Real Estate Holdings of Public Firms and Collateral Discount*

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Abstract

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JEL Classification: G32, G33, R33

Keywords: Collateral discount, distressed sales, real estate transactions, asset quality

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Abstract

Using a novel and detailed transaction-level data on commercial real estate assets, we construct real estate asset portfolios for a comprehensive set of public firms between 2000 and 2013. We find that a commercial real estate asset is sold at a significant discount when the real estate asset is not redeployable for alternative uses, when potential buyers in the geographical region are limited, and when the industry is concentrated. These effects are further exacerbated for distressed firms and cannot be fully reconciled by the quality of real estate assets. Bank loan spreads incorporate information on the expected commercial real estate discounts due to collateral channel.

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1 Introduction

Public firms invest significant amounts in real estate assets although they may not operate primarily in the real estate business. While empty offices, warehouses, and idle land offer growth opportunities when companies expand, they often become a burden when companies become distressed. This happens partially because real estate assets are frequently used as collateral to borrow from banks. Their value change affect not only the equity investors but also the banks that lent them the funds. Although literature has shown that real estate assets, on average, cannot be traded quickly without compromising significant value, less is known about whether loan contracts incorporate information on a borrower's real estate portfolio characteristics and its motivation to liquidate its assets. Our main contribution in this paper is to document which micro-level real estate factors contribute to commercial real estate price changes, and to test whether information in borrowers' real estate portfolio holdings is priced in debt markets. Specifically, we study whether firms borrow at higher rates due to higher collateral discounts when their real estate holdings are not redeployable for alternative uses, when potential buyers in the geographical region are limited, and when the industry is concentrated and few firms are able to pay for the best-use price.

In our context, the main mechanism linking real estate prices to debt markets is collateral. Collateral is an important part of debt contracts. For instance, Cvijanovic (2014) illustrates that a one-standard-deviation increase in predicted value of a firm's pledgeable collateral translates into a 3-percent increase in leverage ratio. Banks often require borrowers to pledge some of their assets, primarily real estate assets, as collateral to secure payments.[1] Collateral increases a lender's incentive to monitor (Rajan and Winton, 1995), and it helps to mitigate moral hazard in loan contracting (Boot, Thakor,

[1]According to the Federal Reserve's Surveys of Terms of Business Lending, more than half of the value of all commercial and industrial loans made by domestic banks in the United States is currently secured by collateral (Leitner, 2006).

and Udell, 1991).[2] Analyzing micro-level-value determinants of a major asset class that is often used as collateral is a first-order issue because when firms are financially constrained, a positive shock to the value of their collateral makes it easier to borrow, and therefore to invest (Bernanke and Gertler, 1986; Kiyotaki and Moore, 1997).[3]

A positive relation between loan rates and the existence of collateral can arise if banks require collateral from high-default-risk borrowers. This moral hazard-induced selection effect was documented in several papers, including Berger and Udell (1990), John, Lynch, and Puri (2003), and Knox (2005).[4] Benmelech and Bergman (2009, 2011) caution that research designs using extensive margins to study existence (or value) of collaterals and loan rates suffer from endogeneity and selection bias. They suggest that looking at the intensive, rather than the extensive, margin of collateral would circumvent these issues.

Following the innovation suggested in Benmelech and Bergman (2009) and the rich nature of our data, we construct measures of collateral values as a proxy for creditors' expected value of the collateral upon default. Our measures incorporate two important features of real estate assets: location and redeployability. Commercial real estate assets have specific locations that allow us to develop several measures to capture the level

[2]Collateral can be used to alleviate financial frictions originated by moral hazard and adverse selection effects. See, for example, Aghion and Bolton (1992), Hart and Moore (1994), Hart (1995), Hart and Moore (1998), Bester (1985), Chan and Thakor (1987), Boot, Thakor and Udell (1991), and Boot and Thakor (1994). Berger and Udell (1990) suggest that firms with long-term relationships with a lender are less likely to pledge collateral. Stulz and Johnson (1985) show that secured debt enhances firm value since it reduces the incentive to underinvest, which is the case when a firm relies on equity or unsecured debt. Degryse, Kim, and Ongena (2009) review the empirical evidence on collateral and bank-firm relationships.

[3]Gan (2007) shows that a negative shock to collateral leads to reduced debt capacities and investments of firms. Recent literature on the real effects of collateral supply shocks focuses on real estate collateral. Chaney, Sraer, and Thesmar (2012) focus on the effect of real estate prices on corporate investment. Mian, Rao, and Sufi (2011) and Mian and Sufi (2011) document the effect of housing prices on household consumption both in the house price run-up of 2002–2006, and in the economic slump of 2007–2009. Adelino, Schoar, and Severino (2015) and Schmalz, Sraer, and Thesmar (2013) look at the impact of house prices on entrepreneurial activity.

[4]Hertzel and Officer (2012) note that "...Spreads are also significantly higher for loans containing covenants or pledged assets that protect lenders interests. This, seemingly counterintuitive, result has been a facet of almost all empirical analyses using Dealscan data (for an early example, see Booth, 1992) and is probably the result of these variables picking up some component of credit risk that is missing from the other control variables."

of interest in the sold asset. If an asset is located in an area where the number of potential buyers is low, higher discounts can be expected. Using three different measures of potential buyers based on the spatial distribution of industries and firms across the United States, we find that assets are likely to be priced higher in areas with more potential buyers and that these effects are further exacerbated for distressed firms.[5]

Asset redeployability particularly affects managerial choice. An office can be purchased and used by several buyers both within and outside of the seller's industry; thus offices are redeployable assets. A distribution center with a specific layout, however, is not a redeployable asset since it can only be utilized by a buyer that bears similar characteristics as the seller, such as industry, location, and customer base. Our results show that assets that are redeployable do not suffer any discount in case of distress, unlike specialized assets. This result complements the findings of Benmelech and Bergman (2009), who find that asset redeployability is adversely related to credit spreads.

There are two other important aspects of corporate real estate transactions that could potentially affect our inferences: asset selection and asset quality. When we compare the characteristics of the asset selected by the manager to be sold with the assets held in the firm's real estate portfolio, we find evidence that firms seek to sell assets that are less likely to be discounted. Moreover, assets sold by a distressed firm may be of lower quality if the firm has taken actions that could potentially reduce the quality of the sold assets. For example, a distressed seller is more likely to neglect real estate property maintenance and instead use funds for more immediate purposes, such as servicing a loan due in a short period of time. It is also possible that the same factors that initially placed a firm in a distressed state may also affect the price of the sold asset. An underperforming CEO is more likely to lead the firm into distress and lack the efficiency to find better deals for the sold asset. In this scenario, the correlation between a discount and financial distress

[5]Our results are consistent with Granja, Matvos and Seru (2014) who show that most failed banks are sold very locally such that a geographically proximate bank is more likely to acquire a failed bank.

indicates an unobserved CEO characteristic that is correlated with both factors, but does not necessarily indicate a relationship between seller distress and discounted real estate prices.[6]

Our data allow us to investigate metrics that potentially capture the intentions of buyers in a transaction. For example, we observe whether the buyer intention is to renovate, redevelop, occupy, or keep the property as is to sell later (i.e., investment). For certain types of assets, we can even observe occupancy rate, which is defined as the floor space or units occupied by tenants as a percentage of the total leasable area of the building. These measures are useful as they are likely to capture the quality status of real estate at the time of the transaction. An asset purchased with the intention of renovating later is more likely to fetch a lower price since renovation is likely to remedy deficiencies of the property. Likewise, a real estate asset that is not occupied at higher rates signals low demand for the asset, which may be reflective of how well the property has been maintained. When we compare the proportion of assets with low quality relative to total transactions across seller groups (distressed vs. not distressed), we do not find any economically or statistically significant differences across these groups, indicating that asset quality is not likely to explain our results.[7]

Our study is naturally related to the burgeoning literature on fire sales as we investigate the importance of each real estate-specific factor for firms with different levels of financial distress. Shleifer and Vishny (1992) suggest that large discounts in asset prices can occur if a financially distressed seller is forced to look for transaction opportunities when the best users of the asset are also constrained. The price of a

[6]Our findings support the notion that industry and location effects could be important determinants of economic decisions in corporate reorganizations as studied in Maksimovic and Phillips (1998). In their paper, Maksimovic and Phillips (1998) examine the importance of bankruptcy deadweight costs and the effect of plant-level efficiency, firm characteristics, and industry demand on the decisions to redeploy assets or close (or sell) manufacturing plants in bankruptcy. They show that industry conditions affect the marginal product of capital, and consequently create incentives to sell or restructure assets. Our paper shows that these results are not confined to bankruptcy situations and that both industry conditions and location factors affect a firm's borrowing cost in debt markets.

[7]This result is consistent with the findings of Cerqueiro, Ongena, and Roszbach (2014), who show that riskier borrowers are more likely to be required to pledge collateral.

distressed firm's asset is affected simply because potential bidders are operating in similar business lines and are subject to similar shocks.[8] Consistent with predictions of Shleifer and Vishny (1992), we show that real estate asset discounts are larger when potential buyers in the geographical region are few and when those assets are not readily redeployable in other industries.

2 Data and Summary Statistics

2.1 Sample Construction

We use the Real Capital Analytics (RCA) database to identify commercial real estate transactions. This database tracks commercial property and portfolio sales in the U.S. of $2.5 million or greater since 2000. RCA's data sources include press releases, news reports, SEC filings, public records, and listing services. As of 2015, the RCA database includes a total of over $3 trillion U.S.-based commercial real estate deals. Each record in the database contains both property- and transaction-specific information. The property characteristics include property size, physical address, year built, an indicator for the year the property was renovated, an indicator for whether the property is purchased within a portfolio, and an indicator for whether the property is located in a central business district (CBD). The geographic region of the property is denoted by an RCA Market identifier, which is an RCA-defined metropolitan area.

