered deals conducted by a national broker within a 10 mile radius, and the Herfindahl index of brokerage activity within a 10 mile area. Panel A reports the regression coefficients on the instruments from this instrumented variable regression of brokerage activity. Panel B then reports results from the two-stage binary response regressions of the probability of new bank financing on the instrumented broker variable, which is first estimated under a first-stage linear probability model. The dependent variable in the second stage regression is one if new bank financing is obtained and zero otherwise. Panel C reports results from the two-stage truncated regressions of the magnitude of new bank financing on instrumented brokerage activity. The dependent variable in the second stage regression is the fraction of the property's value financed by the loan. The data is truncated to only those observations where the dependent variable is positive. Panel D reports these regressions using the non-instrumented broker variable for comparison. Two sets of dependent variables are used: new mortgage financing from a bank (Newm) and new mortgage financing conditional on no seller financing being present (Newm†). Coefficient estimates are calculated via Klein and Spady's (1993) robust semiparametric binary response model and Powell's (1986) truncated model, with t-statistics reported in parentheses, where the time-series average of the coefficient estimates and their associated t-statistics are calculated in the style of Fama and MacBeth (1973). All regressions include state dummies, which are omitted from the table for brevity.

	Panel A: Broker Instrumented Regression (Klein-Spady Binary Response)				
Dep. var.	Population Radius	Personal Crime	σ_{local}	$\frac{\$\text{National}}{\$\text{Brokered}}$	Broker Herfindahl
Broker Presence	0.037	-0.383*	-0.113**	-1.493**	-3.995*
(t-stat)	(0.75)	(-2.63)	(-1.79)	(-1.88)	(-2.80)

	Panel B:		**Panel C:**		**Panel D:**	
Regression:	*Klein-Spady Binary Response*		*Powell Truncated*		*Klein-Spady*	*Powell*
Dep. var.:	Newm> 0	Newm† > 0	Newm	Newm†	Newm> 0	Newm
Non-Corporate Buyer	0.086*	0.223*	-0.006	-0.006	0.122	-0.007*
	(4.17)	(2.11)	(-1.48)	(-1.45)	(1.06)	(-2.57)
SellDist	-0.002	0.035	0.001	0.001**	-0.006	0.000
	(-0.93)	(1.59)	(1.47)	(1.80)	(-1.63)	(1.15)
BuyDist	-0.011*	0.003	0.000	0.000	-0.086*	0.000
	(-3.13)	(0.28)	(0.41)	(0.06)	(-1.99)	(1.21)
Dev.	-0.030	-0.057*	0.008	0.004	0.639	0.014*
	(-1.27)	(-2.94)	(0.91)	(0.45)	(1.54)	(2.14)
Age	0.001*	0.000	0.000	0.000	0.006**	0.000
	(3.82)	(-0.41)	(-0.53)	(1.39)	(1.82)	(0.59)
Land	-1.263*	-2.410*	-0.011	-0.006	-6.124*	0.005
	(-7.51)	(-2.36)	(-0.55)	(-0.26)	(-2.26)	(0.26)
Apt.	0.595*	0.653*	0.023*	0.022*	1.936*	0.010**
	(7.02)	(2.73)	(2.69)	(2.94)	(2.45)	(1.82)
City-Center	-0.010	-0.030	-0.001	-0.002	-0.073*	-0.004
	(-1.31)	(-1.26)	(-0.21)	(-0.39)	(-3.78)	(-0.92)
Property Crime	-0.015*	0.004	0.001	0.002	0.068**	0.003*
	(-2.03)	(1.19)	(1.03)	(1.57)	(1.84)	(3.86)
Broker (Instr.)	1.362*	3.909*	-0.131**	-0.173*		
	(4.69)	(2.17)	(-1.85)	(-2.67)		
Broker					1.383*	-0.017*
					(2.35)	(-6.20)
log(Price)	-1.000	-1.000	-0.006*	-0.005**	-1.000	-0.006*
	–	–	(-2.10)	(-1.83)	–	(-4.32)

† All property sales that do not employ any form of seller financing.

