Confronting Information Asymmetries: Evidence from Real Estate Markets

Mark J. Garmaise and Tobias J. Moskowitz*

*Graduate School of Business, University of Chicago. We thank the Center for Research in Security Prices and the Dimensional Fund Advisors Research Fund for financial support. Special thanks to Michael Arabe, John Edkins, and Peggy McNamara as well as COMPS.com for providing the U.S. real estate data, and to John Marsh for providing the Toronto real estate data. We are grateful to Stephen Cauley for his assistance and advice and we have benefitted from discussions with Ulf Axelson, David Barker, Doug Diamond, Gene Fama, Owen Lamont, Todd Milbourn, Ari Weinberger, and seminar participants at MIT and the University of Rochester. We also thank Kathy Burson and Xia Chen for excellent research assistance.

Correspondence to: Mark Garmaise or Tobias Moskowitz, Graduate School of Business, University of Chicago, 1101 E. 58th St., Chicago, IL 60637. E-mail: mark.garmaise@gsb.uchicago.edu, tobias.moskowitz@gsb.uchicago.edu.

Confronting Information Asymmetries: Evidence from Real Estate Markets

Abstract

This paper studies the role of asymmetric information in commercial real estate markets in the U.S. and Canada. We propose a novel and exogenous measure of information based on the quality of property tax assessments in different regions and time periods. Employing direct and indirect information variables, we find strong evidence that information considerations are significant in this market. We show that market participants resolve information asymmetries by purchasing nearby properties, trading properties with long income histories, and avoiding transactions with informed professional brokers. The evidence that the choice of financing is used to address information concerns is mixed and weak.

I. Introduction

This paper studies the role of asymmetric information in the commercial real estate market. Whether information considerations are important in real estate is an unresolved question. There are two reasons why information issues might be relevant. First, the market is highly illiquid and the price mechanism, therefore, is very slow to convey information to market participants. Second, the assets (commercial properties and vacant land) are idiosyncratic and are, accordingly, difficult for outsiders to value. Indeed, this suggests that information considerations may be more important in the real estate market than in Akerlof's (1970) canonical example of the used car market. A 1994 used Toyota Tercel, to take a case in point, is a rather homogeneous and well-traded good compared to a distinctive office building in a recently gentrified neighborhood on the West Side of Chicago.[1] Conversely, one may argue that information problems are not significant in this market; tangible real estate assets might be thought relatively easy to value and adverse selection may be alleviated through the use of hired appraisers. In this paper we find strong evidence that information concerns are important in our study of several commercial real estate markets in the U.S. and Canada. Using direct and indirect information variables, we show that market participants mitigate information asymmetries by purchasing properties in nearby, rather than distant, locales, by trading properties with long income histories, and by avoiding trades with professional brokers who are known to be informed. The evidence that the choice of financing is used to address information concerns is mixed and fairly weak. We also find little support for signalling theories that predict a link between sale price and financial structure.

Although there is a large and important theoretical literature on asymmetric information, the number of empirical papers testing for its effects is much smaller. The empirical relevance of asymmetric information has been studied in the used car market (Genesove (1993) and Porter and Sattler (1999)), the labor market (Campbell and Kamlani (1997) and Landers, Rebitzer, and Taylor (1996)), the insurance market (Chiappori and Salanié (2000)) and the software contracting market (Duflo and Banerjee (1999)), among other settings. In this paper we find that information asymmetries are important in real estate, but that they are mitigated only in some of the ways suggested by theory; in particular, limited participation, selective offering, and market segmentation

[1] Models of real estate pricing quite typically make reference to the severe information problems in this market (e.g., Downs and Guner (1999) and Ling and Ryngaert (1997)).

appear to be more important than the use of appropriate forms of financing. Our unique data set allows us to contrast transactions undertaken in environments (i.e., regions and time periods) in which all agents are provided with precise and timely valuation information, with those made in environments in which this information is lacking. Information concerns should be of greater relevance in the latter case.

We test several theories of asymmetric information in this paper. First, we consider the "no-trade" implications of Milgrom and Stokey (1982) who show that uninformed agents will not trade with informed counterparts. This should lead to limited market participation on the part of agents who are particularly informationally disadvantaged. If there is asymmetric information about local market conditions, then property buyers should, in general, be local and this tendency will be more pronounced when information asymmetries are severe. We find strong evidence that these two predictions hold. Likewise, uninformed buyers will focus on properties with long income histories that are easy to evaluate. This tendency will also be more pronounced when information concerns are heightened. We find evidence consistent with these predictions. Furthermore, if informed agents can be identified, then it is efficient for them to trade with other informed agents, rather than with the uninformed. This should lead to a form of market segmentation in which the informed and uninformed markets are to some degree distinguished. We find that informed brokers are likelier to sell to other informed brokers, particularly in environments where information asymmetries are severe. We argue that the proximity, selective offering, and market segmentation results clearly indicate that information asymmetries are important in commercial real estate.

In addition, we examine the effects of asymmetric information on the choice of financing. A central theme in the literature on capital structure is that the private information of insiders can have an important influence on the optimal financial organization of firms. The implications of asymmetric information for firm capital structure were studied by Myers and Majluf (1984), Diamond (1991a), Nachman and Noe (1994), DeMarzo and Duffie (1999), and others. Myers (1984) proposed a "pecking order" in securities in which insiders are better off issuing safe securities such as debt when the market recognizes their informational superiority. We consider the implications of several information models and find only weak evidence that market participants use the form of financing to mitigate information problems.

In this paper we examine two data sets, one with information on commercial real estate transactions in eight states in the U.S. and the second covering Toronto, Canada. We characterize high- and low-information environments by exploiting exogenous differences in property assessment quality across regions and time. In the U.S. there are significant disparities in the quality of assessments across counties and local assessment jurisdictions. We test whether these exogenous differences give rise to variation in the proximity of buyers, the types of properties brought to market, the extent of market segmentation, and the form of financing. In Toronto in late January, 1998 there was an important change in the way property tax assessments were reported. We contrast transactions prior to this change with those following it in order to determine if this exogenous information shock had an impact on the pattern of financing choices. We also conduct indirect tests of the predictions of information models.

Our data contain nearly 13,000 individual property transactions, providing us with substantial power. The data also permit both time-series and cross-sectional tests of the information hypotheses. An additional advantage of using real estate data is that the financings are almost always nonrecourse.[2] Hence, the only information that is relevant for financing is information about the property itself. This is in marked contrast to many studies for which it is difficult to distinguish, for example, between information pertaining to assets in place and information pertaining to any one of many new projects. We develop the implications of asymmetric information models for the forms of financing that are widespread in real estate markets, though less common elsewhere (such as seller financing and the assumption of existing mortgages), in order to generate testable hypotheses for our data.

Although the relevance of information considerations has proven difficult to document (e.g., Genesove (1993)), our tests provide compelling evidence on the importance of adverse selection in the commercial real estate market. We find, however, only weak evidence on the importance of financing in resolving information issues. In this sense, the paper is consistent with the previous direct empirical evidence on the Myers pecking order, which is largely inconclusive. Best and Best (1995), for instance, show that firms issuing equity have higher analyst forecast errors than firms issuing debt. If analyst forecast errors proxy for information asymmetries, then this finding is not consistent with the pecking order hypothesis. Likewise, Helwege and Liang (1996) find that firms

[2]Nonrecourse loans are guaranteed only against the property and not against other personal assets of the borrower. Stein (1997) discusses the pervasiveness of nonrecourse loans in commercial real estate.

do not generally follow the pecking order in approaching the financial markets for funding. Shyam-Sunder and Myers (1999), however, show that the funds flow deficit of firms is mainly financed by debt issues, which is consistent with the pecking order hypothesis. They also show that the pecking order model has greater explanatory power for firm's financial policies than the traditional static trade-off theory.[3] We find that the separating signalling equilibria posited in theories of asymmetric information and capital structure appear not to obtain in the commercial real estate market. Our results suggest that standard models of asymmetric information and financial policy signalling may not be relevant in real estate, even though information asymmetries are significant in this market.

In addition to making use of a new data set that is well-suited to testing information effects, this paper provides an analysis of the impact of asymmetric information on participation, selective offering, market segmentation, and financial choice that is novel in two respects. First, we are able to test directly some of the central implications of asymmetric information models. As indicated above, only a few empirical papers have directly studied this issue, and many of the predictions of information theory are abstract and difficult to test. Furthermore, it is often the case that indirect and possibly endogenous measures such as analyst coverage, firm size, and bid-ask spread are used as proxies for the level of asymmetric information. We study the effects of information shocks and *exogenous* variation in the information environment, thereby directly capturing shifts in information quality. Second, we use robust estimation techniques for both binary response and truncated regression models to gauge the impact information considerations have on capital structure. The estimators used in this study are consistent and asymptotically normal under rather general conditions. One of the contributions of this paper is its application of the new robust methodologies of Powell (1986) and Klein and Spady (1993), which are not yet in common use.

The rest of the paper is organized as follows. Section II outlines and discusses the theoretical hypotheses to be tested. Section III contains a discussion of our data sets, highlighting the various forms of financing in real estate markets. Section IV describes how we characterize the information environment across regions and time and argues that property tax assessments provide informative signals to market participants. Section V details our empirical results. Finally, Section VI concludes.

[3]The indirect evidence on the importance of information considerations for capital structure choice is generally more supportive. See, for example, Titman and Wessels (1988), Rajan and Zingales (1995), Korajczyk, Lucas, and McDonald (1991), Opler and Titman (1996), and Fama and French (1999).

II. Theoretical Hypotheses

In this section we develop the hypotheses tested in this paper. These hypotheses are derived from empirical implications emerging from the theoretical literature on asymmetric information.

A. Limited Participation, Information Availability, and Market Segmentation

Models of asymmetric information demonstrate that rational but uninformed agents will be reluctant to trade with informed counterparts (see, for example, Milgrom and Stokey (1982)). Our first prediction is that informationally disadvantaged agents will limit their participation in the real estate market. We presume that prospective buyers located far away from a property will be less knowledgeable about local market conditions. Their informational disadvantage will be further pronounced in high-asymmetric-information environments.

Prediction 1. *Property buyers are primarily drawn from nearby locales.*

Other theories would also suggest Prediction 1. If, for example, monitoring of tenants is important, then we would expect buyers to be local. Prediction 2, however, is a prediction of information models only.

Prediction 2. *The distances between buyers and properties are relatively shorter in high-asymmetric-information environments.*

Properties also vary in the amount of information available about their value. Less informed (distant) agents who might otherwise limit their participation in high-asymmetric-information environments, will choose to purchase properties with more information available. Properties with longer income and price histories provide uninformed buyers with more information than new properties and can mitigate the importance of the general information environment.

Prediction 3. *The effect in Prediction 2 will be particularly strong for properties with short income histories.*

Furthermore, properties with limited information available are less likely to be brought to market when information asymmetries are particularly severe.

Prediction 4. *Properties with short histories are less likely to be sold in high-asymmetric-information environments.*

Finally, market participants will be unwilling to trade with agents who are known to be particularly well-informed. Rather than deserting the market, as above, the less-informed may elect to participate by trading only with other less-informed agents. In equilibrium, the well-informed will prefer to sell to other well-informed agents rather than incur sizeable information costs in dealing with the less-informed. This form of market segmentation requires that informed agents be identified. Commercial real estate brokers selling property on their own account may be regarded as identifiably well-informed traders. Brokers may prefer to sell to other brokers for information reasons, despite the fact that by doing so they preclude the possibility of a commission and forego their market power advantage over non-brokers. Market segmentation implies the following predictions.

Prediction 5. *Brokers selling property on their own account are relatively more likely to sell to other brokers.*

Prediction 6. *Brokers selling property on their own account are particularly likely to sell to other brokers in high-asymmetric-information environments.*

B. Financial Structure

Information issues may also be mitigated by the appropriate design of the financial contract underlying the sale of the property. In this subsection we discuss the predictions of two models of capital structure in the presence of asymmetric information. As will be discussed in greater detail in Section III, our data sets specify the following four types of financing for each commercial property. In our sample, we find financing provided by the seller, known as vendor-to-buyer (VTB) financing, and new mortgages provided by banks and other financial institutions. In some cases, the buyer assumes the existing mortgage on the property. Buyers pay cash for the portion of the sale price that is not financed in one of these ways. Most transactions involve a combination of these four types. The importance of finance to real estate activity is established by Hancock and Wilcox (1997).

Information Model A: VTB and Bank Debt Substitution. This model presumes that the sale price is agreed upon prior to the arrangement of financing. The purchaser may then choose to seek financing from the seller or from a bank (or from some other financial institution). VTB financing and new mortgage financing possess very different characteristics from an information standpoint. VTB financing is provided by an investor who possesses superior information about the property; indeed, the seller almost certainly has greater familiarity with the property than the bank. As a result, financing provided by the seller will not be subject to the same information costs as financing provided by an outside investor such as a bank (e.g., Myers and Majluf (1984)). Sellers, however, generally face tighter liquidity constraints than banks. This trade-off is similar to the one faced by the entrepreneur in the Leland and Pyle (1977) model. In their model, the entrepreneur has superior information about his project but faces diversification costs if he takes a stake in his own firm. When information problems are severe, the seller's relative information advantage will be important, and the buyer will seek more financing from him. This yields our first prediction from this model.