We identify both the seller and the buyer of the industrial, retail, and office properties

[8] Commercial real estate assets differ from other types of assets that have been studied in literature. Pulvino (1998), for example, uses a large sample of commercial airline transactions in order to show that airlines with low spare debt capacities sell aircraft at a 14% discount relative to the average market price. While commercial aircraft is a very specialized asset type that is likely to be subject to a discount, it is difficult to test the specific predictions of Shleifer and Vishny (1992) using an asset that is hardly redeployable in other industries. Financial assets also result in deep discounts if sellers are motivated to unload the positions quickly. For example, Coval and Stafford (2007) estimate more than 10% gains from buying stocks that experience price pressure due to mutual fund outflows. Albuquerque and Schroth (2015) present evidence that the sale of block holdings might occur at discounts due to search frictions. Finally, Chu (2013) tests the fire sale theory in the context of bank-owned commercial real estate sales during the 2008 financial crisis.

by their full legal corporate names, and hand match RCA seller names with firms in the Compustat Annual Files. Since the capital structure of financial firms (SIC code between 6000 and 6999) is significantly different than the capital structure of industrial firms, we focus only on industrial companies. We also exclude real estate investment trusts (SIC code 6798), as they buy or sell real estate for investment purposes. Utility firms and government entities are also excluded. Our matching procedure yields 323 unique public firms that were involved in 2,295 transactions. Because our interest lies in relative prices, we use remaining transactions whose sellers are not Compustat firms to calculate the implied price of a property with the same property characteristics, in the same location (RCA Market), and in the same quarter. We obtain firm characteristics from Compustat Annual Files.

Data allow us to group each type of properties into subgroups based on certain asset features. For example, industrial properties include warehouses and flex assets, where the property can be used for both industrial and office activities. Retail properties include malls and strip centers. Offices are divided into two subtypes based on their location as either central business district or suburban area.

In our analysis, we use the natural logarithm of price per square footage plus one as the dependent variable. Explanatory variables include various property-specific variables such as the logarithm of the property's size, property age dummies, a dummy variable indicating whether the property is renovated at any point in time, a dummy variable indicating whether the property is purchased within a portfolio, a CBD dummy indicating whether the property is located in a central business district, and RCA market fixed effects as physical location controls.

We divide property age into six categories for each ten years, as we expect a nonlinear relation for each age category and the transaction price per square footage. *Age Group 1* is a dummy variable which takes one if the property age is between 11 and 20. *Age Group 2* is a dummy variable which takes one if the property age is between 21 and 30 and so forth. *Age Group 5* is a dummy variable which indicates that the property age exceeds 50.

2.2 Descriptive Statistics

In Table **??** we summarize the characteristics of the properties and of the sellers (Appendix (Table **??**) provides the details of variable construction.) Panel A reports the summary statistics for the company-level variables. One of the most important differences between the sellers and an average Compustat firm is size. Since the transactions in our sample exceed $2.5 million, our RCA sample is composed of medium and large size firms. Median size, measured by natural logarithm of total assets, in our sample is 9.786, whereas Compustat median for the same time period is 5.347. Secondly, the median firm in the RCA sample is more profitable, and has more tangible assets relative to the average firm in Compustat. In the Compustat universe, median tangibility is 0.135, and median ROA is 0.054, whereas in our sample they are 0.403 and 0.151, respectively. Finally, book leverage and industry-adjusted book leverage are higher for sellers compared to the average firm in Compustat.

Panel B reports the summary statistics for property characteristics. *Unit Property Price* equals the natural logarithm of price per square feet plus one. *Size* is natural logarithm of property size measured in square feet. *Renovated* equals one if there is non-missing data for the year that the property was renovated or expanded. *Portfolio* indicates that the sale is part of a portfolio transaction. *CBD* is a dummy variable that takes one if the property is located in a central business district or in the "downtown" of a city. *Occupancy Rate* is defined as the floor space or units occupied by tenants as a percentage of the total leasable area of the building at the time of a sale. The final sample is restricted to transactions for which we have non-missing data for the following variables: Industry-Adjusted Leverage, Tangibility, ROA, Market-to-Book Ratio, Unit Property Price, Size, Age, Renovated, Portfolio and CBD.

The average property in our sample is about 22 years old and the average price per square footage is \$87. About 12% of the properties in our sample have been renovated before, and 33% of the sales are part of a portfolio transaction.

Panel C of Table **??** shows the distribution of sub-property types for *Industrial*, *Retail* and *Office* properties. *Flex* denotes a property that is flexible in that it can be used for industrial or office activities. While 36.25% of the properties in our sample are industrial, retail properties constitute 44.53% and offices constitute 19.22% of our sample. Panel D of Table **??** indicates that 28% of the properties in our sample were vacant at the time of the sale and 75% of the buyers' main intention was investment.

In Table **??** we analyze the likelihood of a Compustat firm being in our sample. In the specification reported $Seller\ Dummy_{i,t}$ is a binary variable that takes one if firm i sold at least one commercial property in year t and zero otherwise. *Distress Proxy* denotes one of the following variables: *Leverage* is the ratio of total book debt to book value of assets; *Industry-Adjusted Leverage* equals book leverage minus median industry leverage, where industries are defined by the three-digit SIC codes; *High Leverage–Low Current Assets Dummy* is a binary variable that equals one for firms with leverage above the industry median and current assets below the industry median, and zero otherwise; and *Interest Coverage Ratio* is the ratio of income before depreciation divided by interest expense. For industry adjustments, we require at least three non-missing observations for each three-digit SIC industry in a given year. Since firms with negative book equity are likely to be in financial distress, we do not exclude observations with total debt greater than total assets. Instead, we use the discretized values of our financial distress variables in order to make sure that the results are not driven by the outliers. More specifically, we split *Industry-Adjusted Leverage* into three equal-size groups: *Low*, *Medium* and *High Industry-Adjusted Leverage*. We use book value of total assets (*Assets*) in order to account for firm size. *Tangibility* is defined as the ratio of property, plant, and equipment (PPE) to total assets. Return of assets (*ROA*) is defined as operating income scaled by total assets and *Market-to-Book Ratio* is the ratio between the market value and the book value of total assets. Finally, u_i and $Year_t$ denote firm and year fixed effects, respectively. The coefficient estimates reported in Table **??** show that all of our financial distress proxies are statistically significant, indicating that financially distressed firms are likely to appear as sellers in our sample.

3 Analysis

3.1 Determinants of Real Estate Prices

In this section, we analyze the impact of financial distress on the selling price. We split the sample into three equal-size groups depending on the seller's *Industry-Adjusted Leverage*. *Medium (High) Ind.-Adj. Leverage Dummy* takes one if the seller's three-digit SIC industry-adjusted leverage is between the 33rd and 67th (above the 67th) percentile of the sample. Table **??** Panel A.1 reports the average transaction prices for *Low*, *Medium* and *High Industry-Adjusted Leverage* groups which are 4.674, 4.559 and 4.201, respectively. To control the effect of confounding factors on the correlation between distress measures and real estate discount, we estimate a model that directly relates the selling price to financial distress. In this specification, we include controls for the geographical location of the property as well as seller characteristics. Results in Table **??** Panel B show a strong negative relationship between the selling price and the seller's leverage ratio (Columns (1)–(3)). When all the control variables are included, an increase from the lowest leverage tercile to the highest leverage tercile leads to a 23.8% decrease in price with other variables held constant. This finding is consistent with the real estate appraisers' estimate that rapid real estate sales lead to price discounts of

15% to 25% relative to orderly sales (Shleifer and Vishny, 1992).[9][10]

Real estate assets can be considered as a composite good which can be reduced to its constituent parts. Hedonic models are often used to find the market value of those constituent parts. We run a hedonic model in which selling price is estimated as a function of a detailed set of property characteristics using a larger sample of transactions for both private and public firms (Table **??**). Using the estimates of the hedonic model, we calculate residual price as the difference between actual price and model implied price, which represents how much the market valued a given real estate with respect to its components. We find that, on average, low-leverage firms and high-leverage firms have residual prices of –0.039 and –0.344, respectively (Table **??** Panel A.2). The last column of Table **??** Panel B shows that the correlation between distress proxies and residual price is negative, consistent with the evidence obtained using one-stage analysis. The economic significance of the distress impact on prices is comparable to those estimated using one-stage analysis in Table **??** Panel B and univariate analysis: an increase from the lowest leverage tercile to the highest leverage tercile leads to a 22.9% decrease in residual price.[11]

3.2 Asset Redeployability

We now turn our attention to the link between real estate prices and asset redeployability. As discussed before, Shleifer and Vishny (1992)'s main prediction is that assets should

[9]Note that because the dependent variable equals the logarithm of 1 plus the transaction price, the discount is calculated by taking the exponent of the coefficient. For example, the discount associated with the selling firm's leverage being in the highest tercile equals $1 - exp(\beta_2)$, which is the percentage change in 1+price if the selling firm's leverage changes from the lowest- to the highest-leverage tercile.

[10]In this specification, all company-level variables are measured at least one month and at most eleven months before the transaction date, depending on the selling firm's fiscal year end. Heteroskedasticity adjusted standard errors are clustered at the firm level. Results are robust to two-way clustering at the RCA market and quarter levels.

[11]Table **??** report the results from the first-stage model estimated for each property type (*Industrial*, *Retail* and *Office*) separately and together. The coefficient estimates reported in the last column are for the base property type (Apartment). All regressions include RCA Market-Year fixed effects. Results show that smaller properties, renovated properties, and properties in central locations have higher values.

sell for less if the asset is of use to few buyers. Our dataset allows us to identify the properties that are potentially more redeployable than others. Since the same office can be used by firms from different industries, we expect offices to have higher demand than other property types. The variable *Flex* indicates whether a property is flexible in that it can be used for both industrial or office activities. Similar to offices, we also expect such properties to attract a larger investor base.

