Brokerage, Intermediation, and Agency: The Financing and Pricing of Commercial Properties

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Abstract

This paper examines a novel form of financial intermediation by studying the role of professional property brokers in the commercial real estate market. We find that broker intermediation is an important feature of the financing of commercial properties. Controlling for endogenous broker selection, we determine that hiring a broker significantly increases the probability of obtaining a bank loan by a striking 18 percent. We find, however, that brokers have only a modest effect on the sale price. Our results are most consistent with the theory that brokers and lending institutions establish informal relationships, and provide less support for theories of broker monitoring or certification.

I. Introduction

This paper examines a novel form of financial intermediation by studying the role of professional property brokers in the commercial real estate market. Brokerage is an important agency activity, yet the economic function of brokers is not well understood. This paper analyzes the intermediary role of professional brokers in the commercial real estate market. We find that property broker intermediation is a very important feature of real estate finance. Brokered transactions are 18 percent more likely to be financed with bank debt than non-brokered transactions. We also determine that the presence of a real estate broker has only a modest effect on sale price; sellers who hire list brokers do not enjoy significantly higher prices. We consider four theories of financial intermediation: cooperation, monitoring, certification, and agent selection. Our results best support the theory that brokers and banks develop relationships and cooperate. Controlling for endogenous broker selection, we find that brokers provide their clients with better access to bank finance through this relationship. We also find strong evidence that brokers are hired by liquidity-constrained sellers.

Research on financial intermediation forms a central part of the theoretical literature in corporate finance. We test the relevance of several intermediation theories in a novel setting using data from commercial real estate transactions. There are several reasons for considering the commercial real estate market. First, it is a large and important asset market.[1] It is therefore of significant economic interest to have theories that explain empirical regularities in property financings. Second, broker intermediation is an unusual form of financial intermediation. Our study shows that brokers serve an important 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). 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)).

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

[1]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.

the realized sale price (e.g., Williams (1998)). Our data does not permit us to analyze the former, but we will provide evidence on the latter. We find that hiring a list broker increases the realized sale price by only a statistically insignificant percentage. We display evidence, however, that brokers significantly improve access to finance, suggesting a new and important role for brokers that is not well-studied in the literature.

We consider four brokerage intermediation theories in this paper that explain the association between broker presence and bank financing. The first theory focuses on 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. This is similar to a volume discount, though the bank may offer access to finance rather than attractive loan terms. This theory resembles Diamond (1984), although it is repeated interactions rather than information acquisition that is important here.

The second 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. Brokers are anxious to bring deals to completion in order to realize their commissions, so they will provide this assistance. Brokers engage in far more transactions than individual buyers and can therefore provide useful information to the principals. Brokers employed by the seller are eager to close transactions and will provide advice to the buyer, even if he is not their client.

The third 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 venture capitalists (Brav and Gompers (1997)) and commercial and investment banks (Puri (1994)). If brokers only present banks with high-quality properties, then we would expect that brokered properties will receive finance more often and that the size of these loans will be relatively larger. On this theory, brokers are skilled at evaluating properties and will only agree to support loan applications secured by high-quality buildings or land.

The first three theories suggest that access to finance is part of the package of services sold by brokers to their clients. Whether through relationships, advice, or certification, a broker improves the probability that the transaction will be financed through bank debt. The fourth hypothesis we consider, however, suggests that the statistical relation between brokerage activity and financial structure may not be causal. Rather, it may be the endogenous hiring of brokers by certain types of sellers or buyers that generates this apparent relation. In other words, it is possible that buyers in brokered deals are simply likelier, because of their own characteristics, to receive bank loans. For example, it may be that active buyers have access to both brokerage and banking services. Another possibility 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. Many other theories of broker selection are also possible.

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.

The following is a summary of our main findings. First, we find strong evidence that brokers increase the probability of bank finance dramatically, though they have little effect on the size of the bank loan granted. Second, hiring a list broker does not significantly increase the sale price. These results are obtained by instrumenting brokerage activity and therefore do not depend on endogenous broker selection. Third, the data best support the theory that brokers provide access to finance by developing relationships with banks. There is also some support for the theory that brokers direct their clients to the bank that is likeliest to approve a loan; brokers may thus provide information, as well as contacts. There is little evidence that brokers certify properties, however. Finally, the data strongly suggests that liquidity-constrained sellers do indeed hire brokers and that this accounts for some of the association between brokerage and bank finance found in the raw data.

In addition to testing the implications of several broad theories of intermediation in a novel setting and expanding our understanding of the role of brokerage, we provide several insights into the commercial real estate market. The determinants of the patterns of commercial lending have been the subject of much research in the real estate literature. Ambrose, Benjamin, and Chinloy

(1996) relate commercial lending patterns to variables thought to be important to practitioners. Hancock and Wilcox (1997) study the impact on real estate lending of the credit crunch of the early 1990's. Weber and Devaney (1999) examine the effects of changes in capital standards. Most of the papers in this literature, however, either analyze broad historical trends or study the effects of specific regulatory changes. This paper presents much greater detail about variation in real estate financing across individual properties than previous work, providing a more comprehensive understanding of financial structure in this market. In particular, we consider the effects of local crime risk on property financings. The reluctance of insurance firms and other loan providers to lend in sub-grade neighborhoods might be thought to have a serious effect on the ability of buyers to finance properties in high-crime districts. We find that crime does not reduce the probability of bank debt. It is the case, however, that properties in areas with high personal crime risk are less likely to be brokered. This may lead to a reduction in financing. The small magnitude of the crime results suggests that real estate development in high-crime areas is not hindered by inefficiencies in financing.

The rest of the paper is organized as follows. Section II details our data set, highlighting the various forms of financing in commercial real estate markets and describing the characteristics of properties and market participants. In this section we also conduct a preliminary analysis of brokerage activity. Section III addresses the endogeneity issue by instrumenting brokerage activity. Section IV presents various brokerage intermediation theories and describes their predictions for commercial property financial structures and prices. In Section V we conduct our empirical tests of these theories and analyze the results. Finally, Section VI concludes.

II. Data and Preliminary Analysis

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.[2] Of the 36,678 commercial real

[2]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

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,[3] Table I reports that fewer than half of all transactions occur in 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.

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)[4] 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

broker details.

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

[4]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.

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 local police, victim, and loss reports.[5] 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).[6] 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.[7]

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. The crime scores are based on Census data and current police and victim reports, and are designed to capture the probability of crime over a 3 to 5 year period. In addition, however, CAP Index, Inc. provides crime scores from the past (based on Census data and previous police and victim reports). Therefore, we also compute the percentage change in crime risk for each property location by subtracting the past score from the current score and dividing by the past score. As Table I indicates, crime risk has

[5]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.

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

[7]Results in the paper are robust to several other crime score measures.

increased slightly for our property locations, more so for personal rather than property crimes.