Prediction A1. *Vendor-to-buyer financing is relatively more prevalent in high-asymmetric-information environments.*

When information problems are not severe, buyers should prefer to receive loans from well-capitalized banks rather than from liquidity-constrained sellers.

Prediction A2. *New bank financing is relatively less prevalent in high-asymmetric-information environments.*

Our data sets detail some transactions in which the buyer assumes the existing mortgage on the property. The data on assumed mortgages provides information on the *previous* financial structure that governed the allocation of the property's cash flows. When a seller sells a property with a large outstanding mortgage, he is in effect selling a highly levered equity claim on the property. Leveraged equity is subject to high asymmetric information costs; indeed, for this reason debt and debt-like securities are shown to be optimal in many theoretical studies of security design in the presence of asymmetric information (see, for example, Nachman and Noe (1994)). The purchaser, in seeking financing for a highly informationally-sensitive claim, will prefer to receive a loan from the well-informed seller. We refer to the leveraged equity claim as the seller's equity.

Prediction A3. *VTB loans are a larger proportion of the seller's equity when the existing mortgage is large.*

Information Model B: Separating Signalling Model. In this model, the sale price and form of financing are determined simultaneously. This model is analogous to the DeMarzo and

Duffie (1999) and Leland and Pyle (1977) separating signalling models which predict that sellers will retain a claim on the assets they bring to market in order to signal their quality. The retained claim perfectly signals to the market the seller's type. In these models the retained claim is an equity stake, but the retention of debt in the form of a VTB loan is an analogous transaction. In high-asymmetric-information environments, the value of the underlying assets will be more variable from the buyer's perspective. In several asymmetric information models (e.g., DeMarzo and Duffie (1999)), this higher variation leads to higher average retention of equity on the part of sellers. The analogous prediction in this setting is given below.

Prediction B1. *Vendor-to-buyer financing is relatively more prevalent in high-asymmetric-information environments.*

If there is a large existing mortgage on the property, the residual seller's equity will be very risky. As a result, when information problems are grave, property owners with large mortgages should be reluctant to sell their stakes because of a severe information discount; the cost of signalling will be too high. Indeed, in high-asymmetric-information environments, property owners will be reluctant to assume large mortgages in anticipation of the difficulties they will later face in selling their levered equity claims. Finally, the sale of debt claims (i.e., mortgages) is also less attractive relative to forgoing financing when information issues are pertinent. The implication of this argument is given in Prediction B2.

Prediction B2. *The sale of properties with large existing mortgages is relatively less common in high-asymmetric-information environments.*

Substantially leveraged equity claims marketed by the seller are likely to be very risky. The values of such claims will be highly variable across sellers. This higher variation will lead to greater retention.

Prediction B3. *VTB loans are a larger proportion of the seller's equity when the existing mortgage is large.*

Both models make similar predictions about financial choice. Predictions A1 and B1 are identical, as are Predictions A3 and B3. Predictions A2 and B2 differ and arise from the different assumptions made in the two models about the timing of the financing decision.

To better distinguish between the two models we analyze whether financial choice affects the sale price of the property. Model A makes no prediction about financial design influencing the price, since prices are assumed to be set first under this model. Model B, however, claims that the seller's retained stake in the property is used as a signal of the property's quality.

Prediction B4. *The sale price of the property is positively related to the seller's retained stake in the property.*

Finally, in real estate markets, two broad types of asymmetric information can be distinguished. First, sellers are likely to possess superior information about the current local market conditions and are also likely to be better informed about economic and social dynamics in the area surrounding the property; in addition, sellers will usually know more about local government regulations and will be more familiar with environmental considerations that may affect property values in the neighborhood. Second, sellers will typically have more accurate information about the condition of the property and will be aware of possible deficiencies in the structure itself (this latter type of information applies more to buildings than to vacant land). In the analysis that follows, when describing an informative signal we specify which of these two types of information it conveys. In this paper, we identify high-asymmetric-information environments as those time periods or locations in which sellers possess information about the value of their properties that is significantly more accurate than the information possessed by outsiders (including the buyer). The next two sections describe our data and how we characterize the information environment.

III. Data

Our sample consists of approximately 12,700 commercial real estate transactions over a 30 month period in the U.S. and Canada, containing detailed financing information as well as a large set of buyer, seller, and property attributes. We draw our data from two sources: The COMPS database, covering eight states in the U.S. commercial real estate market, and the Marsh database, covering commercial property sales in Toronto, Canada.

A. The COMPS Database (U.S. Commercial Real Estate)

The first data source is from COMPS.com, a leading provider of commercial real estate sales data in the U.S. 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 characteristics, and buyer, seller, and broker details.

There are 12,754 commercial real estate transactions from the COMPS database that occurred between January 1, 1997 and March 30, 1999. Of these, 7,620 met our initial data requirements (i.e., recorded sale price, financing data, identities of principals and property location), and 4,340 had information about brokers used in the deal. The data span 8 states: California, Nevada, Massachusetts, Maryland, Virginia, Texas, Illinois, and Colorado. In addition, we have 10,745 California real estate sales from COMPS over the period January 1, 1992 to March 30, 1999. In a later section of the paper, we conduct tests specifically on this longer sample of California transactions. 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 (including suburbs) in each state,[4] Table I reports that only slightly more than half of all transactions occur in the city center of each state.

Table I Panel A reports summary statistics on the COMPS database. Buyers are on average 235 km away from the property, while sellers are located more than 266 km away.[5] The respective median distances are the same for buyers and sellers (47 km). These distances indicate an interesting aspect of the commercial real estate market: the industry is highly localized. We will argue that proximity helps mitigate the severe information concerns that exist in the real estate market. Furthermore, we also group market participants more coarsely by state. Only 14.1 percent and 16.9 percent of buyers and sellers, respectively, reside in a different state from the property. The distance between market participants and the property decreases for properties located in major cities and for the smallest deals.

We group the properties into three mutually exclusive types: apartments (defined as multi-family dwellings, apartment complexes, condominiums, and townhouses), vacant land, and commercial and industrial buildings. As Panel A indicates, about 21 percent of property sales are of

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

[5]COMPS provides the location (city and state) of the buyer and seller, as well as eight digit latitude and longitude coordinates of each property. We match the city locations of buyers and sellers with latitude and longitude coordinates provided by the *Geographic Names Digital Gazetteer*, published by the U.S. Geological Survey. Using these coordinate values, we compute the actual distance (in km) between each buyer and the property and each seller and the property, using the arclength formula given by Coval and Moskowitz (1999a). For details on this distance calculation, see Coval and Moskowitz (1999a).

vacant land, 27 percent are of apartments, and the remaining 52 percent are comprised of commercial and industrial buildings. We further identify properties with planned imminent development by assuming that purchasing development firms plan to develop the property in the near future. In addition, we presume that properties that are zoned "PUD" (planned unit development)[6] are scheduled for immediate development.

Panel A of Table I also reports summary statistics across the eight states covered by COMPS over our sample period. There is substantial variation across states in property types and buyer and seller characteristics, including buyer and seller proximity.

Another interesting aspect of the data is the detailed financing information available for each property transaction. Four types of financing appear in the data. Buyers either use cash, receive 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.[7] 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. This grouping together of retained cash and outside equity complicates the evaluation of the effects of asymmetric information on financing choice, since the information costs associated with issuing equity are high, while the use of retained cash carries the lowest information costs. Consequently, our tests focus exclusively on tradeoffs between the three other types of financing, as discussed in Section II.

Panel B of Table I contains information about property financing. Examining the U.S. financing data, the average sale price of the properties is just over $2.7 million, ranging from $20,000 to $734 million over the sample period, with a median sale of $657,000. Approximately 3 percent of buyers assume an existing mortgage on the property, which typically comprises 74 percent of the purchase price when present. More than 60 percent of buyers obtain a new mortgage, comprising almost 75 percent of the price when this form of financing is utilized. Perhaps one of the most interesting features of the real estate market is the extent of VTB financing. VTB financing is used in 15 percent of cases, and comprises over 62 percent of the purchase price when used. There is little difference between city and non-city transactions in terms of financing choice. Smaller deals have a greater proportion of VTB and new mortgage financing and a smaller proportion of assumed mortgages. The total loan to value ratio is 74.3 percent across all properties, with little difference

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

[7]A general overview of real estate finance is found in Williams (1999).

between smaller and larger deals. Looking across the states, there is significant dispersion in the occurrence of each financing type, with slightly less dispersion in the percentage of the sale price each type of financing comprises when used. The total loan-to-value ratio exhibits very little variation across states. Since all of our financing types other than cash are forms of debt, this suggests that there is little variation in institutional practices or regulation across states that affects the amount of leverage taken on a property. Therefore, the only significant variation exhibited across states is in the type of debt contract used. In this respect, vendor and bank financing may be considered substitutes, as described in our discussion of the information models in Section II.[8]

B. The Marsh Database (Canadian Commercial Real Estate)

The second database is compiled from the *Marsh Report on Toronto Real Estate Sales*, covering all commercial real estate sales of $1 million (Canadian) or more in the 25 municipalities surrounding Toronto, Ontario, Canada. We consider only properties in the six municipalities that form Metropolitan Toronto. The data are collected from deeds and other land registry documents as well as from site visits. Table II Panel A contains summary statistics on the 971 real estate transactions in the Marsh database over the period May, 1996 to April, 1999. We classify properties as either apartments, vacant land, or commercial and industrial buildings, as we did for the COMPS database. Approximately 19 percent of the properties sold are vacant land, and roughly 25 percent are apartments. The remaining 56 percent of sales are of commercial and industrial buildings. The Marsh Report also details the identity and location of each buyer and seller, and indicates whether the buyer or seller occupied the property prior to sale. Approximately 10 percent and 5 percent of the sellers and buyers, respectively, occupied the property prior to sale, and 20 percent of all buyers and 22 percent of all sellers do not reside in Toronto. In addition, we determine whether the property is slated for development in the immediate future. We make this determination in two ways. First, the Marsh Report in some cases states that development is planned. Second, when this explicit cue is not present, we assume that all development firms purchasing a property plan

[8] The low occurrence of VTB financing in Illinois and Virginia is notable. The average across the other states is over 20%. The unusual pattern of financing in Illinois and Virginia is due, however, to these states' recognition of land trusts. 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 in states where land trusts are recognized. Land trusts are used in Florida, Illinois, Indiana, North Dakota, and Virginia. Since we cannot identify land trusts in our data, we include a dummy variable in our regressions for states that recognize land trust deals.

to develop it in the near future. This more direct approach of classifying development allows us to link 20 percent of Marsh properties (Panel A Table II) to imminent development plans compared to only 6.7 percent for COMPS (Panel A Table I). Dividing the sample in half by sale price, the smaller deals have a higher proportion of out-of-town sellers, and a lower proportion of apartment and development sales.

Table II Panel B provides descriptive statistics on property financing. Marsh reports the same four types of financing as those in COMPS: VTB, assumed or existing mortgage, new mortgage, and cash. Comparing Panel B of Table II (Marsh) to Panel B of Table I (COMPS), one notable statistic is the small 3 percent occurrence of assumed mortgages in the U.S. data compared to their nearly 15 percent frequency in Toronto. One possible explanation for this discrepancy is that U.S. mortgages, for institutional reasons, are often due upon the sale of property. Hence, there is little opportunity to assume an existing mortgage. In addition, U.S. mortgages also tend to have longer maturities than those in Canada. This provides a greater incentive for U.S. buyers to renegotiate the loan or refinance the property rather than assume an existing mortgage. Canadian investors are less likely to be willing to incur refinancing transactions costs if the loans are of short maturity.

C. Vendor-To-Buyer Financing

The presence of vendor-to-buyer financing, which is exhibited strongly in both the COMPS and Marsh data sets, is an interesting feature of real estate markets that raises questions about the influence of information asymmetries on financing choice. The mere existence of seller financing is somewhat hard to rationalize under an asymmetric information framework. The seller is better informed than either the buyer or the bank about the property, so he should be expected to take the riskiest position in the property rather than the less risky debt claim. One typical rationale for seller financing might be the seller's need for liquidity; if the seller needs cash, he may be prepared to offer financing in order to sell quickly. Under such circumstances, however, the seller would be better off obtaining a mortgage from the bank and retaining equity in the property. This would allow him to alleviate his liquidity concerns while continuing to hold an informationally efficient stake. If the owner wishes to sell the property for other reasons and information asymmetries are important, then uninformed buyers should first acquire a relatively safe debt contract (mortgage) on the property. In only 0.8 percent of transactions in our databases did the purchaser previously hold a mortgage on the property.[9] By contrast, when buyers purchase a property and obtain VTB financing, they are first acquiring the most informationally sensitive claim and only later do they acquire the safe debt claim. This is difficult to explain in an asymmetric information framework. We do find, however, that VTB loans are typically junior to bank loans, which is consistent with information theory. Finally, one can argue that if liquidity is motivating the sale, then at least some form of vendor financing provides a signal of property quality to buyers. Although the seller should take the riskiest position, by providing VTB financing he is retaining at least some claim on the property, which should mitigate information problems. If this is the case, then the extent of VTB financing will vary with the information environment as predicted in Section II.[10]

IV. Characterizing the Information Environment

The basic aim of this study is to examine the influence of asymmetric information in the real estate market. In order to do so, we must clearly characterize the information environment. We capture information asymmetries by using various indirect and direct measures of information.