In order to capture the incremental impact of asset redeployability on prices, we introduce *Asset Redeployability Dummy* which takes one if the property is an office or can be used for both industrial and office activities. Panel A.1 of Table **??** reports the average residual price for the two redeployability groups which shows that when the property is non-redeployable, the average residual price of firms' real estate sales is significantly lower than others. In Panels A.2 and A.3, we measure distress using industry-adjusted and raw leverage, respectively. In Panel A.4, we split the sample into two groups depending on whether the seller has above-median leverage and below-median current assets or not. In all three panels, the difference between average prices of the highest- and the lowest-leverage terciles is both economically and statistically less significant for redeployable properties. The price difference resulting from distress is much smaller and insignificant or marginally significant if the property is an office or has flexible usage.

The results from multivariate analyses, reported in Table **??** Panel B, are consistent with the findings in Panel A. While our distress proxies demonstrate negative and significant coefficient estimates for the subsample of low-redeployability assets, the coefficient estimates are not significant for offices and flexible properties, which suggests that generic assets such as offices indeed get better prices when they are sold by distressed sellers.[12]

The asset redeployability measure defines the space of potential buyers. Generic

[12] The fraction of observations in each leverage tercile does not vary significantly between asset redeployability classes so that the results are not driven by uneven distribution of observations for offices. We obtain similar results for the continuous industry-adjusted leverage variable.

assets such as offices and industrial complexes with flexible use can serve companies outside of a given industry. If an industry experiences a shock that puts most firms in financially disadvantaged position, then generic assets provide a better means to raise capital to survive. Analysis of commercial real estate assets is also useful to generate novel measures that the previous literature cannot construct. Unlike airplanes (Pulvino, 1998) and financial assets (Coval and Stafford, 2007), commercial real estate assets have specific locations that allow us to develop measures of potential buyers that are likely to have higher valuations.

If an asset is located in an area where the number of potential buyers is limited, we expect higher discounts. This expectation is motivated by Almazan et al. (2010) who investigate the relation between firms' locations and their corporate finance decisions. They argue that being located within an industry cluster increases opportunities to make acquisitions, and to facilitate those acquisitions, firms within clusters maintain more financial slack. Almazan et al. (2010) find that firms located within industry clusters make more acquisitions, and have lower debt ratios and larger cash balances than their industry peers located outside clusters. Motivated by the prevalence of local factors in shaping financial transactions, we test whether the discount is stronger in concentrated industries, where there is a smaller group of potential buyers who could pay for the best-use price. Our study complements Almazan et al. (2010) by showing that being located in an industry cluster positively affects the price of commercial properties in that industry, and reduces the sale discount.

We use three different measures to capture the number of potential buyers. First, we calculate the number of companies operating in the same three-digit SIC industry as the seller who mentions the state of the property in 10-Ks at least once during the transaction year (Garcia and Norli, 2012).[13] Note that this measure is available only up to 2008. Our second measure is the number of companies operating in the same three-

[13]We thank Diego Garcia and Oyvind Norli for graciously sharing their data with us.

digit SIC industry as the seller whose headquarters are located in the same state as the property. Our final measure is *1-Herfindahl Index* where Herfindahl Index is the sum of squared market shares of firms in the seller's three-digit SIC industry.

Panel A of Table **??** reports the average residual price for different industry-adjusted leverage and number of potential buyers groups. On average, selling price is higher for properties with more potential buyers. When the number of potential buyers is low, we observe a statistically significant difference between the average residual price of the high- and low-leverage sellers. However, the difference is much smaller for properties with a large number of potential buyers. For instance, if the number of potential buyers (calculated using headquarters) is low, the average residual price for high-leverage transactions is 0.393 less than the average residual price for low-leverage transactions, whereas the difference is only 0.087 if the number of potential buyers is high.

In Panel B of Table **??**, we estimate our baseline specification given in column (4) of Table **??** including our number of potential buyers measures and their interactions with the seller's leverage. Columns (1), (3) and (5) report the estimation results for the direct effects of our number of potential buyers measures without leverage interactions. The coefficient estimates for all three measures are positive and significant, indicating that average residual price is higher when there are more firms that might potentially be interested in buying the property. The coefficient estimates for the interaction between the high-leverage indicator and the number of potential buyers measures are all positive and statistically significant. For instance, for the measure calculated using headquarters, the coefficient estimate of the interaction term is 0.088 and the direct effect of high leverage is –0.376. This implies that one standard deviation increase in the logarithm of number of potential buyers (1.22) decreases the impact of high leverage from –0.376 to –0.269. Collectively, these results suggest that the discount is low or does not exist when there are more potential buyers.

3.3 Expected Collateral Discount

Our analysis in section 3.1 and 3.2 shows that two identical sellers will get two different prices for their assets if their financial leverage differ. Using this insight, we calculate the value of a given firm's real estate portfolio value (REPV) using the firm's actual leverage and a hypothetical leverage which represents a distressed situation within the firm's industry. The ratio of these two values indicate how much real estate discount a firm will suffer when it gets financially distressed. Specifically, we define the expected collateral discount as as follows:

$$Expected\ Collateral\ Discount = Actual\ REPV_t / Hypothetical\ REPV_t$$

where,

$$Actual\ REPV_t = \sum_{i}^{N} Size_i \times Price/sqf | Actual\ Leverage_{i,t}$$

$$Hypothetical\ REPV_t = \sum_{i}^{N} Size_i \times Price/sqf | Hypothetical\ Leverage_{i,t}$$

To execute this idea, we first construct the real estate portfolios of companies using all the transactions contained in the RCA database. Every transaction's date and property's unique identifier help us to identify the time period the seller held the property. Moreover, every transaction helps us to identify the first time the property was included in a buyer's real estate portfolio and also reveals time-invariant characteristics of the property. After constructing real estate portfolios from transaction data, we first estimate the unit price for each of the firm's properties twice, first assuming that the leverage equals the firm's current industry-adjusted leverage, and then assuming that the leverage is 23% higher than the industry median (23% refers to the 90th percentile value of the industry-adjusted leverage in our sample).

We use size of the properties as our portfolio weights to calculate actual and hypothetical portfolio values. RCA covers transactions over a minimum asset size threshold (2.5 million USD), therefore our actual and hypothetical portfolio are tilted toward larger properties. Because our collateral discount measure is the ratio of these two portfolios, we do not expect the *Expected Collateral Discount* to be over or understated due to RCA's coverage choice. More importantly, the direct impact of high leverage on *Expected Collateral Discount* is absorbed by *Industry-Adjusted Leverage*, thus the variation in *Expected Collateral Discount* mainly results from the interaction term of industry-adjusted leverage with property type dummies and the number of potential buyers.[14]

To investigate whether loan spreads vary with expected collateral discount, we obtain loan level data from Loan Pricing Corporation's (LPC) Dealscan database which contains detailed information about commercial (primarily syndicated) loans made to US corporations since the 1980s. According to Carey and Hrycray (1999), the Dealscan database contains between 50% and 75% of the value of all commercial loans in the US during the early 1990s with increased coverage after 1995. Our initial sample of loans contains all commercial loans denominated in US dollars. We link Dealscan dataset to the Computstat database using the links provided by Chava and Roberts (2008). While each observation in the Dealscan database represents a facility (or a tranche), multiple facilities with similar loan terms and pricing are frequently packaged into deals. Following Hertzel and Officer (2012), we choose the largest tranche in each deal as our unit of observation. We require non-missing data on loan amount, loan maturity, loan type and loan purpose.[15]

Following the literature, we evaluate loan prices using all-in-drawn spread, which is the amount the borrower pays in basis points over LIBOR including any recurring annual

[14]In instances where *Actual REPV* is less than *Hypothetical REPV*, we normalize the minimum value of *Expected Collateral Discount* to unity by substituting it with one. We obtain similar results when we do not normalize it.

[15]Loan types are indicators for term loans, revolver loans, 364-day facility and others. The primary purpose of the facilities in our sample are corporate purposes, debt repayment, working capital, and acquisition-related (including mergers, LBOs and takeovers).

fees on the loan. Our final sample consists of 1,283 loans with a median spread of 68.7 basis points. There are 704 loans for which we are able to determine whether or not they are secured by a collateral.

Table **??** reports the results from the regression of loan spread on *Expected Collateral Discount* and loan- and firm-level controls. We find that there is a positive relationship between collateral discount and loan spread after controlling for firm leverage, industry fixed effects, and year fixed effects. More specifically, one-standard-deviation (12%) increase in expected collateral discount is associated with about 14.07 basis points higher loan spread which coincides with a 0.115 standard deviation increase in loan spread. In column (2) of Table **??**, we control for the secured status of the loan. Strahan (1999) investigates the impact of non-price terms of loans on loan pricing and shows that although secured loans have higher expected rates of recovery in default, they carry 32% to 51% higher interest rates than unsecured loans. Furthermore, loans to small firms, firms with low ratings, and firms with little cash available to service debt are more likely to be secured by a collateral. Result in column (1) continues to hold after controlling for the existence of a collateral. In column (3) of Table **??**, we interact our collateral discount measure with the *Secured Loan Dummy.* The coefficient estimate of the interaction term is positive whereas the coefficient estimate for the direct effect of our collateral discount becomes insignificant. This finding indicates that collateral discount is an important factor in pricing particularly of those loans that are backed by a collateral.