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

Table III:
Broker-Bank Relationships and the Impact on Capital Structure

Panel A reports direct measures of broker-bank relationships. The concentration of brokered deals among banks is examined 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 non-brokered deals and their average differences along with t-statistics (in parentheses) are reported below. 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 simply a regression across brokers of the broker's share of deals sent to the bank (measured from 1997 to 1999) on the age of the earliest deal the broker did with that bank (measured prior to 1997). We repeat the regression using the bank's share of deals conducted by the broker as the dependent variable, estimated across banks. Panel B reports results from the two-stage binary response regressions of the probability of new bank financing on brokerage activity and broker-bank concentration and longevity measures. Brokerage activity is first estimated using instrumental variables under a first-stage linear probability model to account for the endogenous choice of brokers. The instrumented broker variable is then interacted with a dummy variable indicating whether the broker concentrates his deals among fewer banks than the population of deals (i.e., if the broker's bank Herfindahl index is greater than the matched sample) and is interacted with the broker's age in this market. The regressors in the second stage regression include property, buyer, and seller characteristics, which are not reported for brevity. Coefficient estimates are calculated via Klein and Spady's (1993) robust semiparametric binary response model, with t-statistics reported in parentheses, where the time-series average of the coefficient estimates and their associated t-statistics are calculated in the style of Fama and MacBeth (1973). All regressions include state dummies, which are also omitted from the table for brevity.

	Bank Concentration Measures		
	Brokered	Non-Brokered	Difference (t-stat)
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		0.0036*	0.0568*
(t-stat)		(3.15)	(14.98)
	Impact on Capital Structure Klein-Spady Binary Response Model (Fama-MacBeth Regressions)		
Dep. var.:	Newm	Newm	Newm
Broker (Instr.)	8.992*	0.856*	0.224
	(2.01)	(2.37)	(1.10)
Broker(Instr.) $\times$ Conc.($Herf$)	0.809*		
	(2.94)		
Broker(Instr.) $\times$ Conc.($Share$)		0.327*	
		(3.84)	
Broker(Instr.) $\times$ Broker Age (years)			0.0365*
			(5.62)

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

Table IV:
Broker Herding, Loyalty, and the Impact on Capital Structure

Panel A reports measures of broker-bank loyalty and herding. The loyalty of brokered deals among banks is assessed via the elasticity of the change in a broker's share of business with the bank with respect to the change in the bank's share of the commercial market. This is simply a regression of the change in the broker's share devoted to a particular bank on the change in the bank's share of the market. The change in the share of broker business devoted to each bank is measured both by number of transactions (Loyalty (Num)) and by dollar volume (Loyalty ($)). Also reported is a measure of herding among brokers in certain banks. This measure is 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 estimated using a simulation under a binomial distribution. The average loyalty and herding measures are reported across brokers and banks, respectively, along with 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. Panel B reports results from the two-stage binary response regressions of the probability of new bank financing on brokerage activity and broker-bank loyalty. Brokerage activity is first estimated using instrumental variables under a first-stage linear probability model to account for the endogenous choice of brokers. The instrumented broker variable is then interacted with a dummy variable indicating whether the broker is loyal to his banks (i.e., if the broker's elasticity measure is less than 1). We also report results for the interaction between broker presence and non-loyalty (i.e., broker elasticity greater than 1). The regressors in the second stage regression include property, buyer, and seller characteristics, which are not reported for brevity. Coefficient estimates are calculated via Klein and Spady's (1993) robust semiparametric binary response model, with t-statistics reported in parentheses, where the time-series average of the coefficient estimates and their associated t-statistics are calculated in the style of Fama and MacBeth (1973). All regressions include state dummies, which are also omitted from the table for brevity.

		Bank Herding Measures	
	All Banks	Small Banks ($<$ 10 Deals)	Large Banks ($\geq$ 10 Deals)
Broker Herding into Banks	0.0222*	0.0064	0.0584*
Different from 0 (t-stat)	(6.08)	(1.32)	(14.89)
		Broker-Bank Loyalty Measures	
	All Brokers	Small Deals ($<$ \$10m)	Large Deals ($\geq$ \$10m)
Elasticity of Broker-Bank Business	1.08	0.80*	1.38**
Different from 1 (t-stat)	(0.77)	(-2.56)	(1.78)
		Impact of Loyalty on Capital Structure	
		Klein-Spady Binary Response Model	
		(Fama-MacBeth Regressions)	
Dep. var.:	Newm	Newm	Newm
Broker (Instr.)	0.343*	1.108*	-0.528
	(2.19)	(4.71)	(-0.49)
Broker(Instr.) $\times$ Loyalty(Num)	0.052*	0.122*	
	(5.04)	(2.87)	
Broker(Instr.) $\times$ Disloyalty(Num)		-0.085*	
		(-2.88)	
Broker(Instr.) $\times$ Loyalty($)			0.047*
			(4.47)
Broker(Instr.) $\times$ Disloyalty($)			-0.157*
			(-2.69)

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

Table V:
Do Brokers Influence Other Forms of Financing?