A. Indirect Information Variables

We begin with several indirect measures of information asymmetry. We argue that buyers located closer to a property likely have better information about it. Local residents have a better understanding of local market conditions and can more easily and cheaply evaluate the property. We use the distance between the buyer and the property as a measure of the degree of information asymmetry. This measure of limited participation captures the extent to which poorly informed (i.e., distant) buyers choose not to participate in the market, rather than face high adverse selection costs.

In addition, we consider the age of the property. Properties with longer income and price histories provide investors with more information about the property and the local real estate market. Finally, our data also contain information on whether the buyer or seller is a professional broker. Since brokers are both well-informed and identifiable, we examine whether these agents predominantly trade with each other; this provides a measure of market segmentation.

[9] Foreclosures exhibit this pattern, but our data sets do not include foreclosures. In any case, banks do not typically expect to take an equity stake in a property when providing a mortgage.

[10] VTB financing is not typically short-term "bridge" financing used to expedite the deal. The maturities of VTB loans are often as long as (or longer than) the maturities of bank loans. The role of VTb finance in the residential market is discussed by Haurin and Hendershott (1986)

B. Informative Signals: Property Tax Assessments

In addition to the indirect variables previously discussed, we employ a direct measure of information asymmetry using exogenous differences in the quality of property tax assessments. We argue that property tax assessments provide useful and accurate information about the value of real estate. This fact is widely recognized and utilized by practitioners, but is less well-known in the academic literature. Government assessments of real estate property value are conducted for the purposes of assessing property taxes. These assessed values are publicly available, and measures of their accuracy (relative to market value) are publicly reported. Our study makes use of the fact that these assessments vary widely in their quality across regions and time.[11]

Real estate brokers we have spoken with explain that they pay attention to government property assessments, often using them as a benchmark for property value. In addition, and perhaps more importantly, assessments provide useful information about the value of surrounding properties. While it is the case that buyers and sellers often hire their own private appraisers to value the properties, these appraisals are costly. Hence, one would not normally hire an appraiser to value all of the properties in a given area. In addition, appraisals on the same property can vary widely, and often are correlated with the views of the client.[12] The government assessments, therefore, provide unbiased, useful, and free information about the property and nearby properties to aid in determining market value. Moreover, we surveyed nearly a dozen private appraisers across the U.S., and found that many of them acknowledged making use of public assessments. Most importantly, as we will discuss, public assessments in certain regions reflect market prices very accurately.

B.1 U.S. Commercial Market

We first consider the U.S. real estate market from the COMPS data set. We examine the quality of assessments across the geographic regions covered by COMPS. Assessment practices and quality differ across states, counties, and even towns. Most states perform the assessing function at the county level, while some assess at the city or town level. In order to gauge the quality of these assessments, most states perform "ratio studies" periodically.[13] The studies are used to evaluate assessment performance and ensure that local assessment jurisdictions comply with state standards. Most state ratio studies derive their methodology and criteria from the International Association

[11] Assessed values are determined by various pricing models, comparison to similar properties, and site visits.
[12] In fact, several appraisers either hinted or explicitly stated that this occurs.
[13] Every state in our sample conducted ratio studies either annually or biennially.

of Assessing Officers (IAAO), the major professional society of property tax assessment. These studies compare market values of properties recently sold to their *prior* assessed values. In some cases, market value is estimated by an independent appraisal if insufficient recent sales took place in the region, or if certain types of properties are underrepresented in the data.[14] The assessment ratio of a property is defined as the ratio of assessed value to market value. The ratio study then examines the central tendency and variation of these ratios within an assessing jurisdiction. The two most popular measures are the median (for central tendency) and the coefficient of dispersion (COD) around the median, defined as

$$COD = \frac{\frac{1}{N}\sum_{i=1}^{N}|R_i - R^{med}|}{R^{med}} \times 100 \tag{1}$$

where N is the number of properties, R_i is the assessment-to-market value ratio for property i, and R^{med} is the median of these ratios. This is the measure recommended by the IAAO and is used in all eight states in the COMPS sample.

For our purposes in characterizing the information environment, we are interested in the variation of assessment ratios, not their central tendency. For example, if properties in Cook county, IL are uniformly assessed at 50% of market value, this is equally as informative as if they had been assessed at 100% of value, since market participants can precisely extract market prices from assessed values. Conversely, even if the median property is assessed at 100% of market value, if the dispersion around the median is high, then the assessments are less informative.

We employ the COD measure reported for each state, county, or town to characterize the informativeness of a region's assessments. We obtained the 1998 and 1999 property assessment ratio studies for each state, which report the COD measure for all assessment jurisdictions within the state. If these were not available, then we used the most recent ratio study we could find.[15] Ratio studies evaluate assessments made in the previous year, and hence are available to buyers *before* the sale occurs in our database. When CODs were reported for various property types within an assessment jurisdiction, we assigned the COD measure corresponding to the appropriate property type within the region (i.e., land, apartment, or commercial and industrial building).[16]

[14]The only state where estimates of market value were used in conjunction with actual sale prices was Texas. Appraised values comprise 24 to 60 percent of the comparison data used in Texas ratio studies. In addition, Nevada employs appraised values exclusively in its ratio studies. We verified, however, that the results in this paper are robust to the exclusion of Nevada properties.

[15]The earliest ratio study used for our sample is the 1996 Illinois study.

[16]All ratio studies were careful to distinguish between COD measures for commercial and residential properties,

The only state for which a ratio study does not exist is California. Hence, we do not assign COD measures to California properties. The state of California is unique, however, in that it is the only state in our sample which bases its assessments on the property value at the time the current owner acquired it, rather than on current market value.[17] This makes California assessments particularly uninformative, since they are based on potentially very old values. Finally, in speaking with appraisers, we found that those who reside in areas with high COD measures place little weight on public assessments, while those who reside in areas with low CODs tend to pay attention to government assessments. The only state where appraisers completely ignored assessments, claiming they were worthless, was California. This is consistent with our characterization of the information environment, and suggests that the COD is a reasonable measure of the degree of information asymmetry.

Table III reports the mean, standard deviation, minimum, and maximum of COD measures across the entire sample (excluding CA) and for apartments, vacant land, and commercial and industrial buildings separately. As the table indicates, the mean COD is under 30 percent, indicating that assessments in general are of fair quality. There is, however, substantial variation in COD measures, ranging from 0.79% to over 128%. Table III also reports summary statistics for COD measures for various subsamples and across states. Interestingly, properties from the largest cities appear to have less accurate assessed values. There is wide dispersion in the accuracy of public assessments across states, with somewhat less dispersion within states. We exploit this dispersion in order to characterize various regions and types of properties as being subject to high or low degrees of information asymmetry. Initially, we sort all properties with assigned CODs (i.e., excluding California properties) into two groups: those with COD measures below the median measure ($COD \leq 13.31$) and those above. Since California assessments are particularly uninformative, we then assign all California properties to the high COD category. In later analysis, we employ the continuous COD measure and exclude California properties, and analyze California transactions separately.

Table III reports summary statistics on the COD measures for these two groups,[18] and indicates large differences in assessment quality between them. The average COD measure for low COD

and reported each separately. We only employ the COD measure corresponding to commercial properties, and within commercial properties according to property type (i.e., land, apartments, and commercial and industrial buildings).

[17] This practice was instituted under Proposition 13 in 1978 and makes California assessments incomparable with those in other states.

[18] Reported statistics on COD naturally exclude California properties.

properties is only 6.93%, with a cross-sectional standard deviation of only 2.38%. This is a compelling testament to the accuracy of assessments in better districts; these CODs do not much exceed typical broker's commissions in this market. High COD properties have an average 52.22% COD with a cross-sectional standard deviation of 26.25%, indicating that assessments in these regions are of very low quality. Every state except California has representation in the low COD group, and every state except Nevada is represented in the high COD category. Table I reports summary statistics and financing information for the low and high COD properties (including California).

In the next section, we document the relation between the COD and our indirect measures of information, and argue that the COD is useful for characterizing the information environment. We then examine the relation between our information proxies and the choice of financing.

B.2 Canadian Commercial Market

We now consider the Canadian real estate market from the Marsh data set. In June, 1996 the province of Ontario began the enormous undertaking of re-assessing all property values in Metropolitan Toronto. The project took 18 months to complete, and in late January, 1998 the government released the new assessment values, which were designed to reflect the value of all properties on June, 1996. These assessments would then be updated biennially.[19] Prior to this date, the only publicly available property values on record were from assessments done at the time of construction or sometime between 1930 and 1954, which was the last time the six Toronto boroughs conducted general assessments (the precise dates differ across boroughs). Thus, in late January, 1998 the quality of publicly assessed property values increased dramatically, now reflecting recent values rather than very stale values from heterogeneous time periods. This significant improvement in information quality implies that property transactions occurring after February 1, 1998 likely suffered less severely from information problems than those transactions occurring prior to this date.

Table II reports summary statistics and financing information for Toronto real estate sales before and after February 1, 1998. From the table, we see some informal evidence that information problems may be less severe in the "Post-Feb'98" period. For instance, the proportion of out-of-town buyers is larger in this period. If information asymmetries are less severe after February 1, 1998, then less informed agents (i.e., those from out-of-town) face smaller adverse selection costs,

[19]The COD measure for commercial and industrial properties in Ontario was 14.19 percent after the late January, 1998 reassessment.

and hence more willingly participate in the market. More striking is the fact that sellers who previously occupied the property were twice as likely to sell after February, 1998. Adverse selection costs are likely to be highest for sellers who previously occupied their properties. These sellers would face significantly lower information costs after February, 1998 if the assessments are informative.

Our two unique data sources provide distinct tests of information: one that employs cross-sectional differences across states, counties, and cities to characterize the information environment (COMPS), and one that uses a time-series shift in the information environment (Pre- and Post-February 1, 1998 in Marsh). We also employ a number of indirect information variables previously discussed. The commercial real estate data from two countries, covering diverse geographic regions and property types, and subject to wide dispersion in information quality provide a rich laboratory in which to investigate the influence of asymmetric information in this market.

V. Empirical Results

We investigate the hypotheses described in Section II by applying robust semiparametric estimation schemes to the data. We begin by focusing on the limited participation, selective offering, and market segmentation theories, and then shift attention to property financing. As discussed in Section II, there are two types of information with which investors are concerned. The first is information about the local market (e.g., economic, social, and regulatory dynamics), and the second is information specific to the property itself. For each of our tests, we describe which type of information our variables convey.

A. Limited Participation, Selective Offering, and Market Segmentation

Our first prediction from information theory is that less informed agents will limit their participation in the market. If distance proxies for the degree to which an investor is informationally disadvantaged, then market participants will predominantly reside near the property. (See Dolde and Tirtiroglu (1997) for a study of spatial information diffusion in real estate.) As the previous section documented, the median distance between buyers and properties is a mere 47 km. This degree of localization is unmatched in other economic arenas. Geographic proximity has been found to be economically important for asset allocation (French and Poterba (1991), Kang and Stulz (1997)), household equity investment (Huberman (1999)), the mutual fund industry (Coval and Moskowitz (1999 a,b)), venture capital financing (Lerner (1995)), as well as innovation and production (Audretsch and Feldman (1996) and Audretsch and Stephan (1996)), but the degree of proximity in these markets is much weaker than in the real estate market. The extreme proximity of market participants provides compelling support for Prediction 1, indicating that limited participation is used in the real estate market to address information concerns.