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 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 list and sale brokers in the deals. In many cases, the seller hires a broker to list the property. This broker markets the property and attempts to solicit offers. It is also common for a second broker to participate in the transaction. This broker, the sale broker, may read or hear about the listing and find a potential buyer. In some cases the list broker finds the buyer and also acts as the sale broker. Upon sale of the property, the seller pays the commission to *both* brokers (typically split evenly between them). List brokers participate in almost 57 percent of property sales in our database and 59 percent of deals involve a sale broker. In roughly half of the cases where both a list and sale broker are used, the same brokerage firm provides both services. 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 this question by examining the role of brokers in the financing and pricing of commercial properties.

One of the goals 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.

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 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, and comprises almost 60 percent of the purchase price when used. VTB loans are typically junior to bank loans and are not typically short-term "bridge" financing used to expedite the deal. The maturity of VTB loans is often as long as (or longer than) the maturity of bank loans. 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. Preliminary Analysis: The Relation Between Brokerage and the Financing and Pricing of Commercial Property

Table II examines the relation between brokerage activity and various forms of financing. 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.[8] 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

[8]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).

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. For both the binary response and truncated regressions we employ the methodology of Fama and MacBeth (1973): 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 running regressions separately for each year.[9]

Panel A reports the results from the binary response regressions. The dependent variable here is one if the financing type is used in the deal and zero otherwise. Two types of financial contracts are examined: VTB loans and new bank loans. The frequency of each of these financing types is regressed on various measures of brokerage activity and a set of control variables for property, buyer, and seller characteristics. These control 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 and statistically significant coefficient estimate on log(Price) (for further details on this model, see Klein and Spady (1993) and Garmaise and Moskowitz (2000a)).

The first regression in Panel A regresses the frequency of VTB financing on two measures of brokerage activity: a dummy indicating if a broker, acting as an agent, is present in the deal, and a dummy indicating if a broker is acting as a principal (i.e., trading on his own account), as well as the control variables. The regressions are run for each year separately under the Klein and Spady (1993) 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). This regression is then repeated by separating the presence of a broker variable into two dummies indicating the presence

[9]For an example and discussion of the Fama-MacBeth methodology applied to a binary response model, see Fama and French (2000).

of a national broker, defined as one of the 9 largest national commercial real estate brokerage firms,[10] and the presence of a local broker (i.e., any non-national broker). The third and fourth columns of Panel A repeat these regressions with the probability of new mortgage financing as the dependent variable.

Panel B reports regressions under Powell's (1986) truncated model, where the sample is truncated to only those observations for which the financing type 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).

Several interesting patterns of brokerage activity emerge from the regressions. First, the presence of a broker appears to decrease the probability of VTB financing and increase the probability of obtaining a new mortgage from a bank. However, upon receiving either form of financing, Panel B indicates that the broker's presence decreases the size of the loan. This illustrates the importance of examining the frequency of loan type separately from the size of the loan. The decreased probability of VTB financing is primarily driven by the presence of a local broker, while the increase in frequency of new bank financing is largely due to the presence of a national broker. The presence of either type of broker, however, appears to decrease the size of both loan types. These results also hold true for the case in which the broker acts as a principal.

There appears to be a strong relation between brokerage activity and financial choice. The broker variables in these regressions, however, are endogenous. That is, the choice of employing a broker in a deal is an endogenous decision. Although we control for various buyer, seller, and property characteristics that might influence the choice of using a broker, there may be unobservable attributes that determine the broker's presence and are correlated with the financial decision. Hence, we should view the previous regressions as providing information about partial correlations rather than causal relationships. In the next section we address this endogeneity issue by instrumenting brokerage activity with exogenous variables related to broker involvement, but otherwise unrelated to financial choice. Using these instruments, the remainder of the paper focuses on the impact brokers have on financial choice, evaluating whether a causal link exists between brokerage

[10]These are Coldwell Banker, Grubb and Ellis, Cushman, Galbreath, Koll, Insignia, REMAX, Century 21, and Staubach.

activity and financial structure.

In addition to financial choice, we also analyze the impact brokers have on the sale price. As a starting point, Table III regresses the capitalization (cap) rate of the property, defined as net operating income on the property divided by the sale price, on the control variables as well as various endogenous measures of brokerage activity. Again, these regressions should be viewed as simply documenting statistical correlation between brokerage and prices. The regressions are estimated via least squares, and are computed in the style of Fama and MacBeth (1973).[11] The brokerage variables employed include dummies for the presence of a broker, presence of local and national brokers, presence of list and sale brokers, and the presence of two different brokers (defined as a list and sale broker from two different brokerage firms). Table III documents that the presence of a broker is positively related to the cap rate consistently across each of the broker variables. This implies that broker presence is *negatively* related to the sale price, despite the fact that the seller has to pay the broker's commission, and therefore might be expected to increase the sale price to accommodate this cost. When the broker acts as the principal, or when there are two different brokers, however, there is a positive effect on price. Once again, these correlations may be driven by endogenous broker selection rather than broker influence. The remainder of the paper distinguishes between these two possibilities.

The preliminary analysis in this section highlights some interesting statistical relations between brokerage activity and the financing and pricing of commercial real estate. The question is whether this relation is driven by endogenous broker selection or whether brokers play an active role in determing market prices and influencing buyers' access to capital. In the next section we address the endogeneity issue in order to examine the causal impact of broker involvement.

III. Broker Selection

A. Predicting Brokerage Activity

We begin by analyzing the conditions under which brokers are used. The goals of this analysis are twofold. First, brokerage is an important aspect of the commercial real estate market, and it is useful to understand which buyer, seller and property types are associated with the hiring of brokers. Second, we seek to identify exogenous predictors of brokerage activity that are otherwise unrelated to financial choice or the sale price for use in instrumental variable regressions.

[11] Least squares is appropriate here since cap rates are not censored or truncated in any way.

Table IV analyzes 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 certain type of broker is present in the deal (acting as an agent, not as a principal) and zero otherwise. Five sets of dependent variables are used: the presence of a broker, presence of a local broker, presence of a national broker, presence of a list broker, and presence of a sale broker. The regressions are estimated under the Klein and Spady (1993) binary response model,[12] with Fama and MacBeth (1973) coefficient estimates and t-statistics. As Table IV indicates, brokers are used more often in transactions involving non-corporate buyers, distant sellers, properties not scheduled for development, younger properties, the sale of apartment complexes, properties residing outside of major cities, and high property-crime locations. The presence of local and national brokers exhibits a similar pattern with three notable differences. Distant sellers tend to hire national rather than local brokers, properties scheduled for imminent development involve national brokers more often than local brokers, and larger cities tend to exhibit more local brokerage than national brokerage. The presence of a list broker (who is hired by the seller to represent him) occurs more frequently among deals involving a local buyer, property not scheduled for development, and within city-centers. The presence of a sale broker occurs more often for local sellers, older properties, and properties outside of major cities.