A property that was never traded between 2000 and 2013 is not observed in our real estate portfolios. Because we do not observe the unit price of this non-traded real estate asset, we can not determine how much non-traded real estate assets contribute to the collateral discount. However, in section 4.2, we demonstrate that firms choose the assets that are less likely to be discounted in distress, indicating that our collateral discount coefficient is underestimated if the size of the non-traded property is significantly larger than that of all traded properties for all firms. In our data, the average ratio of the real estate portfolio value to tangible assets is 9.39%.[16] Because tangible assets include several asset types such as machinery, this ratio presents considerable variation across industries. For example, industries that employ large amounts of heavy equipment (such as airlines or mining), have a mean ratio of less than 1%. For industries that are more likely to own real estate properties (such as retail), the ratio goes up to 21%. In our specification, industry fixed effects enable us to capture across-industry variation in terms of share of real estate properties in the tangible assets. Moreover, we include the value of property, plant and equipment (scaled by total assets) to capture the effect of tangible assets on loan rates (see Acharya et al., 2013). To capture the relative size of non-traded properties, we also include the ratio of real estate asset portfolio to the size of a firm's property, plant and equipment as a separate covariate. Column (4) of Table **??** shows that controlling for the size of real estate holdings relative to tangible assets does not change our results.

Collectively, our findings suggest that when banks price collaterals, they consider marketability of a borrower's real estate portfolio when the borrower becomes distressed. A borrower with assets that are not redeployable for alternative uses borrows at higher rates. Likewise, a borrower faces a higher loan rate if its real estate assets are located in an area where potential buyers in that geographical region are limited, and when the industry is concentrated and few firms are able to pay for the best-use price. The link between a firm's real estate holdings and bank loan rates collaborates the findings of Benmelech and Bergman (2009) which show that debt tranches that are secured by more redeployable collateral exhibit lower credit spreads. Using evidence from airline industry, Benmelech and Bergman (2009) point out that the previously documented positive correlation between existence of collaterals and loan prices could be misleading because of endogeneity and selection bias. Our findings complement their findings by

[16] In 1993, the last year in which the SEC required firms to report the accumulated depreciation of buildings, 54% of Compustat firms reported some real estate ownership on their balance sheet (Cvijanovic (2014)).

showing a similar relation between prices of an asset type that is frequently used in almost all industries and loan prices.

4 Robustness Tests

4.1 Asset Quality

If the factors that forced the seller to dispose assets at unfavorable prices have also reduced the quality of assets sold, then prices reflect the most up-to-date quality of the assets. Consequently, the finding that distressed sellers transact at lower prices suggests that these properties may be lower quality. Fortunately, our data allow us to observe the buyer intentions that can serve as a proxy for whether buyers intend to spend extra resources to make the assets more appealing/functional for future usage. Specifically, the data allow us to see whether the purpose of the transaction is to occupy, renovate, redevelop, or invest. Of these alternatives, renovation and redevelopment indicate further commitment, thus potentially requiring buyers to bid lower. We also observe tenancy status as well as occupancy rate which capture the quality status of a property at the time of the transaction.

In Table **??** Panel A, we regress residual price on each of the quality proxies, namely buyer purpose, tenancy status and occupancy rate. *Buyer Purpose* can be investment, occupancy, redevelopment or renovation. *Tenancy Status* is the occupancy type at the time of a sale, which can be multi-tenant, single tenant or vacant. *Occupancy Rate* is defined as the floor space or units occupied by tenants as a percentage of the total leasable area of the building. Results confirm our prior findings: residual price is lower for properties to be renovated after the purchase, vacant properties and properties with low occupancy.

Panel B of Table **??** compares the average quality measures of properties with different industry-adjusted leverage and residual prices. We split the sample into three equal-size groups by the seller's industry-adjusted leverage and into two groups as above- and below-median residual price independently from leverage. For each leverage-residual price group, Panel B.1 reports the percentage of properties for which the buyer purpose is either redevelopment or renovation, Panel B.2 reports the percentage of vacant properties, and Panel B.3 reports the average occupancy rate. The number of observations and t-statistics for the differences between high-leverage and low-leverage groups are reported in parentheses. The correlation between asset quality and residual prices is either insignificant or the opposite of the expected sign.

In Panel C, we conduct a similar analysis using a multivariate setting. More specifically, we regress our industry-adjusted leverage dummies on our quality proxies. None of the coefficient estimates of industry-adjusted leverage dummies are significant at the 10% level indicating that financial distress is not significantly related to the quality of the properties being sold. Overall, results suggest that asset quality, as measured by the proxies we observe, does not vary across low- and highly-levered sellers.

4.2 Asset Selection

In section 3.3, we explained how we created the real estate holdings using transaction data of the complete universe of commercial real estate transactions. Using this data, we explore whether the properties of firms that are actually sold are different from the rest of the real estate portfolio based on observable characteristics. In order to address the selection of properties, using the real estate holdings of public firms constructed from complete transactions of RCA universe, we estimate a firm's preferences for selling a particular property using the portfolio ranking of that property based on size, age, and liquidity. Specifically, we calculate the liquidity measure by counting the number of transactions for each property type i in each year t and each state j, and then normalizing it by its sample average:

$$Liquidity_{i,j,t} = \frac{\#\ of\ transactions_{i,j,t}}{Average\ \#\ of\ transactions_{i,j}}$$

We use the following formula in order to calculate the percentile rankings based on size, age, and liquidity:

$$Percentile\ ranking_{i,j} = \frac{Ranking_{i,j} - 1}{\#\ of\ properties_j - 1},$$

where i denotes each of the real estate properties in portfolio j. Note that *Percentile ranking* takes a value between zero and one, and we predict that higher rankings are associated with higher prices. Using all properties within the portfolio of a given seller, we estimate the following probit model:

$$\begin{aligned} Sale\ Dummy_{i,j,t} = &\beta_0 + \beta_1 Age\ Rank_{i,t} + \beta_2 Size\ Rank_{i,t} + \beta_3 Liquidity\ Rank_{i,t} \\ &+\beta_4 Renovated_{i,t} + \beta_5 CBD_{i,t} + \beta_6 Property\ Type_{i,t} \\ &+\beta_7 Firm\ Controls_{j,t-1} + Year\text{-}Quarter_t + RCA\ Market_i + \varepsilon_{i,t} \end{aligned} \quad (1)$$

Our (unreported) results show that the ranking variables are all significant. Specifically, as the rankings with respect to size, age, and liquidity increase, the probability of the property being sold increases. Next, we calculate inverse Mills ratio (λ_1) from the probit regression. Table **??** Column (1) reports our price regression with λ_1 included. The coefficient of inverse Mills ratio is positive but statistically insignificant. If we compare this with Column (4), which reports the baseline coefficient estimates, the coefficients for leverage indicators are underestimated when we do not account for the selection.

Table **??** indicates that financially distressed firms are more likely to sell properties. However, it is also possible that some low-leverage firms may sell properties if a profit opportunity arises. In other words, if low-leverage is associated with a firm's ability to time the market, then the coefficients for the high industry-adjusted leverage indicator would be underestimated. In order to address the selection of the selling firms, we estimate the following probit model using the Compustat universe:

$$\begin{aligned} \textit{Seller Dummy}_{j,t} =& \beta_0 + \beta_1 \textit{Ind.-Adjusted Leverage}_{j,t-1} + \beta_2 ROA_{j,t-1} \\ & + \beta_3 Ln(Assets)_{j,t-1} + \beta_4 \textit{Market-to-Book}_{j,t-1} + \beta_5 Tangibility_{j,t-1} \\ & + Year_t + \varepsilon_{j,t} \end{aligned} \tag{2}$$

We calculate inverse Mills ratio (λ_2) from this probit regression. Table **??** Column (2) reports our price regression with λ_2 included. The coefficient of inverse Mills ratio is positive but not significant at 10%. However, the coefficient estimates for leverage dummies in column (1) decrease by about 1/3 relative to those in column (4). This indicates that on average, firms that choose to sell a property receive a higher transaction price relative to a non-seller firm with similar characteristics. Comparing column (2) with column (4) in Table **??** shows that selection does not significantly affect the coefficient estimates of leverage indicators. Finally, in column (3) we include both λ_1 and λ_2 in the price regression. The results are similar to those in columns (1) and (2).

4.3 Past and Future Prices

If the price discount that we find in our analyses is a result of the seller's financial distress, then we should not observe such a discount for the past and future transactions of the same property conducted by other firms. Our data allow us to observe the past and/or future transactions of some of the properties in our sample. Using these transactions, we can compare the impact of seller characteristics while holding the property fixed.

For each property sold in our sample, we determine the *non-distress price* from the past or future transactions on the same property but a different buyer and seller than in the current transaction. When there are more than one such prices, we select the transaction that has the date closest to the distress sale date. Table **??** compares the average residual prices of distressed sales with the average prices of their non-distressed counterparts. On average, sales in our sample have lower residual prices relative to their past or future transaction prices, which confirms our finding in Table **??** that industrial firms' commercial real estate sales are mostly driven by financial difficulties and liquidity problems. However, the difference between average transaction price and non-distress price is not significant for firms in the low industry-adjusted leverage tercile. Similarly, average selling price is not significantly different from the average non-distress price for firms with below-median leverage and above-median current assets. These findings suggest that the discount we find for distress sales is not explained by time-invariant property characteristics.

4.4 Other Robustness Tests

In this section, we run robustness tests for the baseline model presented in column (4) of Table **??**. In Table **??**, we use several alternative distress proxies, namely *Leverage*, *Industry-Adjusted Leverage*, *High Leverage–Low Current Asset Dummy* and *Interest Coverage Ratio*. All results point to the same conclusion: The price of commercial real estate sold by distressed sellers is significantly lower than other transactions.