Prediction 2 states that the distance between buyers and properties should also decline when information asymmetries are high. If the COD measure captures exogenous variation in the degree of information asymmetry, then buyers should be closer to their properties in high COD regions, where property assessment quality is poor. To test this conjecture, we regress the distance between buyers and properties ($BuyDist$) on a set of control variables and two direct measures of exogenous information: COD and HighCOD. The first regression employs the continuous COD measure as a regressor and excludes all California property sales. The second regression employs a dummy variable HighCOD, which is one for all properties with associated COD measures above the median measure (13.31 percent). We include California properties in the second regression by assigning them to the HighCOD category. The control variables include city-center, land, apartment, and planned development dummies, as well as the age of the property and the log of the sale price. In addition, we also include a measure of the price variability in the locale in which the property resides. We define this measure for each property as the standard deviation of commercial property capitalization rates (net income on the property divided by sale price) within a 10 mile radius, excluding the property itself. This variable, σ_{local}, measures the variability of the income-price ratio within a local area, which will reflect property quality heterogeneity as price growth. The regression is estimated via ordinary least squares (OLS) and standard errors are computed using White's (1982) heteroscedastic-consistent covariance estimator. Table IV reports the results from this regression. There is a strong negative relation between either COD or HighCOD and buyer distance, consistent with Prediction 2. Buyers in high COD regions are located almost 78 km closer to their properties than buyers in low COD environments. Since the mean distance between buyers and properties over the whole sample is only about 235 km, this local bias result is quite striking.[20]

Prediction 3 states that the proximity effect of COD will be strongest for young properties. The dearth of historical income and price data for these properties makes them particularly difficult to evaluate in high COD jurisdictions. While information problems relating to the internal struc-

[20]Since COD varies between urban and non-urban areas as well as across states and property types, we also compute standard errors assuming groupwise clustering at the city-center, state and property type levels. The resulting t-statistic for HighCOD is -3.00.

ture of a building may become more severe over time, these problems are orthogonal to the local market condition information provided by an assessment. Careful assessments are very helpful in valuing buildings without significant historical data, but they do not provide much information about potential structural deficiencies in a building. The difference between evaluating buildings in high and low COD environments should therefore be smaller for older buildings. Older buildings in both high and low COD regions will be subject to similar degrees of building-specific uncertainty and local-market-condition uncertainty. Young buildings in both regions will be subject to a similar extent of building-specific uncertainty, but local-market-condition information asymmetries should be more severe in high COD jurisdictions. The distance effect of COD should therefore be particularly strong for recently-built properties.

To test this conjecture, we divide our sample into those properties with less than 10 years history and those older than 10 years, and rerun the previous distance regressions for each of these subsamples. Here, we exclude all vacant land deals since no land has an age greater than zero. Table IV reports the results and shows that the relation between COD and buyer distance is almost 4 times more negative for younger properties than older ones. Thus, the COD proximity effect appears to be particularly important for properties with short income histories. This is strong evidence supporting Prediction 3 and validating the COD as a reasonable measure of information asymmetry.

As discussed earlier, Prediction 1 is an implication of some non-information models as well. Predictions 2 and 3, however, are implications of information theories alone. The empirical evidence thus provides strong support for the importance of information in this market, and for the use of COD as an information proxy.

To further investigate the power of the COD as a measure of information asymmetry, we repeat the previous distance and age subsample regressions for a single state only. The variation in COD is largely inter-state since it mainly arises due to differences in state assessment practices. Hence, restricting the analysis to within a single state greatly reduces the predictive ability of this variable. Confirming the results of the previous regressions within a state provides strong evidence in favor of COD and addresses the concern that our earlier results are explained by inter-state differences other than in COD. Illinois is the only state with sufficient sample size (Table I) and variation in COD (Table III). CODs in Illinois range from 9.04 to 128.55 percent. The mean COD in Illinois is over 58 percent, which we consider to be poor assessment quality. Despite this problems, however,

Table IV shows that the explanatory power of COD is remarkably robust.[21] Even within Illinois, a state with poor assessment quality, and accounting for property type and local price variance, there is a strong negative relation between buyer distance and COD. Furthermore, this relation is twice as strong for younger properties relative to older ones. These results reaffirm our previous findings despite the fact that we eliminate a significant portion of the variation in COD, making a compelling testament for COD as a useful and exogenous measure of information asymmetry.

Table V presents further evidence of the importance of information asymmetries in the real estate market and supports the use of COD. Prediction 4 states that properties with relatively longer income histories will be brought to market when information asymmetries are high. The average age of properties sold in high-asymmetric-information environments should thus be higher. To test this we regress the property's age on COD, controlling for property type, location and price, and local price volatility. Both across states and within Illinois, there is a large positive relation between age and COD, consistent with Prediction 4, and further bolstering COD as an exogenous information variable.

Finally, we examine the market segmentation hypotheses. Prediction 5 states that when brokers trade on their own account, they likely will choose to trade with other brokers.[22] We test this conjecture by determining whether the probability that the buyer is a broker increases when the seller is a broker. The dependent variable in this binary response model is one if the buyer is a broker and zero otherwise ($Buyer = Brok$). The independent variables are a dummy indicating if the seller is a broker ($Seller = Brok$), dummy variables for city-center, land, apartment, and development, and the age of the property, local price standard deviation, the log of the sale price, and distance between the buyer and the property. In addition, we include the COD and an interaction between COD and $Seller = Brok$. The regression is estimated via Klein and Spady's (1993) semiparametric binary response model, which allows the error term to be unspecified and is detailed in the appendix. Although a probit or logit model may be used to estimate this regression, 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). Table V reports the binary response regression results under both the Klein and

[21] We exclude the city center dummy from these regressions since controlling for city-center in addition to property type eliminates the dispersion in COD completely (resulting in perfect multicollinearity). We also tried including city-center but dropping one of the property types and found similar results, which we do not report for brevity.

[22] Yang, Trefzger, and Sherman (1997) analyze the commercial real estate brokerage industry.

Spady (1993) and logit models for comparison. We set the coefficient on $log(Price)$ equal to -1 for scale normalization in the Klein and Spady regression, which is required by this model,[23] and do the same for the logit regression for comparability by scaling $log(Price)$. Table V reports the results from these regressions. Combining the coefficients on $Seller = Brok$ and the interaction term, there is a significant and positive relation between the seller-is-a-broker and buyer-is-a-broker variables. This is strong evidence in support of Prediction 5. Note that the Klein and Spady and logit models produce qualitatively similar results, but generate some significant differences in coefficient estimates and standard errors. We employ the more robust Klein and Spady estimates throughout the paper, but have confirmed our findings under logit.[24]

Prediction 6 argues that the segmentation of well-informed agents should be particularly evident in high-asymmetric-information environments. The interaction term between COD and $Seller = Brok$ is highly significant and positive in the full sample regression, suggesting that brokers tend to trade with other brokers much more in high-asymmetric information environments. The interaction term is also positive, but statistically insignificant, even within Illinois. These findings are consistent with Prediction 6 and lend credence to the COD variable as a measure of information asymmetry. Combining the coefficients on $Seller = Brok$ and the interaction term, the marginal contribution of $Seller = Brok$ is still positive and significant at the 1 percent level even for low COD properties. These results suggest that well-informed agents segment themselves from the market in order to mitigate information concerns, and that they do so particularly when assessment quality (information asymmetry) is low (high).

Overall, the results document that information asymmetries in the real estate market are severe and that agents attempt to resolve them through limited participation, selective offering, and market segmentation. The results also establish that COD is an exogenous variable that captures the degree of information asymmetry in this market. We now consider whether financing decisions are also used to mitigate information problems.

[23]The choice of normalizing on the log of price was made based on logit regression results that indicated a negative and statistically significant (at the 5% level) coefficient estimate on this variable. We note that the constant term is not identified in the binary response model since it is subsumed into the estimated kernel. See the appendix and Klein and Spady (1993) for more details about this model.

[24]Results available upon request.

B. Financial Structure

We examine the influence of our information variables on the frequency and magnitude of various forms of financing using robust estimation methods. 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. One solution is to apply the tobit model or other forms of maximum likelihood estimation. These estimators, however, are not robust to an incorrect specification of the distribution of the error.[25] This paper makes use of semiparametric estimators that are consistent and asymptotically normal for a broad class of error distributions. We analyze the censored financing data in two distinct ways: the semiparametric binary response model of Klein and Spady (1993) and the truncated regression model of Powell (1986). Both regression specifications are detailed in the appendix.

These two forms of analysis describe two distinct aspects of the data. The first model provides information on the factors determining the frequency of various forms of financing, while the second regression indicates which variables increase the magnitude of the types of financing when they are present. The descriptive statistics in Section III show 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 in this paper because they combine both types of information into a single model, obscuring this important distinction. In addition, robust censored estimators such as Powell's (1984) Censored Least Absolute Deviation (CLAD) model are not identified for our data set because of its unusually high degree of censoring. We conduct our tests on each of the data sets separately, since the COMPS and Marsh databases contain different variables, cover slightly different time periods, and are from different countries.

B.1 U.S. Commercial Real Estate Financing (COMPS Data)

Table VI reports results from the COMPS data. To test the first set of predictions from Section II, we regress the extent of VTB financing on the direct information variable COD and several indirect information variables, as well as a large set of control variables. We report regression results using

[25] Goldberger (1983) and Arabmazar and Schmidt (1982) show that maximum likelihood estimators of this form are typically inconsistent when the presumed error distribution is not equal to the true error distribution.

only the continuous variable COD, which excludes California properties. Later, we will analyze California transactions separately, since this is a market where assessment quality is particularly low.[26] Panel A reports results under the binary response model, where the dependent variable is one if VTB financing is used in the property sale and zero otherwise. In addition to COD, the independent variables include buyer distance, city-center, land, apartment, and development dummies, a dummy variable indicating a broker was used in the deal ($Broker$), a dummy indicating if the seller is a broker ($Seller = Brok$), property age, local property heterogeneity (σ_{local}), and the log of the sale price. We also include state dummies for states that recognize land trusts in order to control for distorted reporting effects from land trust deals. These coefficients are omitted from the table for brevity. We set the coefficient on log(price) equal to -1 for scale normalization in the binary response model.[27] Standard errors on the coefficient estimates are calculated via the outer-product matrix, and are robust to any form of heteroscedasticity consistent with equation (A2) in the appendix.

As Table VI documents, there is a negative relation between COD and the frequency of VTB financing, which is significant at the 5% level (t-statistic = -2.19). This contradicts Prediction A1 (VTB and bank debt substitution) and Prediction B1 (separating signalling equilibrium), which hypothesize the presence of more VTB financing when information asymmetries are high. Examining the indirect information variables, there is a strong negative relation between buyer distance and the occurrence of VTB financing. This is also inconsistent with Predictions A1 and B1, since more distant buyers face a greater information disadvantage. In addition, less VTB is used when the seller is a broker, which also seems to contradict the information models, since buyers face a greater information disadvantage when trading against well-informed and identifiable agents. Likewise, when local price volatility is high, VTB financing appears to be less frequent, again contradicting the predictions of information theory. Finally, properties with longer histories, which should help mitigate information problems, are associated with a slightly higher occurrence of seller financing, suggesting that VTB financing is not being used to alleviate information concerns. However, when a broker is employed in the deal, an action which may also mitigate information concerns, the

[26] All of our results were confirmed, however, using the HighCOD dummy in place of COD, where California properties were assigned to the HighCOD category. We do not report these results for brevity.

[27] The choice of normalizing on log(price) was made based on logit regression results that indicated a negative and statistically significant (at the 1% significance level) coefficient estimate on log(price). When employing other dependent variables, we normalize the coefficient on log(price) to be 1 or -1, depending on the sign of the coefficient from the logit regression.

frequency of VTB declines. This supports Predictions A1 and B1. Thus, other than the broker result, the evidence for information asymmetries affecting the choice of VTB financing is weak for either information model A or B.

The binary response model examines only the frequency of VTB financing in the data. We are also interested, however, in the extent of VTB financing, and its relation (if any) to our information proxies. Panel B of Table VI reports the results from Powell's (1986) truncated regression. Here, we first truncate the data to only those property sales which employ VTB financing. The dependent variable is the magnitude of VTB financing as a fraction of the sale price, which is regressed on a constant plus the same set of independent variables used for the binary response model.[28] The truncated regressions assess whether the magnitude of VTB financing changes with our information variables. As the first column of Panel B shows, there is a positive but insignificant relation between COD and the extent of VTB financing. In addition, none of the indirect information variables ($Broker$, $Seller = Brok$, σ_{local}, age, or $BuyDist$) significantly influence the size of VTB financing. In sum, the truncated regression lends little support to the information theories from Section II.

It is interesting to examine the different pieces of information obtained from the two regression specifications above. For instance, VTB financing is more likely to appear for transactions involving the sale of land, but conditional on VTB financing being used, seller financing comprises a smaller portion of the sale price for land deals. Thus, separating the frequency of financing from the extent of financing provides important information about property transactions that may be obscured by a model that combines both, such as the Tobit or Powell's (1984) CLAD.[29]

To test the other predictions, we replace the dependent variable with the two other types of financing, new mortgages and assumed mortgages. Table VI documents an insignificant positive relation between the frequency of new mortgage financing and COD, which is inconsistent with Prediction A2. Similarly, neither buyer distance, property age, local price volatility, or the broker variables seem to influence the use of new bank financing, suggesting that investors are not substituting between these two forms of financing in order to mitigate information asymmetries. There is one piece of evidence consistent with Information Model A, however. The increase in new bank debt and decrease in VTB financing for deals that use brokers is consistent with this model. In the

[28]Note that scale normalization is not required for this model, hence the coefficient on log(price) is not constrained. We compute standard errors via bootstrapping, so they account for cross-correlations and heteroscedasticity of the error terms.

[29]In addition, as noted previously, there are statistical problems with using such models on our data set.

truncated regression (Panel B), however, none of the direct or indirect information variables seem to affect the size of the new mortgage.