Results from the two-stage binary response and truncated regressions of the probability and magnitude of various forms of financing on instrumented brokerage activity are reported below over the January 1, 1992 to March 30, 1999 time period. Brokerage activity is first estimated using instrumental variables under a first-stage linear probability model to account for the endogenous choice of brokers. Three sets of dependent variables are used: vendor-to-buyer financing (VTB), VTB financing conditional on no bank financing being present (VTB†), and the assumption of an existing mortgage (Assm). Panel A reports coefficient estimates for the probability of each form of financing, estimated under Klein and Spady's (1993) robust semiparametric binary response model. Panel B reports coefficient estimates for the magnitude of each form of financing (as a fraction of the sale price), estimated under Powell's (1986) truncated regression model. T-statistics are reported in parentheses, where the time-series average of the coefficient estimates and their associated t-statistics are calculated in the style of Fama and MacBeth (1973). All regressions include state dummies, which are omitted from the table for brevity.

	Panel A: Binary Response Probability of			**Panel B: Truncated Magnitude of**	
Dep. var.:	VTB	VTB†	Assm	VTB	VTB†
Non-Corporate Buyer	0.793**	3.298*	-0.128	-0.172	-0.009
	(1.92)	(2.84)	(-1.36)	(-1.37)	(-0.50)
SellDist	-0.004*	0.006	-0.010	-0.024	0.001*
	(-2.28)	(1.14)	(-1.35)	(-1.50)	(2.34)
BuyDist	0.027	-0.018	0.005**	0.029	-0.003*
	(1.40)	(-1.06)	(1.76)	(1.35)	(-2.93)
Dev.	0.067	0.020	-0.323**	0.396	-0.074*
	(1.24)	(0.09)	(-1.84)	(1.58)	(-4.00)
Age	0.014*	0.055*	0.007*	0.000	0.001*
	(2.37)	(1.97)	(2.65)	(0.68)	(2.08)
Land	0.009	-3.679*	2.148**	-0.042**	-0.100*
	(0.02)	(-2.70)	(1.76)	(-1.91)	(-5.18)
Apt.	0.242*	-0.038	2.357*	-0.809*	0.051*
	(2.15)	(-0.43)	(2.45)	(-2.79)	(4.90)
City-Center	0.014**	-0.429*	-0.065	0.132	-0.012*
	(1.84)	(-2.02)	(-1.00)	(1.51)	(-2.17)
Property Crime	0.058*	-0.084*	0.009	-0.062**	0.014*
	(1.96)	(-3.16)	(1.35)	(-1.71)	(3.29)
Broker as Principal	0.205*	0.169	1.427*	-0.026	-0.027*
	(4.05)	(1.11)	(2.45)	(-1.42)	(-2.41)
Broker(Instr.)	8.232	4.641*	14.392*	-1.195*	-0.464*
	(1.49)	(2.29)	(2.30)	(-1.97)	(-6.51)
log(Price)	-1.000	-1.000	-1.000	-0.065*	-0.014*
	–	–	–	(-5.85)	(-3.54)

† All property sales that do not employ any form of bank financing.

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

Table VI:
The Role of Broker Selection and the Influence on Sale Prices

Panel A reports results from the two-stage least squares regressions of the probability of vendor financing and capitalization rates on instrumented brokerage activity over the January 1, 1992 to March 30, 1999 time period. Brokerage activity is first estimated using instrumental variables under a first-stage linear probability model to account for the endogenous choice of brokers. The dependent variables in the second stage regression are the presence of vendor financing (estimated under the Klein and Spady (1993) binary response model) and the capitalization rate of the property (Cap. Rate), defined as net operating income on the property divided by the sale price (estimated via ordinary least squares). Panel B repeats these regressions using the non-instrumented broker presence variable to gauge the impact of broker selection on vendor financing and price. The time-series average of the coefficient estimates and their associated t-statistics are calculated in the style of Fama and MacBeth (1973). All regressions include state dummies, which are omitted from the table for brevity.