We find that these variables are related to broker presence as well as to property financing and pricing. To clarify the causal effects of hiring a broker, we need exogenous instruments/predictors of brokerage activity that are otherwise unrelated to financial choice or price.

B. Instrumenting Brokerage Activity

We employ five instruments for brokerage activity that we expect to be unrelated to financial structure or price, 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,

[12] We set the coefficient on log(Price) equal to 1 for scale normalization in this model based on logit regression results that indicated a positive and significant coefficient on log(Price) for each broker regression.

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.) The third instrument, σ_{local}, is the standard deviation of scaled prices (cap rates) of all sales within a 10 mile radius, 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. This variable measures the degree to which brokers have penetrated the local market, since national brokers tend to dominate young, remote markets and only over time do smaller, regional brokers emerge. The smaller this fraction, the more developed the local brokerage networks and therefore the higher the likelihood of employing a broker. Finally, the last instrument we employ is the dollar-weighted Herfindahl index of brokerage activity within a 10 mile radius of the property (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 IV demonstrates that the instruments are successful in predicting brokerage activity.[13] Broker presence increases significantly when personal crime risk is low and when the local broker market is more competitive. The exception is increased national broker presence with personal crime. Broker activity is negatively related to local property quality heterogeneity, except for local brokers. Broker presence (other than national broker presence) is decreasing in the fraction of nationally brokered deals. Finally, the presence of a local broker appears to be strongly related to population density, but this result does not hold for the presence of any other broker type.

IV. Theories of Brokerage

Before examining the impact brokers have in this market, it is instructive to consider what economic role these agents might serve. In this section we consider four theories of broker intermediation. In the next section we will use the instrumented broker presence variable to evaluate these theories. Our first hypothesis is that brokers and financial institutions may develop relationships and cooperate. The second 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. The third theory is that brokers may certify the quality of properties and the creditworthiness of borrowers to lending institutions. Finally, the endogenous selection of brokers by certain types of sellers may explain the observed relation between brokerage activity and financing and pricing. Specifically, liquidity-constrained sellers anxious to complete a sale quickly may be more likely to hire brokers.

In our sample, we find VTB financing provided by the seller, new mortgages provided by banks and other financial institutions, assumed mortgages, and cash. We examine the predictions of the brokerage theories for both the frequency and magnitude of these four forms of financing.

A. Cooperation

Brokers and banks interact repeatedly over time and may develop a relationship. A bank may offer a broker special consideration in exchange for the broker's agreeing to direct mortgage-seeking buyers to the bank. Lenders essentially offer brokers a volume discount; buyers introduced to a bank by a broker will receive better terms. This increases the probability that the transaction will be consummated and the brokerage fee paid. In exchange for this benefit, brokers send buyers to the

[13] An F-test that the instruments should be excluded from the regression is clearly rejected (at less than the 0.5% level) for all broker regressions.

bank. 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. This relationship would likely be informal, though some brokers and lenders have established formal joint ventures (Stahl 1993).[14]

If brokers and banks cooperate, then buyers in brokered deals should receive bank loans more often. The size of the loans received is unclear, however. 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. 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. Hence, this model makes the following prediction.

Prediction A1. *Brokered deals are more likely to receive new bank financing, but the size of the loan is unrelated to broker involvement.*

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 financing to complete the deal, will scale back the size of his loan. This provides the second prediction from this model.

Prediction A2. *When the buyer does not receive bank financing, the size of VTB loans will be smaller in brokered deals than in non-brokered deals.*

The bank will be particularly interested in approving loans for brokers themselves, who are trading on their own account, since this is the form of cooperation presumably most valued by brokers.

Prediction A3. *Brokers buying on their own account are particularly likely to receive bank financing.*

If a broker anticipates that seller financing will be difficult to obtain, it will be particularly important for him to negotiate bank financing. If a broker has a relationship with a bank, he will

[14] 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).

seek to obtain bank financing especially in those cases where seller financing is unavailable.

Prediction A4. *Brokered deals are more likely to receive bank financing when there is no seller financing.*

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.

Prediction A5. *Brokered deals are more likely to receive assumed mortgage financing.*

B. Advisory Services

The second 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 predicts that brokers increase the probability of obtaining bank financing. As for the first theory, however, the size of loans in brokered deals is not unambiguously predicted by this model. This leads to the following prediction.

Prediction B1. *Brokered deals are more likely to receive bank financing, but the size of the loan is unrelated to broker involvement.*

In addition, under this second model, as under the first, the failure of a buyer to receive a bank mortgage in a brokered deal is a negative signal about his creditworthiness. Buyers in such transactions should, therefore, receive smaller VTB loans.

Prediction B2. *When the buyer does not receive bank financing, the size of VTB loans will be smaller in brokered deals than in non-brokered deals.*

The main sense in which the second model differs from the first is that under the second model, loan applications in which a broker acts as a principal should be no more favored by a bank than any mortgage request arising from a brokered deal. This model, therefore, does not make prediction A3. Banks will also not be especially concerned with granting loans when there is no seller finance available, so A4 is not a prediction of the second model either. Under the second model,

Prediction B3. *The presence of seller financing should not affect the frequency of bank financing differently in brokered and non-brokered transactions.*

In addition, since the existing mortgage on a property is not determined at the discretion of the buyer, it should therefore be unaffected by the broker's financing advice. This leads to another prediction which distinguishes the advisory services theory from the cooperation theory.

Prediction B4. *Brokered deals are equally likely to receive assumed mortgage financing.*

If the premise of the second theory is correct, however, then distant buyers and non-corporate buyers will be most in need of a broker's advice on the loan-granting policies of local banks. Hence,

Prediction B5. *Distant buyers and non-corporate buyers will hire brokers more frequently.*

As Table IV indicates, non-corporate buyers do, indeed, hire brokers more frequently, but distant buyers do not.

C. Certification

The third intermediation 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)). Brokered transactions would therefore be predicted to receive loans more frequently and to receive larger loans, as the certified pool is of higher quality than the non-brokered pool. The presence of a broker should therefore encourage both bank finance and seller finance under this model. More formally,

Prediction C1. *Brokered deals are more likely to receive bank financing, and the size of bank loans will be greater for brokered deals.*

Prediction C2. *Brokered deals are more likely to receive seller financing, and the size of VTB loans should be greater for brokered deals.*

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 C3. *Properties sold through the agency of a broker will receive higher average prices.*

D. Broker Selection

The fourth 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. 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 D1. *Brokered deals should exhibit less VTB financing.*

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

Prediction D2. *Properties sold through the agency of a broker will receive lower average prices.*

We test for broker selection by examining these predictions using both instrumented and non-instrumented broker variables and comparing the different results.