Evaluating Model B, Prediction B2 states that the sale of properties with large existing mortgages will be less prevalent when information asymmetries are high. The binary response results for assumed/existing mortgages are omitted from Panel A because data on the previous mortgage of the property are only reported when the mortgage is assumed. Therefore, we cannot determine if a property has no assumed mortgage because it did not have a previous mortgage, or because the seller paid off the mortgage upon sale. As a result, the absence of an assumed mortgage does not provide much information about the prior capital structure of the property. The truncated regression, however, is immune to this potential problem because it only examines cases where an assumed mortgage exists. The truncated regression in Panel B fails to find any significant relation between our information variables and the size of the previous mortgage on the property.

Finally, we examine the interaction between seller financing and the size of the previous loan on the property. Examining the relation between the seller's retained stake in the property and the size of the existing mortgage does not rely on the accuracy of our direct information variable, COD, or any of the indirect information variables, as the previous tests did. Rather than concentrating on information asymmetries about local market conditions, this test focuses on information about the property itself. We add the size of the assumed mortgage, scaled by sale price, as an additional regressor to the binary response model. The dependent variable is one if VTB financing is used and zero otherwise. Here, we first truncate the sample to only those transactions for which an assumed mortgage exists, in order to examine only those sales for which we have information about the previous financing structure. As the third column of Panel A indicates, there is a slight negative relation between the frequency of VTB and the magnitude of the previous mortgage assumed by the buyer, which is opposite in sign to that predicted by Predictions A3 and B3. In the truncated regression, we first truncate the sample to only those transactions containing assumed mortgages, and then further truncate the sample to those with VTB financing within this group. This leaves, however, only 20 data points, so we do not run a truncated regression for this case.

B.2 California Commercial Property Financing

Testing Predictions A3 and B3 entails truncating the sample to only those transactions for which assumed mortgages exist, so the sample size of this test is much smaller than for the other tests.

Hence, the power of this test may be too low to detect a coefficient on assumed mortgage that is significantly different from zero. To increase the power of this test, we use a longer time series of property transactions from California over the period January 1, 1992 to March 30, 1999. This sample of California transactions increases the sample size from 125 observations for the binary response regression in Panel A of Table VI to 691 observations. In addition, we also re-examine our other tests on this second sample for robustness. Since the assessment quality is particularly poor in California, we are in effect focusing on a set of properties with perhaps the most severe information problems, thereby providing a stronger test of the information hypotheses. Furthermore, concerns about cross-state effects are clearly irrelevant for this set of regressions.

Since California properties do not have associated CODs, we omit the COD variable from the regressions and focus exclusively on our indirect measures of information and the relationship between VTB financing and the prior (assumed) mortgage on the property. To control for possible serial effects in the data from a longer time series, however, we also add year dummies as regressors, but do not report their coefficient estimates for brevity.

Table VII reports the binary response (Panel A) and truncated regression (Panel B) results for this sample of California transactions. As the table indicates, there is a strong negative relation between the size of the existing mortgage and the frequency of VTB financing, consistent with previous evidence contradicting Predictions A3 and B3. Results from the other tests are also largely consistent with our previous findings, and generally fail to support either Information Model A or B. The only evidence supporting financial decisions as a method of mitigating information asymmetries is the negative relation between brokered deals and frequency and extent of vendor financing. Overall, the evidence supporting the information models is ambiguous and weak.

B.3 Do Financial Decisions Influence the Price?

Thus far, we have examined whether measures of information asymmetry influence the choice of financing in a manner consistent with the predictions from Section II. Both information models (Model A: VTB and bank debt substitution and Model B: Separating signalling) made similar predictions in this regard. Information theories, however, also predict that the choice of financing may influence the sale price. Rather than employ the choice of financing as the dependent variable, therefore, we also examine the role of information by evaluating the impact of financial choice on the sale price. This will allow us to distinguish between the two information models. Model A assumes that the price is determined first and then the form of financing is chosen. Model B assumes the price and financial decision are determined simultaneously, and predicts that the price will be positively related to the seller's retained stake when the buyer faces an information disadvantage (Prediction B4). To test this prediction, we regress the capitalization rate of the property, defined as net income on the property divided by the sale price, on the fraction of the seller's retained stake in the property, defined as the amount of vendor financing divided by the sale price, plus a set of controls for broker usage, buyer, seller, and property characteristics. We employ the capitalization rate as our dependent variable as a scaled measure of price. Since price is in the denominator, Prediction B4 predicts a negative relation between capitalization rate and the seller's claim. Table VIII reports results from the OLS regression of capitalization rate on the size of the seller's retained claim.[30] Consistent with information theory, there is a negative relation between VTB financing and capitalization rate, suggesting that the seller's stake is positively related to the sale price, but this relation is statistically insignificant.

It may, however, be the case that the sale price is determined first, and that the form of financing is determined later (Model A). If this is the case, then vendor financing may just be used to complete the deal, serving as the residual form of financing for the buyer rather than as a signal of the property's quality. The bank may only be willing to lend a certain amount, and VTB financing may be used to fill the remaining loan gap. Therefore, the positive relation between VTB and the sale price may simply reflect the fact that banks aren't willing to lend as large a fraction of the sale price when buyers pay too much for the property. We repeat the previous regression of property capitalization rate but replace the seller's retained stake in the property with the bank's claim, defined as the amount of the new mortgage divided by the sale price. The positive relation between capitalization rate and the bank's claim indicates that financial institutions are indeed less willing to lend against properties for which too high a price was paid. Thus, if VTB fills the loan gap, then the fraction of VTB financing will be larger for these properties. To confirm this interpretation rather than the separating signalling hypothesis, we repeat the regression of capitalization rate on the fraction of VTB financing for only those properties that do not obtain any bank financing. If the signalling interpretation is correct, we should see a strong negative relation between the capitalization rate and the size of the seller's stake, irrespective of the presence of a bank loan. If, however, seller financing is simply the residual loan after the bank's claim, then there should

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

be no relation between capitalization rate and VTB financing among deals that do not contain a bank loan. As column 3 of Table VIII indicates, there is still no significant relation between VTB and capitalization rate for property sales that do not involve bank lending. This suggests that seller financing is really a plug used to complete the deal and is not being used as a signal to less informed buyers. Moreover, the relation between the seller's stake and the price should be most important when information asymmetries are high. To test this, we repeat the regressions by adding an interaction term between the seller's stake and COD. The coefficient on the interaction term is positive (but insignificant), contradicting Prediction B4. Furthermore, the interaction between COD and the seller's claim is still negligible even when we exclude bank financed deals.

Finally, since the California real estate market may harbor the most severe information problems, and to abstract from the COD measure, we repeat the regressions for California properties using a longer time-series of transactions from 1992 to 1999. Table VIII reports a strong negative relation between the seller's claim and the capitalization rate, which appears consistent with Prediction B4. However, an even stronger positive coefficient between the bank's claim and the capitalization rate suggests that VTB financing is merely a plug when the bank limits its loan. Confirmation of this is provided by the positive (but insignificant) coefficient on the seller's stake for deals where no bank debt was employed. Thus, seller financing does not appear to have an effect on the price, contradicting Model B.

B.4 Toronto Commercial Real Estate Financing (Marsh Data)

Finally, Table IX reports regression results from the Marsh data. Panel A reports the coefficient estimates from the binary response model, and Panel B reports results from the truncated regressions. The dependent variables are identical to those used above. The independent variables differ slightly, however, due to differences in the data items provided by Marsh. In addition to the three dummy variables for vacant land, apartments, and planned development, we include a dummy variable indicating whether the property was occupied by the seller (D^{sell}_{occ}), a dummy indicating whether the seller resides outside of Toronto (D^{sell}_{out}), a dummy indicating whether the buyer occupied the property (D^{buy}_{occ}), a dummy indicating if the buyer resides out-of-town (D^{buy}_{out}), and the sale price.[31] The direct information variable for the Marsh data set is Post-Feb'98, which is one for all

[31] We employ the price rather than the log of price in our regressions for the Marsh data since the range of property sizes is far greater in the COMPS data set (from \$20,000 to \$734,000,000) than in the Marsh data set (from \$1,300,000 to \$194,000,000). In addition, we constrain the coefficient on price to be 1 or -1, depending on the sign of

transactions occuring after February 1, 1998 and zero otherwise. Since asymmetric information is reduced after February 1, 1998, we should see a change in financing (ceteris paribus) after this date consistent with the predictions in Section II if information problems influence financing decisions.

As Panels A and B of Table IX indicate, however, there is very little evidence that asymmetric information influences either the frequency or extent of the three forms of financing. Examining the indirect information measures, there appears to be no relation between whether the seller occupied the property and the choice or extent of financing. Whether the buyer is out of town does seem to influence the choice of VTB. In particular, out of town buyers, who presumably are at a greater information disadvantage, are more likely to require VTB financing. This is consistent with Predictions A1 and B1. This relation only appears for the binary response regression, however, having no relation to the size of the loan in the truncated regression. The buyer out of town dummy has no impact on the other forms of financing under either regression specification, which suggests the positive VTB results should perhaps not be given excessive weight. Finally, the size of the existing mortgage (AssM) appears to have no influence on the size of the seller's equity claim (VTB*). Overall, we find little to no evidence of information asymmetries affecting financing decisions in the Marsh data.

Accumulating our results across the COMPS and Marsh data sets, we find mixed but generally weak evidence of information asymmetries affecting financial structure in the real estate market. Given the documented severity of information problems in the real estate market (evidenced by our results in Section V.A) and the extensive theoretical literature devoted to resolving information problems through financial structure, it is surprising that asymmetric information does not play a larger role in real estate firm financial decisions. Rather, agents seem to resolve information problems largely through limited participation, selective offering, and by segmenting the market.

VI. Conclusion

This paper examines the importance of asymmetric information in commercial real estate markets in the U.S. and Canada. Using indirect information variables and exogenous variations in the quality of property tax assessments to characterize high- and low-asymmetric-information environments, we find strong evidence that asymmetric information is significant in real estate. Not all the

the coefficient from logit regressions that indicated a statistically significant (at the 5% level) relation between price and all dependent variables.

mechanisms suggested by theory are used to resolve these information issues, however. We observe striking and clear evidence of limited participation, selective offering, and market segmentation. We find very weak evidence that financial structure is used to allay information concerns. In effect, we find that in the equilibrium in this market informed agents trade with each other, avoid trade with the identifiable experts and avoid selling properties that are particularly difficult to evaluate. In this context, signalling using financial structure is superfluous and is not employed. Our approach differs from that of earlier empirical work in that we conduct direct tests of some of the fundamental implications of information theory using an exogenous information measure and make use of robust estimation techniques.

This paper shows that in responding to information disparities, economic agents first take direct action by not purchasing assets about which they are uninformed, focusing on assets that are easier to evaluate, and avoiding trades with the identifiably informed. The optimal design of capital structure, an indirect response to information concerns, is used rather sparingly, even in commercial real estate, a market with severe adverse selection. This suggests that one should be cautious about regarding financial structure as a device used to minimize information asymmetries in markets, such as the broad equity market, for which the evidence of limited participation, selective offering, and market segmentation is weaker than in commercial real estate.

Appendix

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

A. Semiparametric Binary Response Model

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

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

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

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

where F is an unknown function whose range is contained in $[0, 1]$. The term $\beta' x_n$ is referred to as the index.[32] The intercept component of β is subsumed in F and is therefore not estimated. This model accommodates any form of heteroscedasticity that is consistent with (A2). The estimator of β is the argument that maximizes the quasi-log-likelihood function

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

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

[32] 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. The outer product gradient is used to estimate the covariance matrix. 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

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

where $1(B)$ denotes the indicator function of the event B. Standard errors are computed by bootstrapping.

References

Akerlof, George A., "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism," *Quarterly Journal of Economics*, LXXXIV (1970), 488-500.

Arabmazar, Abbas, and Peter Schmidt, "An Investigation of the Robustness of the Tobit Estimator to Non-Normality," *Econometrica*, L (1981), 1055-1063.

Audretsch, David B. and Maryann P. Feldman, "R&D Spillovers and the Geography of Innovation and Production," *American Economic Review*, LXXXVI (1996), 630-640.

Audretsch, David B. and Paula E. Stephan, "Company-Scientist Locational Links: The Case of Biotechnology," *American Economic Review*, LXXXVI (1996), 641-652.

Best, Roger J., and Ronald W. Best, "An Empirical Analysis of Cross-Security Information Asymmetry and the 'Pecking Order' Hypothesis," *Journal of Economics and Finance*, XIX (1995), 19-29.

Campbell, Carl M., and Kunal S. Kamlani, "The Reasons for Wage Rigidity: Evidence from a Survey of Firms," *Quarterly Journal of Economics*, CXII (1997), 759-89.

Chan, Yuk-Shee, "On the Positive Role of Financial Intermediation in Allocation of Venture Capital in a Market with Imperfect Information," *Journal of Finance*, XXXVIII (1983), 1543-1568.

Chemmanur, Thomas J., and Paolo Fulghieri, " A Theory of the Going-Public Decision," *Review of Financial Studies* XII (1999), 249-279.