Table **??** presents the estimation results for further robustness tests. Particularly, we estimate the baseline model in Table **??** using several different specifications. In column (1), we restrict the sample to the period before 2007. In column (2), we focus on the transactions that are not conducted as part of a portfolio. In column (3), we use the residual prices estimated from separate regressions for each property type. In column (4), we include the seller's industry fixed effects, where the industries are defined according to two-digit SIC codes. Finally, in the last column, we restrict the sample to properties that are outside the state of the seller's headquarter. Note that this specification addresses the possibility of local economic conditions simultaneously affecting real estate prices and the seller's financial health. Results show that our findings are not driven by the recent financial crisis, portfolio sales, or shocks to local economy, and they are robust to an alternative estimate of the residual price. While controlling for industry fixed effects decreases the statistical significance of *Medium Ind.-Adj. Leverage Dummy*, it does not change the statistical significance of the coefficient estimate for the highest leverage tercile.

We also estimate the baseline model using an alternative definition for the dependent variable. We obtain propensity scores from a logistic regression of a dummy variable that takes one if the transaction is a corporate sale and zero if the seller is not a corporation, on the logarithm of the property size, CBD dummy, year-quarter fixed effects and RCA market fixed effects. Using the propensity scores, we determine three and five best-matched properties for each corporate sale. We calculate propensity scores separately for each property type, so that the matches are restricted to the property type of each corporate sale. Then, we calculate the mean of the residual prices estimated using the baseline model. Finally, we calculate the difference of residuals by subtracting the mean of the residual prices of the matched properties from the residual price of each sale in our sample.

Results documented in Table **??** indicate that the relationship between the selling price and the selling firm's leverage ratio is negative and statistically significant. Overall, the matched sample results support the evidence obtained from the single-stage and two-stage analysis.

Conclusion

Our paper contributes to our understanding of how commercial real estate assets affect collateral values and the cost of debt. Evidence suggests that sellers' distress matters as predicted by Shleifer and Vishny (1992) and banks price loan spreads such that they increase with expected real estate discounts. We document that information regarding the expected commercial real estate discounts has a significant impact on loan spreads because of the collateral channel and firms seek to sell the assets that are less likely to be discounted. In line with Shleifer and Vishny (1992), if real estate assets have alternative uses or are located in areas with more potential buyers, the discount is significantly mitigated or eliminated completely. More importantly, we do not find evidence that distressed assets in our sample are of lower quality. If anything, distressed sellers are more likely to sell their better assets to mitigate the rushed sale discount.

Table 1: Descriptive Statistics

This table summarizes the characteristics of the properties and the sellers we analyze in this study. Our sample is restricted to properties sold by non-financial firms, and covers the period between 2000 and 2013. Panel A reports the summary statistics for the company-level variables. *Leverage* is the ratio of total book debt to book value of assets, *Industry-Adjusted Leverage* equals book leverage minus median industry leverage, where industries are defined by the three-digit SIC codes, and it is required that there are at least three firms operating in each industry. *Tangibility* is defined as the ratio of property, plant, and equipment (PPE) to total assets, return on assets (*ROA*) is defined as operating income scaled by total assets, and *Market-to-Book Ratio* is the ratio between the market value and the book value of total assets. All ratio variables are winsorized at the top and bottom 2.5%. Panel B reports the summary statistics for property characteristics. *Unit Property Price* equals the natural logartithm of price per square feet plus one. *Size* is the natural logarithm of property size measured in square feet ($Ln(sqf)$). *Renovated* equals one if there is non-missing data for the year that the property was renovated or expanded. *Portfolio* indicates that the sale is part of a portfolio transaction. *CBD* is a dummy variable that takes one if the property is located in a central business district or in the downtown of a city. *Occupancy Rate* is defined as the percentage of floor space or units occupied by tenants as compared to the total leasable area of the building at the time of a sale. Panel C shows the distribution of subtypes for *Industrial*, *Retail* and *Office* properties. *Flex* denotes a property that is flexible in that it can be used for industrial or office activities. Panel D shows the distribution of properties by *Vacancy* and *Buyer Purpose*. *Single Tenant* is a property that was fully occupied by a single user. *Vacant* indicates that the property was not occupied at time of sale. *Occupancy* is a buyer's objective representing a property that is purchased for use by the buyer in the conduct of business.

Panel A: Company Characteristics	Mean	St. Dev.	p25	Median	p75	N
Leverage	0.259	0.159	0.153	0.254	0.353	2295
Industry-Adjusted Leverage	0.065	0.171	-0.033	0.062	0.177	2295
Interest Coverage Ratio	16.163	15.895	4.888	9.382	22.315	2236
ROA	0.137	0.084	0.088	0.151	0.181	2295
Tangibility	0.366	0.185	0.196	0.403	0.541	2295
Market-to-Book	1.452	0.898	0.855	1.265	1.728	2295
Ln(Assets)	9.481	1.637	8.236	9.786	10.434	2295

Panel B: Property Characteristics	Mean	St. Dev.	p25	Median	p75	N
Unit Property Price	4.478	0.931	3.824	4.535	5.131	2295
Ln(sqf)	11.407	1.299	10.645	11.496	12.264	2295
Age	21.916	18.353	9	18	30	2295
Renovated Dummy	0.120	0.325	0	0	0	2295
Portfolio Dummy	0.328	0.470	0	0	1	2295
CBD Dummy	0.053	0.224	0	0	0	2295

Table 1 Continued

Panel C: Property Subtypes

Industrial		
Flex	243	29.96
Warehouse	568	70.04
Total	811	

Retail		
Mall & Other	904	90.58
Strip	94	9.42
Total	998	

Office		
CBD	68	15.81
Sub	362	84.19
Total	430	

Panel D: Vacancy and Buyer Purpose

Vacancy		
Multi Tenant	273	13.95
Single Tenant	1,135	58.00
Vacant	549	28.05
Total	1957	

Buyer Purpose		
Investment	1,718	75.05
Occupancy	320	13.98
Redevelopment/Renovation	251	10.97
Total	2289	

Table 2: Transaction Prices and Firm Distress

Panels A.1 and A.2 report the average selling price and average residual price for sellers in different industry-adjusted leverage terciles. We split the sample into three equal-size groups depending on the seller's *Industry-Adjusted Leverage*. *Medium (High) Ind.-Adj. Leverage Dummy* takes one if the seller's 3-digit SIC industry-adjusted leverage is between the 33^{rd} and 67^{th} (above the 67^{th}) percentile of the sample. Panel B reports the multivariate results. All company-level variables are measured at least one month and at most eleven months before the transaction date. All regressions include RCA Market fixed effects and year-quarter fixed effects. Standard errors are clustered at the firm level. Heteroskedasticity-robust t-statistics are reported in parentheses under coefficient estimates. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

Panel A: Univariate Results

Panel A.1: Unit Property Price

	Average Unit Property Price			Difference in Avr. Unit Property Prices	t-stat
Low Leverage	4.674	(N=762)	High-Low	-0.474	(9.95***)
Medium Leverage	4.559	(N=770)	High-Medium	-0.359	(7.91***)
High Leverage	4.201	(N=763)	Medium-Low	-0.115	(2.47**)

Panel A.2: Residual Price

	Average Residual Price			Difference in Avr. Residual Prices	t-stat
Low Leverage	-0.039	(N=762)	High-Low	-0.304	(9.25***)
Medium Leverage	-0.196	(N=770)	High-Medium	-0.148	(4.63***)
High Leverage	-0.344	(N=763)	Medium-Low	-0.157	(5.50***)

Table 2 Continued

Panel B: Multivariate Analysis

	Unit Property Price			Residual price
	(1)	(2)	(3)	(4)
Medium Ind.-Adj. Leverage Dummy$_{t-1}$	-0.173*	-0.141**	-0.148**	-0.122**
	(-1.913)	(-2.280)	(-2.363)	(-2.145)
High Ind.-Adj. Leverage Dummy$_{t-1}$	-0.311***	-0.257***	-0.272***	-0.260***
	(-3.605)	(-3.354)	(-3.419)	(-3.146)
ROA$_{t-1}$			-0.615*	-0.373
			(-1.837)	(-1.126)
Tangibility$_{t-1}$			-0.075	-0.142
			(-0.502)	(-0.942)
Market-to-book$_{t-1}$			0.029	0.032
			(1.239)	(1.155)
Ln(Assets$_{t-1}$)			-0.007	-0.031**
			(-0.392)	(-2.049)
Property Characteristics	Included	Included	Included	
Quarter FE		Included	Included	Included
Market FE		Included	Included	Included
Observations	2,295	2,295	2,295	2,295
R-squared	0.447	0.586	0.588	0.080

Table 3: Asset Redeployability

Panel A compares the average residual price for different leverage and redeployability groups. *Asset Redeployability Dummy* takes one for offices and for properties that can be used for both industrial or office activities. Panel A.2 reports the results for *Industry-Adjusted Leverage* groups, Panel A.3 reports the results for *Raw Leverage* groups, and Panel A.4 reports the results for firms with *High Leverage–Low Current Assets* whose leverage is above the industry median and current assets are below the industry median. Panel B reports the second-stage regression results (Table **??** column (4)) for two redeployability groups separately. All regressions include firm controls, RCA Market fixed effects and year-quarter fixed effects. Standard errors are clustered at the firm level. Heteroskedasticity-robust t-statistics are reported in parentheses under coefficient estimates. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

Panel A: Univariate Results

Panel A.1: Average Residual Price by Redeployable

Redeployable	Others	Redeployable-Others
-0.121 (N=684)	-0.224 (N=1611)	-0.103 (-3.65***)

Panel A.2: Average Residual Price by Industry-Adjusted Leverage and Redeployable

	Low Leverage	Medium Leverage	High Leverage	High - Low (t-stat)
Redeployable	-0.060 (N=274)	-0.157 (N=216)	-0.166 (N=194)	-0.106 (1.73*)
Others	-0.028 (N=488)	-0.211 (N=554)	-0.404 (N=569)	-0.376 (9.67***)