V. Testing Theories of Brokerage

We analyze the role of brokers in the commercial real estate market by testing the predictions of the four theories. We examine the influence of brokerage activity on three sets of dependent variables: the probability of a particular loan contract, the magnitude of a given loan contract, and the sale price of the property.

A. Do Brokers Influence the Frequency of Financing?

Table V reports Fama-MacBeth regressions of the probability of various financing types on the instrumented measures of brokerage activity and a 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 Table IV under a linear probability model.[15] 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 the financing type

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

is used in the deal and zero otherwise. The regressions are conducted in the style of Fama and MacBeth (1973).[16] Five sets of dependent variables are employed: VTB financing, new mortgage financing, VTB financing conditional on no bank financing being present, new mortgage financing conditional on no seller financing being present, and the assumption of an existing mortgage. The probability of each form of financing is regressed on the instrumented variable of broker presence and the instrumented variables of national and local broker presence.

The results demonstrate a significant and influential role for brokers on the frequency of the type of loan contract employed in the deal. The instrumented broker measures exhibit substantial explanatory power for the probability of various forms of financing. Exogenous broker presence increases the likelihood of new bank financing, but appears to have no statistically significant effect on the probability of VTB financing. The imputed increase in probability of obtaining bank debt from hiring a broker is a striking 18 percent, indicating an economically important impact from broker presence. These results are consistent with the broker-bank cooperation theory and the financial advisory theory, which both predict a higher frequency of new bank loans, but make no prediction regarding the frequency of VTB loans (predictions A1 and B1). The certification theory also predicts more new mortgages, but predicts that VTB loans should be more frequent as well (predictions C1 and C2). The insignificant effect of broker presence on the frequency of VTB financing does not support this model. In addition, national brokers, due to their larger size and more substantial resources, should be more effective certifiers than local brokers. The results suggest, however, that local brokers are more successful in increasing the probability of bank finance. This would appear to undermine the certification theory.

To better distinguish between the cooperation and advisory theories of brokerage, we examine the influence of brokers on the probability of new bank financing when no seller financing is provided. Under the cooperation theory, brokers would exploit their relationships with banks most strongly when other forms of financing are unattainable (prediction A4), whereas no such prediction is made if brokers merely provide advice to their clients (prediction B3). As Table V demonstrates, the effect of broker presence on new bank financing is three times stronger when no seller financing is present, supporting the cooperation model. Cooperation also predicts an increased frequency of assumed mortgages (prediction A5) which the advising model does not (prediction B4). Again, the

[16] In addition to producing robust standard errors that account for cross-correlations in the residuals, the Fama-MacBeth procedure, because it simply takes the average of the coefficient estimates, implicitly produces standard errors that reflect the fact that the broker variables were estimated from the first-stage regression.

results favor the cooperation story as brokers, particularly local brokers, significantly increase the likelihood of assuming an existing mortgage. This increase is also exhibited when brokers trade on their own account (i.e., act as principals), which is when their relationship with banks may be most valuable (prediction A3). However, the effect of brokers acting as principals is insignificant on the probability of obtaining new bank debt.

Finally, comparing Panel A of Table II, which employs the non-instrumented endogenous broker variables, to Table V, which employs the exogenously instrumented variables, we see that broker selection is indeed an important feature of this market. Prediction D1 states that brokered deals will exhibit less VTB financing if liquidity constrained sellers tend to hire brokers. Table II Panel A exhibits a strong negative relation between broker presence and frequency of VTB financing, consistent with this prediction. When employing the instrumented broker variable in Table V, however, this relation disappears. This signifies both that broker selection is important in this market, and that our instruments address the endogenous selection.

B. Do Brokers Influence the Magnitude of Financing?

Table VI reports Fama-MacBeth regressions of the magnitude of various forms of financing on a set of control variables as well as instrumented measures 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 same dependent variables from Table V are employed, except for the assumption of existing mortgages, since buyers cannot choose the size of an existing mortgage.

The results demonstrate a negative but insignificant relation between the size of VTB and new bank loans and the presence of a broker, consistent with both the cooperation and advisory theories (predictions A1 and B1), but inconsistent with the certification theory, which predicts a positive effect on both (predictions C1 and C2). More compelling is the strong negative influence on the size of VTB loans when no bank financing is present. This is consistent with both predictions A2 and B2, but directly contradicts the certification story.

C. Do Brokers Influence the Sale Price?

Finally, we examine whether brokers influence the market prices of commercial properties. Table VII 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 VII 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. However, the certification story predicts that brokered deals will have higher prices (prediction C3) while the endogenous selection of brokers by liquidity-constrained sellers predicts that brokered deals have lower prices (prediction D2). Comparing Table III, which employs the endogenous broker variables, with Table VII, which employs the instrumented broker variables, we see strong evidence of broker selection. In Table III, the presence of brokers is consistently related to lower priced properties, but accounting for endogenous broker selection, Table VII demonstrates 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 in both Table III and Table VII are inconsistent with the broker certification theory, however.

D. Summary and Implications for the Commercial Real Estate Market

The endogenous selection of brokers by certain types of sellers clearly contributes to the observed relation between brokerage activity and the financing and pricing of commercial properties. In particular, we find that liquidity constrained sellers tend to hire brokers more often. Our two-stage instrumented variables approach, however, demonstrates that hiring a broker has a significant causal effect. We find that the exogenous presence of a broker greatly increases buyers' access to bank financing. The broker intermediation theory most consistent with our findings is a model of broker and bank relationship lending. Broker participation is clearly a significant determinant of financial structure in this market; brokers aid buyers in obtaining financing through their relationships with lending institutions. The evidence for the theory that brokers act as informed advisors is weaker, and the data is inconsistent with the theory that brokers provide certification of property quality or buyer creditworthiness. Our findings suggest a new understanding of the economic role of brokerage activity in the commercial real estate industry. Brokers' exogenous effect on price, however, is much weaker. This suggests that the strong negative endogenous relation between price and broker representation is not due to brokers' actions, but rather to the types of sellers who choose brokers. Hence, price effects do not seem to be the primary motivation for hiring a broker in the commercial real estate market. Rather, investors are likely attracted to client services, one of which is better access to bank finance.

The influence of brokers on buyers' access to capital through broker-bank relationships highlights an important new feature of their role in this market. The informal or, increasingly, formal ties between brokers and banks provide brokerage firms with an important financial intermediary function.

Finally, a description of some interesting non-brokerage aspects of the commercial real estate market emerges from the results. In particular, we consider the effects of local crime risk on property financing and pricing. Table VII demonstrates that properties sell for significantly less in high-crime areas. In addition, the reluctance of insurance firms and other loan providers to lend in sub-grade neighborhoods might be thought to have a serious effect on the ability of buyers to finance properties in high-crime districts. Examining Tables V and VI, however, we find that crime does not reduce the probability or size of either bank debt or seller financing. The minor impact of crime on financial structure suggests that real estate development in high-crime areas is not hindered by inefficiencies in financing.