Chiappori, Pierre- Andre, and Bernard Salanié, "Testing for Asymmetric Information in Insurance Markets," *Journal of Political Economy*, CVIII (2000), 56-78.

Coval, Joshua D., and Tobias J. Moskowitz, "Home Bias at Home: Local Equity Preference in Domestic Portfolios,", *Journal of Finance*, LIV (1999a), forthcoming.

Coval, Joshua D., and Tobias J. Moskowitz, "The Geography of Investment: Informed Trading and Asset Prices," Working paper, University of Chicago (1999b).

DeMarzo, Peter, and Darrell Duffie, "A Liquidity-Based Model of Security Design," *Econometrica*, LXVII (1999), 65-99.

Diamond, Douglas, "Debt Maturity Structure and Liquidity Risk," *Quarterly Journal of Economics*, CVI (1991a), 709-737.

Diamond, Douglas, "Monitoring and Reputation: The Choice between Bank Loans and Directly Placed Debt," *Journal of Political Economy*, XCIX (1991b), 689-721.

Dolde, Walter, and Dogan Tirtiroglu, "Temporal and Spatial Information Diffusion in Real Estate Price Changes and Variances," *Real Estate Economics*, XXV (1997), 539-565.

Downs, David, and Nuray Guner, "Is the Information Deficiency in Real Estate Evident in Public Market Trading?" *Real Estate Economics*, XXVII (1999), 517-541.

Duflo, Esther, and Abhijit V. Banerjee, "Reputation Effects and the Limits of Contracting: A Study of the Indian Software Industry," Working Paper, Massachusetts Institute of Technology (1999).

Fama, Eugene and Kenneth R. French, "Testing Tradeoff and Pecking Order Predictions About Dividends and Debt," Working paper, University of Chicago (1999).

French, Kenneth R. and James M. Poterba, "Investor Diversification and International Equity Markets," *American Economic Review*, LXXXI (1991), 222-226.

Garmaise, Mark J., and Tobias J. Moskowitz, "Brokerage, Intermediation and Agency: The Pricing and Financing of Commercial Properties" Working Paper, University of Chicago (2000).

Gerfin, Michael, "Parametric and Semi-Parametric Estimation of the Binary Response Model of Labour Market Participation," *Journal of Applied Econometrics*, XI (1996), 321-339.

Genesove, David, "Adverse Selection in the Wholesale Used Car Market," *Journal of Political Economy*, CI (1993), 644-665.

Goldberger, Arthur S., "Abnormal Selection Bias," in Samuel Karlin, Takeshi Amemiya and Leo A. Goodman, eds., *Studies in Econometrics, Time Series, and Multivariate Statistics* (New York, NY : Academic Press, 1983).

Hancock, Diane, and James A. Wilcox, "Bank Capital, Nonbank Finance, and Real Estate Activity," *Journal of Housing Research*, VIII (1997), 75-105.

Haurin, Donald R., and Patric H. Hendershott, "Affordability and the Value of Creative Finance: An Application to Seller Financed Transactions," *Housing Finance Review*, V (1986), 189-206.

Helwege, Jean, and Nellie Liang, "Is There a Pecking Order? Evidence from a Panel of IPO Firms," *Journal of Financial Economics*, XL (1996), 429-458.

Horowitz, Joel L., "Semiparametric Estimation of a Work-Trip Mode Choice Model," *Journal of Econometrics*, LVIII (1993), 49-70.

Horowitz, Joel L., *Semiparametric Methods in Econometrics* (New York, NY : Springer-Verlag, 1998).

Huberman, Gur, "Familiarity Breeds Investment," Working Paper, Columbia Business School (1999).

Kang, Jun-Koo, and René M. Stulz, "Why Is There a Home Bias? An Analysis of Foreign Portfolio Equity Ownership in Japan," *Journal of Financial Economics*, XLVI (1997), 3-28.

Klein, Roger W., and Richard H. Spady, "An Efficient Semiparametric Estimator for Binary Response Models," *Econometrica*, LXI (1993), 387-421.

Korajczyk, Robert A., Deborah Lucas, and Robert L. McDonald, "The Effect of Information Releases on the Pricing and Timing of Equity Issues," *Review of Financial Studies*, IV (1991), 685-708.

Landers, Renee M., James B. Rebitzer, and Lowell J. Taylor, "Rat Race Redux: Adverse Selection in the Determination of Work Hours in Law Firms," *American Economic Review*, LXXXVI (1996), 329-348.

Leland, Hayne E., and David H. Pyle, "Information Asymmetries, Financial Structure, and Financial Intermediation," *Journal of Finance*, XXXII (1977), 371-387.

Lerner, Josh, "Venture Capitalists and the Oversight of Private Firms," *Journal of Finance*, L (1995), 301-318.

Ling, David C., and Michael D. Ryngaert, "Valuation Uncertainty, Institutional Involvement, and the Underpricing of IPOs: The Case of REITs," *Journal of Financial Economics*, XLIII (1997), 433-456.

Lizzeri, Alessandro, "Information Revelation and Certification Intermediaries," *Rand Journal of Economics*, XXX (1999), 214-231.

Milgrom, Paul, and Nancy Stokey, "Information, Trade and Common Knowledge," *Journal of Economic Theory*, XXVI (1982), 17-27.

Myers, Stewart C., "Presidential Address: The Capital Structure Puzzle," *Journal of Finance*, XXXIX (1984), 575-592.

Myers, Stewart C., and Nicholas S. Majluf, "Corporate Financing and Investment Decisions When Firms Have Information that Investors Do Not Have," *Journal of Financial Economics*, XIII (1984), 187-221.

Nachman, David C., and Thomas H. Noe, "Optimal Design of Securities Under Asymmetric Information," *Review of Financial Studies*, VII (1994), 1-44.

Opler, Tim, and Sheridan Titman, "The Debt-Equity Choice," Working paper, Ohio State University, (1996).

Porter, Robert H., and Peter Sattler, "Patterns of Trade in the Market for Used Durables: Theory and Evidence," Working Paper, National Bureau of Economic Research (1999).

Powell, James L., "Least Absolute Deviations for the Censored Regression Model," *Journal of Econometrics*, XXV (1984), 303-325.

Powell, James L., "Symmetrically Trimmed Least Squares Estimation for Tobit Models," *Econometrica*, LIV (1986), 1435-1460.

Puri, Manju, "Commercial Banks in Investment Banking: Conflict of Interest or Certification Role?" *Journal of Financial Economics*, XL (1996), 373-401.

Rajan, Raghuram, and Luigi Zingales, "What Do We Know About Capital Structure? Some Evidence From International Data," *Journal of Finance*, L (1995), 1421-1460.

Ramakrishnan, Ram T. S., and Anjan Thakor, "Information Reliability and a Theory of Financial Intermediation," *Review of Economic Studies*, LI (1984), 415-432.

Shyam-Sunder, Lakshmi, and Stewart C. Myers, "Testing Static Tradeoff Against Pecking Order Models of Capital Structure," *Journal of Financial Economics*, LI (1999), 219-244.

Stein, Joshua, "Nonrecourse Carveouts: How Far is Far Enough," *Real Estate Review*, XXVII (1997), 3-11.

Stiglitz, Joseph E., "The Theory of "Screening," Education, and the Distribution of Income," *American Economic Review*, LXV (1975), 283-300.

Titman, Sheridan, and Roberto Wessels, "The Determinants of Capital Structure Choice," *Journal of Finance*, XLIII (1988), 1-19.

Williams, Joseph T., "What is Real Estate Finance?" *Journal of Real Estate Finance and Economics*, XIX (1999), 9-19.

Yang, T. L., Joseph W. Trefzger and Lawrence F. Sherman, "A Microeconomic Study of Commercial Real Estate Brokerage Firms," *Journal of Real Estate Research*, XIII (1997), 177-194.

Table I:
Descriptive Statistics on the COMPS (U.S.) Database

Descriptive statistics on the COMPS commercial real estate transactions from the U.S. over the period January 1, 1997 to March 30, 1999 are reported below. Panel A reports general statistics on the properties in the database, reporting the number of sales, average and median distance buyers are from the property, percentage of buyers from out of state, average and median distance sellers are from the property, percentage of sellers from out of state, as well as the percentage of sales that are for planned development (Dev.), are apartments (Apt), are vacant land (Land), and are commercial and industrial buildings (Comm. & Ind.). Panel B 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 and median sale price ($U.S.) are 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, for each state separately, and for transactions occuring in municipalities with high and low coefficients of dispersion (COD) of real estate assessment-to-value ratios. The high COD category contains the largest half of measured COD properties plus all California properties.

Panel A: General Information

	# Sales	Buyer Distance mean (median)	Buyer Distance Out of State	Seller Distance mean (median)	Seller Distance Out of State	Dev.	Apt	Land	Comm. & Ind.
Overall	7,620	235.31 (46.70)	14.1%	266.29 (47.14)	16.9%	6.6%	27.4%	20.9%	51.7%
City-Center	4,423	222.86 (47.34)	12.7%	257.27 (47.48)	15.0%	6.4%	30.0%	23.2%	46.7%
Non-City	3,197	252.52 (45.22)	16.0%	278.78 (46.13)	19.5%	7.0%	23.7%	17.8%	58.5%
Small Deals	3,794	118.75 (43.58)	5.9%	187.99 (45.19)	10.9%	4.7%	29.2%	20.8%	50.1%
Large Deals	3,826	350.89 (49.09)	22.3%	343.94 (48.76)	22.8%	8.6%	25.6%	21.1%	53.3%
CA	943	229.95 (37.56)	5.5%	265.31 (40.28)	5.4%	3.5%	39.4%	16.1%	44.4%
NV	1,293	353.44 (16.88)	27.1%	309.86 (16.93)	25.5%	8.0%	12.1%	55.5%	32.5%
MA	260	168.76 (22.95)	14.2%	159.66 (22.19)	12.3%	3.8%	76.9%	23.1%	0.0%
MD	585	253.38 (40.94)	23.9%	307.20 (45.14)	31.6%	2.6%	18.6%	2.2%	79.1%
VA	301	321.94 (41.86)	32.6%	349.98 (45.22)	38.5%	5.6%	0.3%	0.3%	99.3%
TX	846	385.84 (54.20)	18.1%	479.94 (57.83)	24.6%	17.7%	29.6%	19.7%	50.7%
IL	2,918	128.26 (48.61)	6.0%	170.74 (49.00)	9.8%	5.8%	34.2%	12.9%	52.9%
CO	474	273.20 (47.61)	14.6%	311.18 (47.56)	16.9%	1.9%	0.0%	23.0%	77.0%
High COD	4,451	167.19 (47.58)	7.6%	213.54 (48.09)	10.8%	4.8%	31.5%	12.0%	56.5%
Low COD	3,169	330.98 (43.39)	23.3%	340.40 (44.46)	25.5%	9.3%	21.6%	33.6%	44.8 %

Panel B: Financing Information

	Sale Price ($,000) mean	Sale Price ($,000) median	Vendor-to-Buyer freq.(%)	Vendor-to-Buyer % Price	New Mortgage freq.(%)	New Mortgage % Price	Assumed Mortgage freq.(%)	Assumed Mortgage % Price	Loan/ Value
Overall	$2,731	$657	15.6%	62.7%	60.1%	74.5%	3.1%	73.7%	74.3%
City-Center	$2,856	$625	16.6%	62.2%	60.9%	74.9%	3.1%	76.8%	74.9%
Non-City	$2,559	$710	14.1%	63.8%	59.0%	73.7%	3.1%	65.6%	73.2%
Small Deals	$398	$385	18.5%	68.3%	61.6%	76.9%	1.3%	61.8%	76.7%
Large Deals	$5,045	$1,500	12.7%	61.5%	58.6%	74.2%	4.9%	73.8%	74.1%
CA	$1,530	$575	27.0%	56.2%	55.6%	72.3%	7.2%	70.2%	72.0%
NV	$2,335	$780	33.9%	65.7%	47.0%	71.5%	4.4%	64.5%	71.3%
MA	$2,547	$658	16.5%	56.0%	62.7%	80.2%	5.4%	68.0%	78.0%
MD	$2,942	$700	19.7%	69.9%	53.5%	72.9%	1.2%	64.1%	72.7%
VA	$5,538	$1,100	11.3%	69.2%	54.2%	70.0%	1.7%	64.6%	70.2%
TX	$4,013	$1,100	12.4%	49.6%	67.5%	77.5%	5.0%	64.8%	74.9%
IL	$2,695	$540	3.9%	65.2%	70.3%	75.2%	1.1%	81.5%	76.6%
CO	$2,200	$675	17.3%	69.1%	39.0%	67.8%	2.5%	60.8%	71.5%
High COD	$2,507	$560	10.9%	63.1%	64.4%	74.1%	2.6%	78.1%	75.3%
Low COD	$3,046	$850	22.2%	62.5%	54.0%	74.8%	3.8%	65.0%	73.2%

Table II:
Descriptive Statistics on the Marsh (Toronto) Database

Descriptive statistics on the Marsh commercial real estate transactions from the six boroughs of Toronto, Canada over the period May, 1996 to April, 1999 are reported below. Panel A reports general statistics on the properties in the database, reporting the number of sales, and percentage of sales containing buyers from out of town, buyers who occupied the property prior to sale, sellers from out of town, sellers who occupied the property, as well as the percentage of sales that are for planned development (Dev.), are apartments (Apt), are vacant land (Land), and are commercial and industrial buildings (Comm. & Ind.). Panel B 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 and median sale price ($Canadian) are 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). General and financing information are reported for the whole sample, for the smallest and largest half of deals, and for transactions occuring before and after February 1, 1998, the date when the government published the new assessment values of properties in metropolitan Toronto.