Panel A.3: Average Residual Price by Raw Leverage and Redeployable

	Low Leverage	Medium Leverage	High Leverage	High - Low (t-stat)
Redeployable	-0.115 (N=257)	-0.097 (N=261)	-0.168 (N=166)	-0.054 (0.87)
Others	-0.078 (N=566)	-0.345 (N=446)	-0.272 (N=599)	-0.195 (5.47***)

Panel A.4: Average Residual Price by High Leverage–Low Current Asset Dummy and Redeployable

	High Leverage – Low Current Assets	Others	Difference (t-stat)
Redeployable	-0.087 (N=370)	-0.139 (N=292)	-0.053 (1.04)
Others	-0.153 (N=862)	-0.314 (N=670)	-0.161 (5.17***)

Table 3 Continued

Panel B: Multivariate Analysis

	Residual price					
	Office & Flex	Others	Office & Flex	Others	Office & Flex	Others
Medium Industry-Adjusted Leverage Dummy$_{t-1}$	-0.023	-0.144*				
	(-0.314)	(-1.675)				
High Industry-Adjusted Leverage Dummy$_{t-1}$	-0.056	-0.351***				
	(-0.672)	(-3.295)				
Medium Leverage Dummy$_{t-1}$			0.008	-0.338***		
			(0.123)	(-2.790)		
High Leverage Dummy$_{t-1}$			-0.075	-0.208*		
			(-0.851)	(-1.902)		
High Leverage-Low Current Asset Dummy$_{t-1}$					0.014	-0.236**
					(0.213)	(-2.538)
ROA$_{t-1}$						
	0.261	-1.003**	0.299	-0.972*	0.249	-0.622
Tangibility$_{t-1}$	(0.663)	(-2.016)	(0.774)	(-1.957)	(0.622)	(-1.205)
	-0.013	-0.041	0.049	0.073	0.042	-0.024
Market-to-book$_{t-1}$	(-0.070)	(-0.231)	(0.269)	(0.364)	(0.230)	(-0.125)
	-0.013	0.067	-0.017	0.046	-0.015	0.055
Ln(Assets$_{t-1}$)	(-0.537)	(1.548)	(-0.694)	(1.238)	(-0.617)	(1.319)
	-0.037**	-0.031	-0.039**	-0.032	-0.033**	-0.037
	(-2.396)	(-1.575)	(-2.492)	(-1.457)	(-1.997)	(-1.482)
Quarter FE	Included	Included	Included	Included	Included	Included
Market FE	Included	Included	Included	Included	Included	Included
Observations	684	1,611	684	1,611	662	1,532
R-squared	0.065	0.127	0.066	0.124	0.060	0.122

Table 4: Number of Potential Buyers

This table reports the results from univariate (Panel A) and multivariate analysis (Panel B) of the number of potential buyer interactions which is measured by one of the following three variables: (i) *1-Herfindahl Index* of the seller's three-digit SIC industry where Herfindahl Index is the sum of squared market shares of each firm within the same industry, (ii) *Number of potential buyers based on headquarters* which is the number of companies operating in the same three-digit SIC industry as the seller whose headquarters are located in the same state as the property, (iii) *Number of potential buyers based on 10-Ks* calculated as the number of companies operating in the same three-digit SIC industry as the seller who mentions the state of the property in its 10-Ks at least once during the year preceding the transaction (Garcia and Norli, 2012). Panel A reports the average residual price for each *Industry-Adjusted Leverage* and the number of potential buyers group. All regressions include firm controls, RCA Market fixed effects and year-quarter fixed effects. Standard errors are clustered at the firm level. Heteroskedasticity-robust t-statistics are reported in parentheses under coefficient estimates. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

Panel A: Univariate Results

Panel A.1: Number of potential buyers based on:

	1-Herfindahl Index	Headquarters	10-Ks
Few buyers	-0.385 (N=765)	-0.195 (N=1025)	-0.173 (N=495)
Many buyers	-0.090 (N=763)	-0.093 (N=545)	-0.122 (N=434)
Many-Few	0.295 (9.21***)	0.102 (3.21***)	0.052 (1.33)

Panel A.2: 1-Herfindahl Index

	# of Buyers bin	Low Leverage	Medium Leverage	High Leverage	High-Low Leverage
Few buyers	1	-0.113 (N=134)	-0.311 (N=256)	-0.533 (N=375)	-0.420 (6.00***)
	2	0.015 (N=324)	-0.153 (N=264)	-0.248 (N=179)	-0.263 (5.25***)
Many buyers	3	-0.066 (N=304)	-0.123 (N=250)	-0.087 (N=209)	-0.022 (0.38)

Panel A.3: Headquarters

	# of Buyers bin	Low Leverage	Medium Leverage	High Leverage	High-Low Leverage
Few buyers	1	-0.027 (N=364)	-0.202 (N=401)	-0.420 (N=260)	-0.393 (7.91***)
	2	-0.072 (N=224)	-0.227 (N=207)	-0.441 (N=294)	-0.369 (6.11***)
Many buyers	3	-0.025 (N=174)	-0.142 (N=162)	-0.112 (N=209)	-0.087 (1.41)

Panel A.4: 10-Ks

	# of Buyers bin	Low Leverage	Medium Leverage	High Leverage	High-Low Leverage
Few buyers	1	-0.099 (N=188)	-0.185 (N=192)	-0.276 (N=115)	-0.176 (2.80***)
	2	0.083 (N=82)	-0.189 (N=71)	-0.481 (N=252)	-0.565 (6.40***)
Many buyers	3	-0.050 (N=135)	-0.106 (N=119)	-0.186 (N=180)	-0.135 (1.73*)

Table 4 Continued

Panel B: Multivariate Analysis

	Residual price					
			Number of Potential Buyers based on			
	1-Herfindahl index		Headquarters		10-Ks	
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Potential Buyers$_t$	0.575***	0.071	0.036*	0.012	0.064***	0.053**
	(3.770)	(0.332)	(1.869)	(0.440)	(3.544)	(2.194)
X Medium Ind.-Adj. Leverage Dummy$_{t-1}$		0.255		0.015		0.007
		(0.994)		(0.487)		(0.201)
X High Ind.-Adj. Leverage Dummy$_{t-1}$		0.861***		0.088**		0.063*
		(3.132)		(2.486)		(1.792)
Medium Ind.-Adj. Leverage Dummy$_{t-1}$		-0.313		-0.134*		-0.141
		(-1.447)		(-1.919)		(-1.571)
High Ind.-Adj. Leverage Dummy$_{t-1}$		-0.875***		-0.376***		-0.409***
		(-3.779)		(-3.881)		(-3.822)
Company Controls	Included	Included	Included	Included	Included	Included
Quarter FE	Included	Included	Included	Included	Included	Included
Market FE	Included	Included	Included	Included	Included	Included
Observations	2,295	2,295	2,295	2,295	1,334	1,334
R-squared	0.082	0.104	0.061	0.090	0.080	0.101

Table 5: Loan Spreads and Collateral Discount

This table reports the results from the regression of loan spreads on *Expected Collateral Discount*. Expected Collateral Discount is the ratio of *Actual REPV* to *Hypothetical REPV* where *Actual REPV* is the sum of the predicted value of each property in the portfolio, and *Hypothetical REPV* is the sum of the predicted value of each property in the portfolio assuming that the firm has a leverage ratio of within the 90th percentile in excess of its industry median. *Spread* is all-in-drawn spread which is the amount the borrower pays in basis points over LIBOR including any recurring annual fees on the loan. Other variables are defined in Table **??**. Industries are defined by two-digit SIC codes. Standard errors are clustered at the firm level. Heteroskedasticity-robust t-statistics are reported in parentheses under coefficient estimates. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Spread			
	(1)	(2)	(3)	(4)
Ind.-Adj. Leverage$_{t-1}$	156.166***	117.048***	119.877***	119.303***
	(4.928)	(3.536)	(3.634)	(3.601)
Expected Collateral Discount$_t$	117.242**	99.622**	42.972	43.599
	(2.274)	(2.138)	(0.897)	(0.900)
X Secured Loan Dummy$_t$			98.481**	99.802**
			(2.005)	(2.027)
Secured Loan Dummy$_t$		75.639***	-37.135	-38.377
		(7.725)	(-0.609)	(-0.628)
Actual REPV$_t$/PPE$_t$				-16.557
				(-0.502)
Ln(Actual REPV$_t$)	1.253	-3.790	-4.091	-2.926
	(0.374)	(-0.974)	(-1.056)	(-0.670)
ROA$_{t-1}$	-496.970***	-388.134***	-388.327***	-395.317***
	(-7.362)	(-4.584)	(-4.619)	(-4.639)
Tangibility$_{t-1}$	33.331	24.555	25.426	21.829
	(1.393)	(1.142)	(1.212)	(0.983)
Market-to-book$_{t-1}$	-4.323	-7.647*	-7.221*	-7.264*
	(-1.393)	(-1.786)	(-1.706)	(-1.718)
Ln(Assets$_{t-1}$)	-12.595***	0.964	1.457	0.235
	(-3.596)	(0.236)	(0.356)	(0.050)
Ln(Loan Maturity$_t$)	-1.389	-13.032	-12.534	-12.538
	(-0.155)	(-1.046)	(-1.012)	(-1.013)
Ln(Loan Amount$_t$)	-9.713***	-9.852**	-11.166**	-11.126**
	(-2.687)	(-2.207)	(-2.493)	(-2.483)
Loan Type Dummy	Included	Included	Included	Included
Loan Purpose Dummy	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Industry FE	Included	Included	Included	Included
Observations	1,283	704	704	704
R-squared	0.629	0.695	0.697	0.696