VI. Conclusion

In this paper we compare the performance of several theories of intermediation in explaining patterns of financing in the commercial real estate market. Broker-bank relationships are found to be the most significant feature of the market. We show that broker involvement strongly increases the probability that bank debt will be granted. Brokers may also direct buyers to the most promising loan sources, thereby providing information as well as 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.

Our evidence also indicates that crime risk is not an important determinant of financing in this market. It is conventionally presumed that the risk-avoiding loan policies of financial institutions significantly impair reconstruction efforts in crime-ridden commercial areas. Our results demonstrate that while property values may be lower in these districts, inefficiencies in financing do not appear to constrain developers' rebuilding projects. Garmaise and Moskowitz (2000b) further analyze the question of crime and real estate development.

This paper argues that an integral part of brokerage services is the provision of access to finance. This access is bundled 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. The economic rationale for broker financial intermediation is unusual; the closest analogy may be to vendor finance. Brokers provide a form of novel financial intermediation that differs from that typically studied in the 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

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

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

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

where F is an unknown function whose range is contained in $[0, 1]$. The term $\beta' x_n$ is referred to as the index.[17] 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

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

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

[17] 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 as well as changes in each crime index score 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 list broker, a sale 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.

Panel A: Property Characteristics

					Crimes Against			
	# Sales	Age†	Dev.	Cap. rate†	Persons	%change	Property	%change
All	22,642	35.55	6.30%	9.35%	1.92	3.60%	1.52	1.30%
City-Center	10,815	42.56	4.70%	9.58%	2.37	1.80%	1.69	0.80%
Non-City	11,827	28.92	7.80%	9.12%	1.50	5.30%	1.36	1.80%
Small Deals	11,325	39.91	5.40%	9.16%	1.99	2.90%	1.62	1.40%
Large Deals	11,317	31.26	7.30%	9.53%	1.85	4.40%	1.41	1.20%
Apt	7,924	37.81	3.50%	10.01%	2.04	1.50%	1.50	0.10%
Land	4,134	35.73	16.30%	7.59%	1.60	8.20%	1.48	1.70%
Comm. & Ind.	10,584	33.73	4.70%	8.26%	1.94	3.50%	1.55	2.10%

Panel B: Participant Information

	Buyer Distance mean(median)	Out of State	Seller Distance mean(median)	Out of State	List Broker	Sale Broker	Buyer is Broker	Seller is Broker
All	193.62 (38.47)	11.8%	255.34 (42.87)	16.3%	56.7%	59.1%	3.2%	2.7%
City-Center	198.72 (39.90)	11.8%	248.79 (43.60)	16.3%	58.0%	60.4%	4.0%	3.3%
Non-City	188.96 (37.77)	11.8%	261.32 (42.34)	16.4%	55.5%	57.9%	2.5%	2.2%
Small Deals	113.35 (35.80)	6.4%	195.94 (40.65)	12.1%	56.3%	58.4%	3.2%	2.7%
Large Deals	273.95 (41.86)	17.3%	314.77 (45.45)	20.6%	57.0%	59.8%	3.2%	2.7%
Apt	170.42 (36.46)	9.0%	221.01 (40.41)	11.7%	69.3%	71.3%	4.5%	2.7%
Land	203.87 (37.40)	15.4%	231.37 (41.55)	18.0%	37.9%	38.0%	3.5%	3.7%
Comm. & Ind.	206.04 (40.57)	12.6%	290.17 (44.94)	19.2%	54.1%	57.8%	2.1%	2.3%

Panel C: Financing Information

	Sale Price	Vendor-to-Buyer		New Mortgage		Assumed Mortgage		Loan/
	($,000)	freq.(%)	% Price	freq.(%)	% Price	freq.(%)	% Price	Value
All	$2,386.77	18.8%	59.5%	52.2%	72.6%	5.3%	67.4%	72.6%
City-Center	$2,814.32	19.5%	60.6%	53.7%	70.9%	5.7%	69.4%	71.2%
Non-City	$1,995.80	18.2%	58.2%	50.7%	75.2%	5.0%	65.3%	74.6%
Small Deals	$355.27	23.2%	63.3%	52.5%	76.6%	5.0%	72.2%	78.0%
Large Deals	$4,419.70	14.4%	58.7%	51.8%	72.2%	5.6%	67.1%	72.0%
Apt	$1,843.65	17.7%	50.7%	69.0%	75.6%	9.6%	70.6%	74.9%
Land	$1,491.90	17.6%	70.9%	25.1%	71.5%	1.3%	74.5%	73.6%
Comm. & Ind.	$3,134.08	20.0%	61.2%	49.8%	71.2%	3.6%	64.1%	71.1%

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

Table II:
The Relation Between Brokerage Activity and Financial Structure

Results from yearly Fama-MacBeth (1973) cross-sectional regressions of various financing types on measures of brokerage activity plus property, buyer, and seller characteristics are reported below over the period January 1, 1992 to March 30, 1999. Included among the regressors is the property crime index score of the property's location relative to the *county* average crime index score, obtained from CAP Index, Inc. Two sets of dependent variables are used: vendor-to-buyer financing (VTB) scaled by sale price and new mortgage (NewM) bank financing scaled by sale price. Panel A reports coefficient estimates under the Klein and Spady (1993) robust semiparametric binary response model, where the dependent variable is one if the financing type is used, and zero otherwise. Panel B reports coefficient estimates under the truncated regression model of Powell (1986), where the data is truncated to only those observations where the dependent variable (financing type) is positive. Each of these cross-sectional regressions are run for each year and the time-series average of the coefficient estimates are reported below along with t-statistics in parentheses, where standard errors are calculated from the time-series of coefficient estimates in the style of Fama and MacBeth (1973). All regressions include state dummies, which are omitted from the table for brevity.