Panel A: General Information

		Buyer		Seller					Comm.
	# Sales	Out-of-town	Occupied	Out-of-town	Occupied	Dev.	Apt	Land	& Ind.
Overall	971	22.1%	5.1%	20.4%	9.7%	20.0%	24.5%	19.3%	56.2%
Small deals	486	23.5%	6.0%	24.1%	10.3%	17.1%	18.7%	18.5%	62.8%
Large deals	485	20.8%	4.3%	16.7%	9.1%	22.9%	30.3%	20.0%	49.7%
Post-Feb'98	423	23.9%	7.8%	23.2%	13.5%	19.9%	22.5%	20.6%	56.0%
Pre-Feb'98	548	20.8%	3.1%	18.2%	6.8%	20.1%	26.1%	18.2%	55.7%

Panel B: Financing Information

	Sale Price ($,000)		Vendor-to-Buyer		Assumed Mortgage		New Mortgage		Loan/
	mean	median	freq.(%)	% Price	freq.(%)	% Price	freq.(%)	% Price	Value
Overall	$6,036	$2,392	23.3%	54.6%	14.8%	58.2%	38.4%	77.7%	77.5%
Small deals	$1,540	$1,512	25.5%	52.5%	11.7%	60.1%	36.6%	74.7%	75.5%
Large deals	$10,541	$5,200	21.0%	55.0%	17.9%	58.0%	40.2%	78.2%	77.8%
Post-Feb'98	$5,652	$2,415	23.6%	54.2%	16.8%	54.8%	40.2%	77.4%	76.8%
Pre-Feb'98	$6,333	$2,300	23.0%	54.8%	13.3%	61.5%	37.0%	77.9%	78.0%

Table III:
Property Assessment Ratio Coefficients of Dispersion (CODs)

Summary statistics on the coefficient of dispersion (COD) measures of the COMPS commercial real estate properties from the U.S. over the period January 1, 1997 to March 30, 1999 are reported below. The COD measures the dispersion around the median sale price-to-assessment value ratio within a region and for a particular property type. These figures are obtained from state property assessment ratio studies. Summary statistics on this measure are reported for the whole sample, for transactions within and outside of the largest metropolitan areas (City-Center)–defined as the largest city (cities) in each state, for the smallest and largest half of deals, and for each state separately. Also reported are statistics on COD measures for the lowest and highest half of COD properties.

	Coefficients of Dispersion (COD)						Comm.
	Mean	Stdev.	Maximum	Minimum	Apt.	Land	& Ind.
Overall	29.37	29.28	128.55	0.79	32.91	26.97	28.93
City-Center	32.86	33.22	128.55	4.80	38.88	27.98	32.82
Non-City	24.94	22.58	87.85	0.79	23.13	25.30	25.18
Small deals	33.30	30.20	128.55	0.79	39.42	29.69	32.04
Large deals	25.56	27.84	128.55	1.06	25.47	24.29	26.17
CA	N/A	N/A	N/A	N/A	N/A	N/A	N/A
NV	5.51	1.04	7.30	4.80	7.30	4.81	6.90
MA	7.66	3.52	17.94	0.79	8.14	6.57	N/A
MD	9.34	4.97	19.00	5.00	9.95	7.58	9.19
VA	16.01	6.07	32.48	7.39	7.39	7.39	16.04
TX	7.36	1.23	14.17	4.52	5.82	6.81	8.45
IL	58.82	23.24	128.55	9.04	52.15	97.34	51.44
CO	13.83	0.98	14.37	4.94	N/A	12.36	14.34
High COD	52.22	26.25	128.55	13.53	50.88	96.61	42.93
Low COD	6.93	2.38	13.31	0.79	6.89	5.75	8.23

Table IV:
Limited Participation and Selective Offering
U.S. Real Estate (COMPS Data)

Results from the regression of buyer distance (*BuyDist*), representing limited participation, on direct and indirect information variables plus property, buyer, and seller characteristics are reported below for all properties over the period January 1, 1997 to March 30, 1999. Regressions are run for the whole sample using the HighCOD dummy, for all properties excluding California using the continuous COD measure, and for all properties within the state of Illinois only. In addition, regressions are repeated for two subsamples: properties younger than 10 years of age, and properties greater than 10 years old. All properties with recorded ages of zero (i.e., land) are excluded from the subsample regressions. The regressions are estimated via ordinary least squares (OLS), with t-statistics reported in parentheses using White (1982) heteroscedastic-consistent standard errors.

	All Properties				IL only		
			$0 < \text{Age} < 10$	$\text{Age} > 10$		$0 < \text{Age} < 10$	$\text{Age} > 10$
Dep. Var.	*BuyDist*	*BuyDist*	*BuyDist*	*BuyDist*	*BuyDist*	*BuyDist*	*BuyDist*
# Obs.	*6,335*	*7,206*	*487*	*3,968*	*2,792*	*125*	*2,177*
const.	-1789.93**	-1611.29**	-2466.51**	-1726.63**	-870.45**	-1296.50	-840.69**
	(-13.78)	(-13.79)	(-5.50)	(-10.82)	(-5.55)	(-1.89)	(-4.62)
City-Center	16.93	1.76	51.47	6.05			
	(1.06)	(0.12)	(0.57)	(0.35)			
Age	-0.67**	-0.63**	-37.70*	-0.37**	-0.31*	-50.29**	-0.26*
	(-2.84)	(-2.93)	(-2.44)	(-3.40)	(-2.22)	(-2.53)	(-2.30)
Land	-14.95	-34.74			121.65**		
	(-0.68)	(-1.71)			(2.63)		
Apt.	13.78	13.21	148.82	15.71	-35.88**	227.58	-41.80**
	(0.79)	(0.85)	(1.08)	(0.95)	(-3.04)	(1.36)	(-3.60)
Dev.	-48.32	-57.57*	-266.22*	-4.19	-35.24	-78.53	-2.89
	(-1.63)	(-2.02)	(-2.05)	(-0.93)	(-1.12)	(-0.38)	(-0.06)
σ_{local}	-12.73	-50.72**	148.97	10.51	26.49	190.18	11.93
	(-0.60)	(-3.29)	(1.13)	(0.41)	(1.30)	(1.01)	(0.68)
COD†	-1.74**		-8.25**	-2.64**	-2.30**	-5.62	-2.47**
	(-6.07)		(-2.95)	(-5.29)	(-3.82)	(-1.16)	(-2.53)
High COD		-77.65**					
		(-4.34)					
log(Price)	154.64**	149.30**	221.45**	145.64**	78.96**	114.58**	80.49**
	(16.66)	(17.27)	(7.38)	(12.86)	(7.46)	(3.37)	(6.37)

*,** Indicates significance at the 5% and 1% levels, respectively.

† Excludes all California properties.

Table V:
Selective Offering and Market Segmentation
U.S. Real Estate (COMPS Data)

Results from the regression of information availability and market segmentation variables on direct and indirect information variables plus property, buyer, and seller characteristics are reported below for all properties over the period January 1, 1997 to March 30, 1999. Regressions are run for the whole sample and for all properties within the state of Illinois only. The dependent variable for information availability is the age of the property (excluding properties with recorded ages of zero, which include all vacant land sales). The regressions are estimated via ordinary least squares (OLS), with t-statistics reported in parentheses using White (1982) heteroscedastic-consistent standard errors. For market segmentation, the dependent variable is whether the buyer is a broker trading on his own account. This binary response regression is estimated via the Klein and Spady (1993) (K-S) robust semiparametric model (detailed in Appendix A) and via logit. T-statistics are reported in parentheses for both binary response models using the outer-product matrix to calculate standard errors.

	All	IL	All	IL	All	IL
Dep. Var.	Age	Age	$Buyer = Brok$	$Buyer = Brok$	$Buyer = Brok$	$Buyer = Brok$
# Obs.	*4,453*	*2,301*	*4,340*	*1,703*	*4,340*	*1,703*
Regression Model:	OLS	OLS	Logit	Logit	K-S	K-S
const.	73.8788**	16.4584	-0.6468	-7.0912**		
	(15.29)	(1.87)	(-0.64)	(-3.92)		
City-Center	12.7040**		0.5541**		0.1907*	
	(17.44)		(3.72)		(2.00)	
Age			0.0027	-0.0040	0.0023	-0.0019
			(1.89)	(-0.92)	(1.69)	(-0.46)
Apt.	8.6481**	10.5160**	-0.2153	0.1607	-0.2996**	0.2035
	(10.59)	(9.94)	(-1.20)	(0.65)	(-2.52)	(0.49)
Land			0.5561**	-0.4622	0.4360**	-0.2209
			(3.39)	(-0.73)	(3.90)	(-0.47)
Dev.	-3.4136*	-3.9103	-1.2282**	-0.0558	-2.1751**	-0.2705
	(-2.24)	(-1.45)	(-3.16)	(-0.11)	(-6.27)	(-0.44)
σ_{local}	8.9946**	11.9866**	-0.7961**	1.3446**	-0.8237**	1.3260**
	(6.96)	(6.61)	(-3.69)	(3.78)	(-4.71)	(3.49)
$Seller = Brok$			0.3115	2.9827**	0.4026**	1.4605**
			(1.19)	(3.64)	(4.41)	(2.49)
$Seller = Brok \times$ COD			0.0549**	0.0090	0.0515**	0.0051
			(6.93)	(0.66)	(5.82)	(0.49)
COD	0.3150**	1.1861**	0.0010	-0.0029	0.0014	-0.0022
	(11.79)	(19.69)	(0.29)	(-0.31)	(0.61)	(-0.38)
$BuyDist$			-0.0504	0.0180	0.0363	0.0062
			(-0.79)	(0.17)	(0.87)	(0.11)
log(Price)	-5.6457**	-4.9925**	-1.0000*	-1.0000*	-1.0000	-1.0000
	(-20.69)	(-10.64)	(-2.17)	(-2.04)		

*,** Indicates significance at the 5% and 1% levels, respectively.

Table VI:
U.S. Real Estate (COMPS Data) Financing
January 1, 1997 - March 30, 1999 (Excluding California)

Results from the regression of various financing types on direct and indirect information variables plus property, buyer, and seller characteristics are reported below over the period January 1, 1997 to March 30, 1999. Four sets of dependent variables are used: vendor-to-buyer financing (VTB) scaled by sale price, new mortgage (NewM) scaled by sale price, assumed mortgage (AssM) scaled by sale price, and VTB scaled by sale price in excess of the amount of assumed mortgage (VTB*). Panel A reports coefficient estimates under the semiparametric binary response model from Appendix A, 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 from Appendix B, where the data is truncated to only those observations where the dependent variable (financing type) is positive. T-statistics are reported in parentheses, with standard errors calculated via the outer-product matrix for the binary response model, and via bootstrapping (250 simulations) for the truncated regression model. All regressions include state dummy variables for states that recognize land trusts (not reported for brevity) to control for distorted reporting effects arising from land trust deals.

	Panel A: Binary Response			**Panel B: Truncated Regression**		
Dep. var.:	VTB	NewM	VTB*	VTB	NewM	AssM
# Obs.	*3,189*	*3,189*	*125*	*608*	*2,537*	*125*
const.				1.4497**	0.7221**	0.6649*
				(5.61)	(15.16)	(2.24)
Land	1.1438**	-1.0818	0.2377	-0.1043*	-0.1032**	-0.1117
	(5.90)	(-0.94)	(0.21)	(-2.37)	(-7.39)	(-1.17)
Apt.	-0.1733	0.0130	-0.3147	-0.0171	0.0166**	0.0811*
	(-1.41)	(0.10)	(-0.36)	(-0.41)	(2.85)	(2.04)
Dev.	0.1791	-0.0153	-0.0163	0.0381	0.0190	-0.0985
	(1.01)	(-0.08)	(0.00)	(0.99)	(1.45)	(-1.75)
City-Center	0.3047**	-0.2843	-0.3938	-0.0391	-0.0273**	-0.1077**
	(2.63)	(-0.89)	(-0.41)	(-1.30)	(-3.81)	(-2.51)
Broker	-0.7759**	0.7613	0.0442	-0.0413	-0.0039	0.0439
	(-5.64)	(0.96)	(0.07)	(-1.58)	(-0.56)	(1.03)
$Seller = Brok$	-0.0423	-0.0317	-2.5680	-0.0756	0.0073	-0.0151
	(-0.21)	(-0.17)	(-0.12)	(-1.85)	(0.54)	(-0.18)
COD	-0.0157*	0.0164	-0.0027	0.0009	0.0005	0.0021
	(-2.19)	(0.92)	(-0.02)	(0.34)	(1.52)	(0.45)
σ_{local}	-0.2598	0.4076	-0.9125	-0.0231	0.0302**	0.0336
	(-1.75)	(0.90)	(-0.54)	(-0.50)	(3.33)	(0.66)
Age	0.0005	-0.0013	0.0002	-0.0007	0.0001	-0.0002
	(0.31)	(-0.45)	(0.01)	(-0.63)	(0.50)	(-0.22)
$BuyDist$	-0.0003*	-0.0000	-0.0001	-0.0001	-0.0000	-0.0000
	(-2.09)	(-0.32)	(-0.13)	(-1.16)	(-0.59)	(-1.03)
Assm			-4.0231			
			(-1.66)			
log(Price)	-1.0000	-1.0000	-1.0000	-0.0438*	-0.0009	-0.0060
				(-2.16)	(-0.28)	(-0.40)

*,** Indicates significance at the 5% and 1% levels, respectively.