Table 6: Asset Quality

Panel A reports results from the regression of residual price on each of the quality proxies, namely *Buyer Purpose*, *Tenancy Status* and *Occupancy Rate*. *Buyer Purpose* can be *Investment, Occupancy, Redevelopment* or *Renovation*. *Tenancy Status* is the occupancy type at time of sale, which can be *Multi-Tenant*, *Single Tenant* or *Vacant*. *Occupancy Rate* is defined as the floor space or units occupied by tenants as a percentage of the total leasable area of the building at the time of a sale. Panel B compares the average quality characteristics of properties with different industry-adjusted leverage and residual price levels. We split the sample into three equal-size groups by the seller's industry-adjusted leverage and into two groups as above- and below-median residual price independently from leverage. For each leverage – residual price group, Panel B.1 reports the percentage of properties for which the *Buyer Purpose* is either *Redevelopment* or *Renovation*, Panel B.2 reports the percentage of vacant properties, and Panel B.3 reports the average *Occupancy Rate*. Number of observations and t-statistics for the differences between *High-Leverage* and *Low-Leverage* groups are reported in parentheses. Panel C reports results from the regression of each of the quality proxies on financial distress proxies. All regressions include RCA Market fixed effects and year-quarter fixed effects. Standard errors are clustered at the firm level. Heteroskedasticity-robust t-statistics are reported in parentheses under coefficient estimates. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

Panel A: Asset Quality Proxies

	Residual price		
Redevelopment or Renovation	-0.131**		
	(-2.272)		
Vacant		-0.247***	
		(-3.979)	
Occupancy Rate			0.186***
			(3.513)
ROA_{t-1}	-0.097	-0.084	-0.322
	(-0.295)	(-0.238)	(-0.837)
Tangibility_{t-1}	-0.181	-0.340*	-0.253
	(-1.016)	(-1.907)	(-1.317)
$\text{Market-to-book}_{t-1}$	0.023	0.028	0.052
	(0.744)	(0.854)	(1.567)
$\text{Ln}(\text{Assets}_{t-1})$	-0.035*	-0.034	-0.035*
	(-1.841)	(-1.567)	(-1.669)
Quarter FE	Included	Included	Included
Market FE	Included	Included	Included
Observations	2,289	1,963	1,655
R-squared	0.062	0.098	0.112

Table 6 Continued

Panel B: Asset Quality and Leverage (Univariate)

Panel B.1: Buyer Purpose=Redevelopment or Renovation

	Low Leverage	Medium Leverage	High Leverage	High - Low (t-stat)
Low residual price	0.132 (N=302)	0.125 (N=393)	0.120 (N=451)	-0.013 (0.52)
High residual price	0.098 (N=458)	0.080 (N=373)	0.106 (N=312)	0.008 (0.34)
All	0.112 (N=760)	0.103 (N=766)	0.114 (N=763)	0.002 (0.13)

Panel B.2: Tenancy Status=Vacant

	Low Leverage	Medium Leverage	High Leverage	High - Low (t-stat)
Low residual price	0.386 (N=228)	0.336 (N=345)	0.331 (N=405)	-0.055 (1.39)
High residual price	0.218 (N=395)	0.205 (N=308)	0.220 (N=282)	0.002 (0.07)
All	0.279 (N=623)	0.274 (N=653)	0.285 (N=687)	0.006 (0.24)

Panel B.3: Occupancy Rate

	Low Leverage	Medium Leverage	High Leverage	High - Low (t-stat)
Low residual price	0.655 (N=189)	0.739 (N=268)	0.781 (N=324)	0.126 (3.28***)
High residual price	0.804 (N=357)	0.819 (N=274)	0.823 (N=243)	0.019 (0.61)
All	0.752 (N=463)	0.779 (N=542)	0.799 (N=567)	0.047 (1.95*)

Panel C: Asset Quality and Leverage (Multivariate)

	Redevelopment or Renovation	Vacant	Occupancy Rate
Medium Ind.-Adj. Leverage Dummy$_{t-1}$	0.007	0.016	-0.007
	(0.343)	(0.342)	(-0.154)
High Ind.-Adj. Leverage Dummy$_{t-1}$	0.027	0.046	0.033
	(1.113)	(0.734)	(0.745)
ROA$_{t-1}$	0.104	-0.136	0.056
	(0.976)	(-0.601)	(0.303)
Tangibility$_{t-1}$	-0.147***	-0.289***	0.286***
	(-2.962)	(-2.627)	(3.067)
Market-to-book$_{t-1}$	-0.039***	-0.008	0.010
	(-4.481)	(-0.402)	(0.452)
Ln(Assets$_{t-1}$)	0.021***	0.038***	-0.029***
	(4.051)	(3.600)	(-3.108)
Quarter FE	Included	Included	Included
Market FE	Included	Included	Included
Observations	2,289	1,963	1,655
R-squared	0.078	0.135	0.223

Table 7: Asset Selection

λ_1 is the inverse Mills ratio calculated from the following probit regression: Sale Dummy$_{i,t}$ = β_0 + β_1Age Rank$_{i,t}$ + β_2Size Rank$_{i,t}$ + β_3Liquidity Rank$_{i,t}$ + β_4Renovated$_{i,t}$ + β_5CBD$_{i,t}$ + β_6Property Type$_{i,t}$ + β_7Firm Controls$_{j,t-1}$ + Year-Quarter$_t$ + RCA Market$_i$ + $\varepsilon_{i,t}$. λ_2 is the inverse mills ratio calculated from the following probit regression: Seller Dummy$_{j,t}$ = β_0 + β_1Ind.-Adjusted Leverage$_{j,t-1}$ + β_2ROA$_{j,t-1}$ + β_3Ln(Assets)$_{j,t-1}$ + β_4Market-to-Book$_{j,t-1}$ + β_5Tangibility$_{j,t-1}$ + Year$_t$ + $\varepsilon_{j,t}$. Standard errors are clustered at the firm level. Heteroskedasticity-robust t-statistics are reported in parentheses under coefficient estimates. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Raw price			
	(1)	(2)	(3)	(4)
Medium Ind.-Adj. Leverage Dummy$_{t-1}$	-0.112*	-0.145**	-0.108*	-0.154**
	(-1.778)	(-2.262)	(-1.729)	(-2.332)
High Ind.-Adj. Leverage Dummy$_{t-1}$	-0.199**	-0.274***	-0.193**	-0.290***
	(-2.288)	(-3.315)	(-2.228)	(-3.382)
λ_1	0.250		0.230	
	(1.632)		(1.488)	
λ_2		0.840	0.714	
		(1.307)	(1.139)	
Property Size	-0.356***	-0.349***	-0.356***	-0.349***
	(-9.212)	(-9.219)	(-9.213)	(-9.184)
Office	0.597***	0.584***	0.596***	0.584***
	(10.661)	(10.211)	(10.581)	(10.264)
Retail	0.247**	0.352***	0.258**	0.349***
	(2.071)	(3.748)	(2.150)	(3.702)
Age Group 1	-0.361***	-0.357***	-0.360***	-0.358***
	(-7.875)	(-7.808)	(-7.918)	(-7.743)
Age Group 2	-0.460***	-0.448***	-0.459***	-0.447***
	(-9.032)	(-9.018)	(-9.060)	(-8.969)
Age Group 3	-0.598***	-0.581***	-0.597***	-0.581***
	(-9.638)	(-9.784)	(-9.662)	(-9.712)
Age Group 4	-0.705***	-0.688***	-0.702***	-0.690***
	(-8.558)	(-8.899)	(-8.602)	(-8.846)
Age Group 5	-0.731***	-0.705***	-0.727***	-0.707***
	(-8.934)	(-9.047)	(-8.872)	(-9.089)
Renovated	0.195**	0.161**	0.191**	0.163**
	(2.585)	(2.422)	(2.522)	(2.467)
Portfolio	-0.001	-0.002	-0.003	0.002
	(-0.010)	(-0.030)	(-0.068)	(0.043)
Central Business District	0.256**	0.257**	0.248**	0.267**
	(2.413)	(2.458)	(2.374)	(2.506)
Firm controls	Included	Included	Included	Included
Quarter FE	Included	Included	Included	Included
Market FE	Included	Included	Included	Included
Observations	2,092	2,092	2,092	2,092
R-squared	0.582	0.581	0.582	0.581

Table 8: Past and Future Prices

This table reports the average past or future residual prices of the properties in our sample. For each property sold in our sample, we determine the *Non-distress price* from the past or future transactions that involve the same property but a different seller or buyer. If we are able to track both a past and future transaction for the same property, we include the price from the transaction whose date is the closest to the sale. We use the residual price estimates from our hedonic model in Table **??** column (4).

	Non-distress Price		Transaction Residual Price	Difference	(t-stat)
Low Industry Adjusted Leverage	0.025	(N=99)	-0.003	0.028	(0.52)
Medium Industry Adjusted Leverage	-0.012	(N=109)	-0.137	0.125	(2.18**)
High Industry Adjusted Leverage	-0.139	(N=108)	-0.269	0.130	(1.83*)
Others	-0.036	(N=186)	-0.102	0.066	(1.36)
High Leverage-Low Current Asset Dummy	-0.047	(N=121)	-0.214	0.167	(3.12***)

Appendix

Table A1: Variable Definitions

This table presents the definitions of the variables used in this paper. Panel A includes the definitions of company-level variables obtained from Compustat Annual Files. Panel B lists the definitions of property characteristics obtained from RCA Database. All company-level variables are measured at least one month and at most eleven months before the transaction date, depending on the firm's fiscal year end month. For instance, if the property was sold in December and the company's fiscal year ends in November, then the company controls are measured in that November, whereas if the property was sold in January and the company's fiscal year ends in February, then the company controls are measured in February prior to the sale.