	Fama-MacBeth Regressions							
	Panel A: Klein-Spady Binary Response Model				**Panel B: Powell Truncated Regression**			
Dep. var.:	VTB	VTB	Newm	Newm	VTB	VTB	Newm	Newm
const.					1.219	4.239	0.848	0.849
					(9.04)	(2.53)	(37.67)	(39.63)
Non-Corporate Buyer	0.869	0.259	0.122	0.140	-0.358	-3.051	-0.007	-0.008
	(1.63)	(2.22)	(1.06)	(3.09)	(-1.57)	(-1.72)	(-2.57)	(-2.49)
SellDist	-0.001	-0.001	-0.006	-0.004	-0.010	-0.026	0.000	0.001
	(-1.80)	(-1.76)	(-1.63)	(-1.56)	(-1.31)	(-1.56)	(1.15)	(1.30)
BuyDist	-0.016	0.037	-0.086	-0.019	0.019	0.223	0.000	0.000
	(-1.40)	(1.86)	(-1.99)	(-4.68)	(1.17)	(1.68)	(1.21)	(1.44)
Development	-0.020	-0.113	0.639	-0.169	0.225	1.649	0.014	0.014
	(-1.89)	(-1.60)	(1.54)	(-1.28)	(1.75)	(1.73)	(2.14)	(2.06)
Age	0.015	0.049	0.006	0.002	0.000	0.007	0.000	0.000
	(1.86)	(1.84)	(1.82)	(1.56)	(0.48)	(1.94)	(0.59)	(1.18)
Land	-0.760	-0.756	-6.124	-1.324	0.010	-0.005	0.005	0.004
	(-1.31)	(-1.60)	(-2.26)	(-5.10)	(0.50)	(-0.28)	(0.26)	(0.20)
Apartment	-0.121	-1.021	1.936	0.503	-0.581	-3.434	0.010	0.009
	(-2.47)	(-2.18)	(2.45)	(6.63)	(-3.52)	(-1.92)	(1.82)	(1.67)
City-Center	-0.004	0.033	-0.073	0.003	0.034	1.378	-0.004	-0.004
	(-0.55)	(1.78)	(-3.78)	(0.56)	(1.01)	(1.70)	(-0.92)	(-1.02)
Property Crime	0.016	0.011	0.068	-0.003	0.046	-0.001	0.003	0.002
	(1.22)	(0.70)	(1.84)	(-0.53)	(1.85)	(-0.09)	(3.86)	(3.18)
Broker as Principal	0.116	0.459	-0.019	-0.124	0.134	-0.837	-0.014	-0.012
	(3.71)	(1.93)	(-1.01)	(-3.31)	(1.17)	(-1.86)	(-3.27)	(-3.29)
Broker	-0.256		1.383		-0.292		-0.017	
	(-5.36)		(2.35)		(-2.68)		(-6.20)	
Local Broker		-0.245		-0.010		-1.561		-0.013
		(-3.91)		(-0.06)		(-1.80)		(-4.87)
National Broker		0.048		0.054		-0.569		-0.010
		(0.70)		(2.01)		(-1.93)		(-5.56)
log(Price)	-1.000	-1.000	-1.000	-1.000	-0.028	-0.160	-0.006	-0.007
	–	–	–	–	(-1.86)	(-2.44)	(-4.32)	(-4.76)

Table III:
The Relation Between Brokerage Activity and the Sale Price

Results from the regressions of property capitalization rates on various measures of brokerage activity plus property, buyer, and seller characteristics are reported below over the period January 1, 1992 to March 30, 1999. The dependent variable is the capitalization rate of the property (Cap. Rate) defined as net operating income on the property divided by the sale price. Coefficient estimates are calculated via ordinary least squares (OLS), where regressions are run every year, and the time-series average of the coefficient estimates, along with time-series t-statistics reported in parentheses, are reported below in the style of Fama and MacBeth (1973). All regressions include state dummies, which are omitted from the table for brevity.

	OLS (Fama-MacBeth Regressions)			
Dep. var.:	Cap. Rate	Cap. Rate	Cap. Rate	Cap. Rate
const.	10.329	10.304	10.366	10.616
	(15.80)	(16.12)	(16.29)	(16.51)
Non-Corporate Buyer	-0.348	-0.357	-0.346	-0.348
	(-10.34)	(-11.29)	(-11.02)	(-12.17)
SellDist	0.009	0.009	0.009	0.008
	(2.17)	(2.12)	(2.44)	(2.08)
BuyDist	-0.007	-0.007	-0.007	-0.006
	(-2.46)	(-2.48)	(-2.75)	(-2.47)
Development	-0.278	-0.297	-0.291	-0.307
	(-2.42)	(-2.59)	(-2.53)	(-2.59)
Age	0.002	0.002	0.002	0.002
	(1.98)	(1.90)	(1.93)	(1.63)
Land	-0.212	-0.242	-0.242	-0.275
	(-1.46)	(-1.72)	(-1.72)	(-2.01)
Apartment	-0.246	-0.241	-0.246	-0.188
	(-3.30)	(-3.49)	(-3.29)	(-2.84)
City-Center	-0.018	-0.015	-0.021	-0.004
	(-0.29)	(-0.25)	(-0.34)	(-0.07)
Property Crime	0.198	0.196	0.198	0.184
	(4.55)	(4.65)	(4.67)	(4.65)
Broker as Principal	-0.199	-0.149	-0.238	-0.263
	(-2.28)	(-1.77)	(-2.67)	(-2.53)
Broker	0.421			
	(6.05)			
List Broker		0.322		
		(4.82)		
Sale Broker		0.058		
		(1.42)		
Local Broker			0.305	
			(4.30)	
National Broker			0.078	
			(2.07)	
2 Different Brokers				-0.102
				(-3.42)
log(Price)	-0.089	-0.083	-0.085	-0.082
	(-2.03)	(-1.92)	(-1.97)	(-1.77)

Table IV:
Predicting Brokerage Activity: When are Brokers Used?

Various types of brokerage activity are regressed on property, buyer, and seller characteristics as well as attributes of the commercial real estate market in order to explain when and why certain brokerage activity is employed in the deal. Results are reported over the period January 1, 1992 to March 30, 1999. Included among the regressors are several 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, defined as the homicide rate for the property's location 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 that were done by a national broker within a 10 mile radius, and the Herfindahl index of brokerage activity within a 10 mile area. The dependent variables are: the presence of a broker, presence of a local broker, presence of a national broker, presence of a list broker, and the presence of a sale broker. The regressions are estimated under the Klein and Spady (1993) robust semiparametric binary response model, where the time-series average of the coefficient estimates and time-series t-statistics (in parentheses) are reported following Fama and MacBeth (1973). All regressions include state dummies, which are omitted from the table for brevity.