Table VII:
U.S. Real Estate (COMPS Data) Financing
January 1, 1992 - March 30, 1999 (California Only)

Results from the regression of various financing types on direct and indirect information variables plus property, buyer, and seller characteristics are reported below for a sample of California property sales over the January 1, 1992 to March 30, 1999 time period. Four sets of dependent variables are used: vendor-to-buyer financing (VTB) scaled by sale price, new mortgage (NewM) scaled by sale price, assumed mortgage (AssM) scaled by sale price, and VTB scaled by sale price in excess of the amount of assumed mortgage (VTB*). Panel A reports coefficient estimates under the semi-parametric binary response model from Appendix A, 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 from Appendix B, where the data is truncated to only those observations where the dependent variable (financing type) is positive. T-statistics are reported in parentheses, with standard errors calculated via the outer-product matrix for the binary response model, and via bootstrapping (250 simulations) for the truncated regression model. All regressions include year dummy variables (not reported for brevity) to control for potential serial effects.

	Panel A: Binary Response			**Panel B: Truncated Regression**		
Dep. var.:	VTB	NewM	VTB*	VTB	NewM	AssM
# Obs.	*6,752*	*6,752*	*691*	*2,008*	*4,750*	*691*
const.				1.2349**	0.8446**	0.4755**
				(5.85)	(19.64)	(3.68)
Land	1.0059**	-0.8532	0.0012	0.0249	-0.0432*	-0.0133
	(5.36)	(-0.40)	(0.00)	(0.75)	(-2.16)	(-0.21)
Apt.	-0.9578**	0.6450	-0.1588	-0.6298**	0.0024	0.1195**
	(-7.25)	(0.40)	(-0.77)	(-8.29)	(0.54)	(6.71)
Dev.	-0.0052	-0.0107	-0.0408	0.0056	-0.0316*	-0.0842
	(-0.03)	(-0.08)	(-0.08)	(0.09)	(-2.23)	(-1.50)
City-Center	-0.0866	0.1615	-0.0867	0.0234	0.0081*	0.0135
	(-1.58)	(0.40)	(-0.40)	(1.13)	(1.96)	(0.91)
Broker	-0.5384**	0.7449	0.4618	-0.0728**	-0.0115	-0.0602**
	(-5.85)	(0.40)	(1.53)	(-3.22)	(-1.62)	(-3.39)
$Seller = Brok$	0.1039	-0.6398	0.2694	-0.1433	-0.0465*	-0.0203
	(0.87)	(-0.39)	(0.64)	(-1.65)	(-2.20)	(-0.71)
σ_{local}	-0.1420	0.4502	0.1034	0.1075**	0.0056	0.0557
	(-1.37)	(0.40)	(0.33)	(2.54)	(0.62)	(1.88)
Age	0.0158**	-0.0138	0.0123	0.0005	0.0001	-0.0010**
	(6.00)	(-0.40)	(1.13)	(0.81)	(0.78)	(-2.43)
$BuyDist$	-0.0001	0.0001	-0.0004	0.0000	0.0000	0.0000
	(-0.91)	(0.37)	(-0.79)	(0.03)	(1.11)	(0.71)
Assm			-3.3705**			
			(-2.61)			
log(Price)	-1.0000	-1.0000	-1.0000	-0.0546**	-0.0085**	0.0037
				(-3.62)	(-3.46)	(0.49)

*,** Indicates significance at the 5% and 1% levels, respectively.

Table VIII:
Do Financial Decisions Influence the Price?
U.S. Commercial Real Estate Financing

Results from the regressions of property capitalization rates (defined as net income on the property divided by the sale price) on direct and indirect variables of asymmetric information plus the lender's retained stake in the property are reported below. Three sets of lenders are examined: the seller's retained stake, the bank's retained stake, and the seller's retained stake if no bank financing is used in the deal. The regressions also include controls for property, buyer, and seller characteristics. Panel A reports regression results for all properties excluding those in California over the period January 1, 1997 to March 30, 1999, and includes the COD variable as a regressor. These regressions include state dummy variables for states that recognize land trusts (coefficient estimates not reported for brevity). Panel B reports regression results for California properties only over the period January 1, 1992 to March 30, 1999. These regressions include year fixed effects (coefficient estimates not reported for brevity) to control for potential serial influences. Coefficient estimates are calculated via ordinary least squares (OLS), with t-statistics reported in parentheses, where standard errors are calculated via White's (1982) heteroscedastic-consistent estimator.

	Panel A: Exclude CA						**Panel B: CA Only**		
Dep. var.:	Cap.	Cap.	Cap.†	Cap.	Cap.	Cap.†	Cap.	Cap.	Cap.†
# Obs.	*1,162*	*1,162*	*74*	*1,162*	*1,162*	*74*	*4,680*	*4,680*	*624*
const.	13.3368**	12.7817**	9.7223**	13.3629**	12.6815**	9.3490**	5.4479**	4.2749**	4.7618*
	(13.66)	(13.38)	(3.28)	(13.74)	(13.20)	(3.21)	(7.09)	(5.64)	(2.20)
Land	-0.6236	-0.6742		-0.6276	-0.7004		0.0507	0.0226	-0.6279
	(-0.77)	(-0.81)		(-0.78)	(-0.84)		(0.09)	(0.04)	(-0.94)
Apt.	-0.2587	-0.2756*	-0.8307	-0.2595	-0.2768*	-0.8374	-0.1861	-0.1793	-0.0854
	(-1.85)	(-1.97)	(-1.28)	(-1.86)	(-1.98)	(-1.27)	(-1.72)	(-1.68)	(-0.39)
Dev.	0.1266	0.1028	0.6798	0.1278	0.1155	0.7219	-0.2588	-0.2050	0.8139
	(0.31)	(0.25)	(0.74)	(0.31)	(0.28)	(0.76)	(-0.87)	(-0.70)	(1.06)
City-Center	-0.1782	-0.1637	-0.0651	-0.1758	-0.1458	-0.0774	0.4225**	0.4025**	0.8738**
	(-1.14)	(-1.05)	(-0.09)	(-1.12)	(-0.93)	(-0.10)	(5.12)	(4.91)	(3.48)
Broker	0.5460**	0.5537**	0.9261	0.5468**	0.5531**	0.8963	0.4677**	0.3814**	0.3502
	(2.86)	(2.90)	(1.67)	(2.85)	(2.90)	(1.56)	(3.94)	(3.21)	(1.43)
$Seller = Brok$	-0.3056	-0.3279	-1.7960*	-0.3079	-0.3225	-1.7166*	-1.2146**	-0.9715**	0.2526
	(-0.98)	(-1.06)	(-2.22)	(-0.98)	(-1.03)	(-2.04)	(-5.42)	(-4.36)	(0.44)
COD	-0.0071	-0.0075	0.0861	-0.0072	0.0031	0.1175			
	(-0.60)	(-0.64)	(0.81)	(-0.61)	(0.20)	(1.21)			
σ_{local}	0.9850**	0.9628**	0.6138	0.9805**	0.9492**	0.6436	1.6141**	1.4694**	0.7701*
	(4.16)	(4.07)	(0.88)	(4.15)	(4.02)	(0.91)	(10.43)	(9.52)	(2.05)
Age	0.0082**	0.0078*	-0.0147	0.0082**	0.0079*	-0.0137	0.0017	0.0022	-0.0112
	(2.44)	(2.34)	(-1.09)	(2.44)	(2.36)	(-0.98)	(0.76)	(0.98)	(-1.86)
$BuyDist$	-0.0001*	-0.0001	-0.0001	-0.0001*	-0.0001	-0.0001	-0.0000	-0.0000	0.0004
	(-1.98)	(-1.74)	(-0.23)	(-1.99)	(-1.74)	(-0.22)	(-0.35)	(-0.29)	(1.33)
log(Price)	-0.3647**	-0.3476**	-0.0615	-0.3655**	-0.3517**	-0.0637	-0.0322	0.0154	0.2092
	(-6.58)	(-6.33)	(-0.26)	(-6.59)	(-6.38)	(-0.27)	(-0.70)	(0.34)	(1.42)
$\frac{VTB}{Price}$	-0.6119		-0.7320	-0.7094		-0.2479	-1.2827**		0.2108
	(-1.66)		(-0.97)	(-1.46)		(-0.20)	(-7.79)		(0.37)
$\frac{VTB}{Price} \times$ COD				0.0058		-0.0440			
				(0.24)		(-0.63)			
$\frac{Newm}{Price}$		0.5243*			0.8030**			1.4215**	
		(2.06)			(2.40)			(11.90)	
$\frac{Newm}{Price} \times$ COD					-0.0146				
					(-1.05)				

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

Table IX:
Toronto Real Estate (Marsh Data) Financing
May, 1996 - April, 1999

Results from the regression of various financing types on direct and indirect information variables plus property, buyer, and seller characteristics are reported below for Toronto real estate sales over the period May, 1996 to April, 1999. Four sets of dependent variables are used: vendor-to-buyer financing (VTB) scaled by sale price, new mortgage (NewM) scaled by sale price, assumed mortgage (AssM) scaled by sale price, and VTB scaled by sale price in excess of the amount of assumed mortgage (VTB*). Panel A reports coefficient estimates under the semiparametric binary response model from Appendix A, 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 from Appendix B, where the data is truncated to only those observations where the dependent variable (financing type) is positive. T-statistics are reported in parentheses, with standard errors calculated via the outer-product matrix for the binary response model, and via bootstrapping (250 simulations) for the truncated regression model.

	Panel A: Binary Response			**Panel B: Truncated Regression**			
Dep. var.:	VTB	NewM	VTB*	VTB	NewM	AssM	VTB*
# Obs.	*971*	*971*	*144*	*226*	*373*	*144*	*46*
const.				0.5371**	0.6952**	0.5216**	0.5727**
				(11.34)	(12.38)	(13.03)	(16.41)
D^{sell}_{occ}	-0.3996	0.2688	-0.4677	0.0478	-0.0136	0.1225	0.0395
	(-1.44)	(1.46)	(-1.56)	(0.44)	(-0.17)	(1.26)	(0.41)
D^{sell}_{out}	0.0629	-0.0929	0.0062	0.0774	-0.0752	0.0740	0.0622
	(0.35)	(-0.71)	(0.05)	(1.46)	(-0.16)	(1.78)	(1.23)
D^{buy}_{occ}	-0.1600	0.0021	-0.2505	0.0803	-0.0936	0.0545	0.1109
	(-0.37)	(0.01)	(-0.89)	(0.84)	(-0.05)	(0.68)	(1.17)
D^{buy}_{out}	0.3848**	-0.1636	0.3685*	-0.0379	0.0223	0.0185	-0.0156
	(3.25)	(-1.30)	(2.10)	(-0.75)	(0.05)	(0.45)	(-0.34)
Post-Feb'98	-0.0510	0.1373	-0.0529	-0.0495	0.0226	-0.0565	-0.0302
	(-0.35)	(1.24)	(-0.50)	(-1.14)	(0.06)	(-1.64)	(-0.68)
Land	0.4258	-0.7983**	0.4153	0.1354*	0.3511	-0.1071	0.0958
	(1.92)	(-3.00)	(1.70)	(2.04)	(1.56)	(-0.63)	(1.54)
Apt	0.1506	0.7068**	0.2835	-0.4593	0.0424	0.0870*	-0.4830
	(0.65)	(4.39)	(1.76)	(-1.20)	(0.05)	(2.54)	(-0.92)
Dev.	0.3833*	0.6535**	0.4849*	0.0878	0.0937	-0.0899	-0.2640
	(2.04)	(3.22)	(2.19)	(1.44)	(0.07)	(-0.49)	(-1.06)
AssM			-0.0159				0.0751
			(-0.10)				(1.21)
Price	-1.0000	-1.0000	-1.0000	-0.0000	0.0000	0.0000	-0.0000
				(-0.46)	(0.08)	(0.38)	(-0.05)

*,** Indicates significance at the 5% and 1% levels, respectively.