	Panel A: Instrumented		**Panel B: Non-Instrumented**	
Regression Model:	OLS	Klein-Spady	OLS	Klein-Spady
Dep. var.:	Cap. Rate	VTB	Cap. Rate	VTB
Non-Corporate Buyer	-0.346*	0.793**	-0.348*	0.869
	(-2.35)	(1.92)	(-10.34)	(1.63)
SellDist	0.011	-0.004*	0.009*	-0.001**
	(1.53)	(-2.28)	(2.17)	(-1.80)
BuyDist	-0.006	0.027	-0.007*	-0.016
	(-0.87)	(1.40)	(-2.46)	(-1.40)
Dev.	-0.225	0.067	-0.278*	-0.020**
	(-1.24)	(1.24)	(-2.42)	(-1.89)
Age	0.002*	0.014*	0.002*	0.015**
	(2.25)	(2.37)	(1.98)	(1.86)
Land	-0.124	0.009	-0.212	-0.760
	(-0.42)	(0.02)	(-1.46)	(-1.31)
Apt.	-0.299**	0.242*	-0.246*	-0.121*
	(-1.66)	(2.15)	(-3.30)	(-2.47)
City-Center	0.029	0.014**	-0.018	-0.004
	(0.46)	(1.84)	(-0.29)	(-0.55)
Property Crime	0.167*	0.058*	0.198*	0.016
	(4.17)	(1.96)	(4.55)	(1.22)
Broker as Principal	-0.293*	0.205*	-0.199*	0.116*
	(-2.93)	(4.05)	(-2.28)	(3.71)
Broker (Instr.)	0.005	8.232		
	(0.26)	(1.49)		
Broker			0.421*	-0.256*
			(6.05)	(-5.36)
log(Price)	-0.144	-1.000	-0.089*	-1.000
	(-1.58)	–	(-2.03)	–

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

Table AI:
Summary of Theoretical Predictions and Results

Prediction	**Predicted By Which Theories?**	**Verified?**
1. Brokered deals are more likely to receive new bank financing.	All	Yes
2. The effect of broker presence in increasing the probability of a bank loan is particularly strong when there is no seller financing.	Cooperation	Yes
3. Brokers will concentrate their deals among a small number of banks.	Cooperation	Yes
4. Brokers with strong bank relationships will have a larger effect on the granting of bank loans than the average broker.	Cooperation	Yes
5. Brokers will direct a greater proportion of their clients to banks with whom they have longer relationships.	Cooperation	Yes
6. Banks will offer more loans to the clients of brokers with whom they have longer relationships.	Cooperation	Yes
7. 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.	Cooperation	Yes
8. When the buyer does not receive bank financing, the size of VTB loans will be smaller in brokered deals than in non-brokered deals.	Cooperation	Yes
9. Brokered deals are more likely to receive assumed mortgage financing.	Cooperation	Yes
A1. Brokers will distribute their deals among a large number of banks.	Advisory	No
A2.i. The elasticity of a bank's brokerage business with respect to its total loan business will be greater than one.	Advisory	large deals
A2.ii. The elasticity of a bank's brokerage business with respect to its total loan business will be less than one.	Cooperation	small deals
A3.i. Disloyal brokers will most improve their clients' probability of receiving a bank loan.	Advisory	No
A3.ii. Loyal brokers will most improve their clients' probability of receiving a bank loan.	Cooperation	Yes
A4. Brokers from different firms will herd in directing their clients to the same banks	Advisory	weak
B1. The size of bank loans will be greater for brokered deals	Certification	No
B2. Brokered properties will receive higher average prices	Cerification	No
C1. Brokered deals will exhibit less VTB financing	Selection	Yes*
C2. Brokered properties will receive lower average prices	Selection	Yes*

* Using the non-instrumented broker variables. Employing the instrumented broker variables, these results do not hold, suggesting our instruments successfully capture the endogenous choice of brokers.