	Klein-Spady Binary Response Model (Fama-MacBeth Regressions)				
Dep. var.:	Broker	Local Broker	National Broker	List Broker	Sale Broker
Non-Corporate Buyer	0.142	0.100	0.014	0.087	0.068
	(1.35)	(1.77)	(0.85)	(2.10)	(2.42)
SellDist	0.016	-0.001	0.013	0.002	-0.019
	(2.72)	(-1.67)	(2.29)	(1.14)	(-1.94)
BuyDist	-0.038	0.000	0.000	-0.005	0.002
	(-1.58)	(-0.03)	(0.26)	(-7.06)	(0.24)
Development	-1.873	-0.170	0.049	-0.186	0.605
	(-2.66)	(-3.23)	(2.12)	(-4.48)	(1.44)
Age	-0.009	0.000	0.000	0.000	0.006
	(-1.86)	(0.57)	(-0.66)	(-0.69)	(2.63)
Land	-2.003	-1.098	-0.085	-1.795	-3.757
	(-3.00)	(-2.14)	(-1.91)	(-2.46)	(-2.46)
Apartment	2.872	0.866	0.086	0.890	2.179
	(2.72)	(3.70)	(1.92)	(2.87)	(2.70)
City-Center	-0.788	0.045	-0.059	0.064	-0.097
	(-2.12)	(1.89)	(-3.43)	(2.78)	(-1.90)
Property Crime	0.055	-0.012	-0.004	-0.002	0.013
	(1.98)	(-1.74)	(-0.86)	(-0.26)	(1.40)
Broker Instruments:					
Radius	0.037	-0.019	0.006	-0.001	0.021
	(0.75)	(-2.64)	(0.75)	(-0.12)	(0.42)
Personal Crime	-0.383	-0.040	0.009	-0.011	0.003
	(-2.63)	(-1.86)	(2.75)	(-1.54)	(0.58)
σ_{local}	-0.113	0.006	-0.030	-0.023	-0.011
	(-1.79)	(1.31)	(-1.68)	(-1.76)	(-3.74)
$\frac{\$National}{\$Brokered}$	-1.493	-0.189	0.163	-0.173	-0.587
	(-1.88)	(-4.87)	(2.75)	(-1.70)	(-1.38)
Broker Herfindahl	-3.995	-0.295	-0.464	-0.167	-1.916
	(-2.80)	(-2.81)	(-2.69)	(-1.93)	(-2.07)
log(Price)	1.000	1.000	1.000	1.000	1.000
	–	–	–	–	–

Table V:
Do Brokers Influence the Frequency of Financing?

Results from the two-stage binary response regressions of the probability of employing various financing types in the deal on brokerage activity are reported below over the January 1, 1992 to March 30, 1999 time period. The various measures of brokerage activity are first estimated using instrumental variables under a first-stage linear probability model to account for the endogenous choice of brokers among various types of buyers, sellers, and properties. In addition to the instrumented broker variables, the regressors in the second stage regression include all of the property, buyer, and seller characteristics from Table II. The dependent variable in the second stage regression is one if the financing type is used and zero otherwise. Five sets of dependent variables are used: vendor-to-buyer financing (VTB), new mortgage financing from a bank (Newm), VTB financing conditional on no bank financing being present (VTB†), new mortgage financing conditional on no seller financing being present (Newm‡), and the assumption of an existing mortgage (Assm). 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 omitted from the table for brevity.

	Klein-Spady Binary Response Model (Fama-MacBeth Regressions)									
Dep. var.:	VTB	VTB	Newm	Newm	VTB†	VTB†	Newm‡	Newm‡	Assm	Assm
Non-Corporate Buyer	0.793	0.259	0.086	0.352	3.298	1.666	0.223	0.296	-0.128	-0.005
	(1.92)	(2.65)	(4.17)	(2.36)	(2.84)	(2.12)	(2.11)	(2.92)	(-1.36)	(-0.13)
SellDist	-0.004	-0.003	-0.002	0.010	0.006	0.017	0.035	0.006	-0.010	0.066
	(-2.28)	(-1.13)	(-0.93)	(1.80)	(1.14)	(1.57)	(1.59)	(3.06)	(-1.35)	(1.89)
BuyDist	0.027	0.035	-0.011	0.056	-0.018	-0.031	0.003	-0.027	0.005	0.002
	(1.40)	(1.54)	(-3.13)	(1.55)	(-1.06)	(-2.21)	(0.28)	(-4.23)	(1.76)	(0.32)
Development	0.067	0.258	-0.030	-0.046	0.020	0.126	-0.057	-0.299	-0.323	-0.026
	(1.24)	(2.08)	(-1.27)	(-0.54)	(0.09)	(1.25)	(-2.94)	(-2.49)	(-1.84)	(-0.97)
Age	0.014	0.020	0.001	0.004	0.055	0.046	0.000	0.003	0.007	-0.001
	(2.37)	(3.51)	(3.82)	(2.07)	(1.97)	(2.08)	(-0.41)	(3.04)	(2.65)	(-2.07)
Land	0.009	-0.081	-1.263	-6.322	-3.679	-1.288	-2.410	-1.201	2.148	-0.251
	(0.02)	(-0.79)	(-7.51)	(-1.93)	(-2.70)	(-2.30)	(-2.36)	(-3.30)	(1.76)	(-2.44)
Apartment	0.242	-0.118	0.595	1.427	-0.038	0.092	0.653	-0.481	2.357	2.860
	(2.15)	(-2.95)	(7.02)	(2.30)	(-0.43)	(1.92)	(2.73)	(-1.06)	(2.45)	(3.00)
City-Center	0.014	0.116	-0.010	-0.012	-0.429	0.217	-0.030	-0.037	-0.065	-0.188
	(1.84)	(2.43)	(-1.31)	(-1.58)	(-2.02)	(2.25)	(-1.26)	(-0.97)	(-1.00)	(-1.11)
Property Crime	0.058	0.003	-0.015	0.139	-0.084	0.134	0.004	-0.020	0.009	0.004
	(1.96)	(0.29)	(-2.03)	(1.78)	(-3.16)	(1.79)	(1.19)	(-1.13)	(1.35)	(1.23)
Broker as Principal	0.205	0.051	-0.055	0.232	0.169	-0.138	-0.265	-0.210	1.427	1.613
	(4.05)	(1.59)	(-1.69)	(1.76)	(1.11)	(-1.08)	(-1.68)	(-2.16)	(2.45)	(2.07)
Broker (Instr.)	8.232		1.362		4.641		3.909		14.392	
	(1.49)		(4.69)		(2.29)		(2.17)		(2.30)	
Local Broker (Instr.)		-0.916		5.542		1.623		-4.093		5.212
		(-1.11)		(2.31)		(7.24)		(-0.95)		(1.84)
National Broker (Instr.)		-0.220		0.778		1.302		-1.034		-6.455
		(-0.12)		(2.09)		(2.54)		(-1.48)		(-1.48)
log(Price)	-1.000	-1.000	-1.000	-1.000	-1.000	-1.000	-1.000	-1.000	-1.000	-1.000
	–	–	–	–	–	–	–	–	–	–

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

Table VI:
Do Brokers Influence the Magnitude of Financing?

Results from the two-stage truncated regressions of the magnitude of various forms of financing employed in the deal on brokerage activity are reported below over the January 1, 1992 to March 30, 1999 time period. The various measures of brokerage activity are first estimated using instrumental variables under a first-stage linear probability model to account for the endogenous choice of brokers among various types of buyers, sellers, and properties. In addition to the instrumented broker variables, the regressors in the second stage regression include all of the property, buyer, and seller characteristics from Table II. The dependent variable in the second stage regression is the fraction of the property's value financed by each type of loan, which is the amount of the loan type divided by the sale price of the property. The data is truncated to only those observations where the dependent variable is positive. Four sets of dependent variables are used: vendor-to-buyer financing (VTB), new mortgage financing from a bank (Newm), VTB financing conditional on no bank financing being present (VTB†), and new mortgage financing conditional on no seller financing being present (Newm‡). Coefficient estimates are calculated via Powell's (1986) robust truncated regression, with t-statistics reported in parentheses, where the time-series average of the coefficient estimates and their associated t-statistics are reported in the style of Fama and MacBeth (1973). All regressions include state dummies, which are omitted from the table for brevity.

	Powell Truncated Regression (Fama-MacBeth Regressions)							
Dep. var.:	VTB	VTB	Newm	Newm	VTB†	VTB†	Newm‡	Newm‡
const.	2.466	6.455	0.920	0.908	1.267	1.216	0.956	0.943
	(4.14)	(2.22)	(21.87)	(21.85)	(15.08)	(12.01)	(24.89)	(23.33)
Non-Corporate Buyer	-0.172	-4.083	-0.006	0.002	-0.009	0.006	-0.006	0.006
	(-1.37)	(-1.71)	(-1.48)	(0.46)	(-0.50)	(0.36)	(-1.45)	(1.53)
SellDist	-0.024	-0.042	0.001	0.001	0.001	0.001	0.001	0.001
	(-1.50)	(-1.58)	(1.47)	(2.63)	(2.34)	(1.16)	(1.80)	(2.27)
BuyDist	0.029	0.102	0.000	0.000	-0.003	0.006	0.000	0.000
	(1.35)	(1.63)	(0.41)	(0.72)	(-2.93)	(0.93)	(0.06)	(-0.12)
Development	0.396	2.944	0.008	0.014	-0.074	-0.069	0.004	0.009
	(1.58)	(1.71)	(0.91)	(1.31)	(-4.00)	(-2.83)	(0.45)	(0.98)
Age	0.000	-0.016	0.000	0.000	0.001	0.001	0.000	0.000
	(0.68)	(-1.69)	(-0.53)	(0.21)	(2.08)	(1.59)	(1.39)	(1.76)
Land	-0.042	-0.047	-0.011	-0.016	-0.100	-0.112	-0.006	-0.017
	(-1.91)	(-2.98)	(-0.55)	(-0.76)	(-5.18)	(-7.06)	(-0.26)	(-0.79)
Apartment	-0.809	-4.503	0.023	0.015	0.051	0.009	0.022	0.014
	(-2.79)	(-1.88)	(2.69)	(1.82)	(4.90)	(0.63)	(2.94)	(1.78)
City-Center	0.132	-0.207	-0.001	0.001	-0.012	-0.021	-0.002	0.004
	(1.51)	(-2.04)	(-0.21)	(0.20)	(-2.17)	(-2.43)	(-0.39)	(0.55)
Property Crime	-0.062	0.169	0.001	-0.001	0.014	0.022	0.002	0.000
	(-1.71)	(1.72)	(1.03)	(-1.19)	(3.29)	(1.65)	(1.57)	(-0.03)
Broker as Principal	-0.026	0.004	-0.009	-0.010	-0.027	-0.031	0.000	0.000
	(-1.42)	(0.16)	(-1.98)	(-2.54)	(-2.41)	(-2.52)	(-0.07)	(0.04)
Broker (Instr.)	-1.195		-0.131		-0.464		-0.173	
	(-1.97)		(-1.85)		(-6.51)		(-2.67)	
Local Broker (Instr.)		-2.126		-0.099		-0.224		-0.192
		(-1.77)		(-1.23)		(-1.70)		(-2.26)
National Broker (Instr.)		-10.747		-0.106		-0.394		-0.080
		(-1.82)		(-3.51)		(-1.79)		(-2.24)
log(Price)	-0.065	-0.098	-0.006	-0.006	-0.014	-0.019	-0.005	-0.004
	(-5.85)	(-3.14)	(-2.10)	(-2.31)	(-3.54)	(-3.13)	(-1.83)	(-1.48)

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

Table VII:
Do Brokers Influence the Sale Price?

Results from the two-stage least squares regressions of capitalization rates on brokerage activity are reported below over the January 1, 1992 to March 30, 1999 time period. Various measures of brokerage activity are first estimated using instrumental variables under a first-stage linear probability model to account for the endogenous choice of brokers among various types of buyers, sellers, and properties. In addition to the instrumented broker variables, the regressors in the second stage regression include all of the property, buyer, and seller characteristics from Table III. The dependent variable in the second stage regression is the capitalization rate of the property (Cap. Rate) defined as net operating income on the property divided by the sale price. Coefficient estimates are calculated via ordinary least squares (OLS), 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.

	OLS (Fama-MacBeth Regressions)			
Dep. var.:	Cap. Rate	Cap. Rate	Cap. Rate	Cap. Rate
const.	11.008	11.085	10.636	10.276
	(13.79)	(14.64)	(9.97)	(10.51)
Non-Corporate Buyer	-0.346	-0.363	-0.476	-0.340
	(-2.35)	(-2.93)	(-4.13)	(-4.60)
SellDist	0.011	0.026	0.006	0.015
	(1.53)	(2.51)	(0.59)	(5.20)
BuyDist	-0.006	0.003	-0.003	-0.004
	(-0.87)	(0.44)	(-0.49)	(-0.81)
Development	-0.225	-0.370	-0.224	-0.496
	(-1.24)	(-1.60)	(-1.34)	(-3.67)
Age	0.002	0.001	0.008	0.002
	(2.25)	(0.81)	(4.64)	(0.65)
Land	-0.124	-0.371	0.423	-0.448
	(-0.42)	(-1.31)	(1.23)	(-1.46)
Apartment	-0.299	-0.726	-0.396	-0.169
	(-1.66)	(-4.65)	(-2.72)	(-1.46)
City-Center	0.029	-0.094	-0.202	-0.026
	(0.46)	(-1.01)	(-2.66)	(-0.26)
Property Crime	0.167	0.159	0.188	0.179
	(4.17)	(3.26)	(2.91)	(3.93)
Broker as Principal	-0.293	-0.291	-0.290	-0.297
	(-2.93)	(-2.97)	(-2.91)	(-2.90)
Broker (Instr.)	0.494			
	(0.26)			
Local Broker (Instr.)		1.461		
		(0.80)		
National Broker (Instr.)		-2.668		
		(-1.26)		
List Broker (Instr.)			-0.774	
			(-0.14)	
Sale Broker (Instr.)			1.834	
			(0.34)	
2 Different Brokers (Instr.)				-1.229
				(-0.73)
log(Price)	-0.144	-0.140	-0.171	-0.030
	(-1.58)	(-1.50)	(-2.55)	(-0.57)