Panel A: Company Variables

Variable	Definition	Compustat Item Name
ROA	Operating Income / Assets	**oibdp / at**
Tangibility	Net PPE / Assets	**ppent / at**
MVA	Market Value of Assets	**prccf** × **cshpri** + (**dltt** + **dlc**) + **pstkl**
Market-to-book	MVA / Total Book Assets	(**prccf** × **cshpri** + (**dltt** + **dlc**) + **pstkl**) / **at**
Ln(Assets)	Ln(Total Book Assets)	**ln(at)**
Total Debt	Short-Term Debt + Long-Term Debt	**dltt** + **dlc**
Leverage	Total Debt / Total Book Assets	(**dltt** + **dlc**) / **at**
Ind.-Adj. Leverage	Leverage - (3-digit SIC) Industry Median	
Interest Coverage	Operating Income / Interest Expense	**oibdp / xint**
Herfindahl Index	Sum of squared market shares of all firms in the same three-digit SIC industry	

Panel B: Property Variables

Variable	Definition
Unit Property Price	Ln[(price / square feet) + 1]
Size	Ln(square feet)
Age	Six categories: ≤10, between 11 and 20, 21 and 30, 31 and 40, 41 and 50, and above 50
Renovated Dummy	= 1 if there is non-missing data for the year that the property was renovated or expanded
Portfolio Dummy	= 1 if the sale is part of a portfolio transaction
CBD Dummy	= 1 if the property is located in a central business district or in the downtown of a city
Occupancy Rate	The floor space or units occupied by tenants as a percentage of the total leasable area of the building at the time of a sale
Flex	Denotes a property that is flexible in that it can be used for industrial or office activities

Table A2: Seller Characteristics

This table reports the estimation results of the following fixed effects model: Seller Dummy$_{i,t}$ = β_0 + β_1Distress Proxy$_{i,t-1}$ + β_2Firm Controls$_{i,t-1}$ + Year$_t$ + u$_{i,t}$ + $\varepsilon_{i,t}$ for all Compustat firms between 2000 and 2013. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. Heteroskedasticity-robust t-statistics are reported in parentheses under coefficient estimates. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Seller Dummy				
Leverage$_{t-1}$	0.002**				
	(2.042)				
Industry-Adjusted Leverage$_{t-1}$		0.002**			
		(2.054)			
Medium Leverage Dummy$_{t-1}$			0.001		
			(1.031)		
High Leverage Dummy$_{t-1}$			0.005***		
			(3.329)		
High Leverage-Low Current Asset Dummy$_{t-1}$				0.004***	
				(3.047)	
Interest Coverage Ratio$_{t-1}$					-0.000***
					(-4.403)
ROA$_{t-1}$	-0.003***	-0.003***	-0.002***	-0.002***	-0.002***
	(-5.271)	(-5.212)	(-4.690)	(-4.668)	(-4.120)
Tangibility$_{t-1}$	-0.001	-0.001	-0.002	-0.002	-0.001
	(-0.423)	(-0.536)	(-0.902)	(-1.004)	(-0.500)
Market-to-book$_{t-1}$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**
	(-2.744)	(-2.755)	(-2.692)	(-2.739)	(-2.022)
Ln(Assets$_{t-1}$)	0.002***	0.002***	0.001***	0.001***	0.001***
	(3.494)	(3.484)	(3.204)	(3.173)	(2.755)
Year FE	Included	Included	Included	Included	Included
Firm FE	Included	Included	Included	Included	Included
Observations	82,725	82,371	82,371	80,943	76,423
R-squared	0.267	0.268	0.268	0.265	0.264

Table A3: Hedonic Model (First Stage)

This table reports the estimation results of the hedonic model: $[\text{Ln(Price/sqf)+1}]_{i,t} = \beta_0 + \beta_1\text{Property Size}_{i,t} + \beta_2\text{Property Type}_{i,t} + \beta_3\text{Age Group}_{i,t} + \beta_4\text{Renovated}_{i,t} + \beta_5\text{Portfolio}_{i,t} + \beta_6\text{CBD}_{i,t} + \text{RCA Market}_i \text{ X Year}_t + \varepsilon_{i,t}$. Columns (1)–(3) report the results for each property type in our final sample, *Industrial*, *Retail* and *Office*, separately. In column (4), the hedonic model is estimated by pooling all transactions together. The coefficient estimates reported in the last column are for the base property type (*Apartment*). All regressions include RCA Market-Year fixed effects. Standard errors are clustered at the RCA Market-Year level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Industrial (1)	Retail (2)	Office (3)	All Properties (Baseline Model) (4)
Property Size	-0.261***	-0.255***	-0.017	-0.035*
	(-19.425)	(-24.168)	(-1.310)	(-1.726)
Development Site				5.207***
				(5.893)
Hotel				-0.383
				(-0.430)
Industrial				2.335***
				(7.481)
Office				0.039
				(0.133)
Retail				7.366***
				(3.870)
Seniors Housing & Care				2.701***
				(9.911)
Other				2.991**
				(2.420)
Age Group 1	-0.187***	-0.313***	-0.229***	-0.308***
	(-8.117)	(-14.001)	(-9.864)	(-14.940)
Age Group 2	-0.329***	-0.498***	-0.409***	-0.485***
	(-12.067)	(-17.930)	(-13.813)	(-19.493)
Age Group 3	-0.418***	-0.464***	-0.533***	-0.580***
	(-14.815)	(-12.783)	(-12.779)	(-20.947)
Age Group 4	-0.535***	-0.402***	-0.581***	-0.439***
	(-13.834)	(-10.128)	(-9.466)	(-5.348)
Age Group 5	-0.486***	-0.294***	-0.602***	-0.591***
	(-8.540)	(-5.865)	(-11.961)	(-10.660)
Renovated	0.182***	0.205***	0.127***	0.091***
	(5.673)	(7.615)	(4.773)	(3.537)
Portfolio	0.028	-0.026	-0.014	0.050
	(1.136)	(-0.985)	(-0.492)	(1.573)
Central Business District	0.266***	0.331***	0.223***	0.382***
	(2.758)	(2.902)	(4.987)	(7.978)
Property Type Interactions	Included	Included	Included	Included
Year-Market FE	Included	Included	Included	Included
Observations	5,867	7,496	5,932	30,649
R-squared	0.546	0.523	0.503	0.565

Table A4: Alternative Distress Proxies

This table reports the results of the following second-stage regression: $\hat{\varepsilon}_{i,t} = \beta_0 + \beta_1 \text{Distress Proxy}_{j,t-1} + \beta_2 \text{Firm Controls}_{j,t-1} + \text{Year-Quarter}_t + \text{RCA Market}_i + \varepsilon_{i,t}$, where the dependent variable is the residual price estimated from the hedonic model (Table **??** column(4)). *Medium (High) Leverage Dummy* takes one if the seller's leverage is between the 33^{rd} and 67^{th} (above the 67^{th}) percentile of the sample. *High Leverage–Low Current Assets Dummy* indicates that the seller's leverage is above the industry median and its current assets are below the industry median. *Interest Coverage Ratio* is the ratio of income before depreciation divided by interest expense, for which the negative values are normalized to zero and values above 50 are normalized to 50. All company-level variables are measured at least one month and at most eleven months before the transaction date. All regressions include RCA Market fixed effects and year-quarter fixed effects. Standard errors are clustered at the firm level. Heteroskedasticity-robust t-statistics are reported in parentheses under coefficient estimates. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Residual price				
	(1)	(2)	(3)	(4)	(5)
Industry-Adjusted Leverage$_{t-1}$	-0.527***				
	(-2.983)				
Leverage$_{t-1}$		-0.418**			
		(-2.515)			
Medium Leverage Dummy$_{t-1}$			-0.193**		
			(-2.156)		
High Leverage Dummy$_{t-1}$			-0.135		
			(-1.635)		
High Leverage-Low Current Asset Dummy$_{t-1}$				-0.160**	
				(-2.416)	
Interest Coverage Ratio$_{t-1}$					0.008***
					(2.731)
ROA$_{t-1}$	-0.463	-0.319	-0.299	-0.171	-0.796**
	(-1.348)	(-0.914)	(-0.896)	(-0.530)	(-1.988)
Tangibility$_{t-1}$	-0.171	-0.088	-0.050	-0.157	-0.075
	(-1.061)	(-0.481)	(-0.284)	(-0.938)	(-0.447)
Market-to-book$_{t-1}$	0.039	0.018	0.015	0.022	-0.025
	(1.354)	(0.637)	(0.588)	(0.813)	(-0.858)
Ln(Assets$_{t-1}$)	-0.034**	-0.037**	-0.030*	-0.030*	-0.037**
	(-2.035)	(-1.992)	(-1.661)	(-1.650)	(-2.099)
Quarter FE	Included	Included	Included	Included	Included
Market FE	Included	Included	Included	Included	Included
Observations	2,295	2,295	2,295	2,194	2,236
R-squared	0.074	0.067	0.070	0.075	0.078

Table A5: Alternative Specifications

This table reports the results from the robustness tests of the baseline model (Table ??). Column (1) estimates the baseline model for the subsample before 2007. The sample in column (2) is restricted to sales that are not part of a portfolio transaction. Column (3) uses first-stage residuals estimated separately for each property type. Column (4) includes two-digit SIC industry fixed effects. Column (5) restricts the sample to properties that are located in a different state than the seller's headquarters. All regressions include RCA Market fixed effects and year-quarter fixed effects. Standard errors are clustered at the firm level. Heteroskedasticity-robust t-statistics are reported in parentheses under coefficient estimates. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Residual price				
	(1)	(2)	(3)	(4)	(5)
Medium Ind.-Adj. Leverage Dummy$_{t-1}$	-0.144**	-0.126**	-0.099**	-0.075*	-0.140*
	(-2.472)	(-2.064)	(-2.098)	(-1.907)	(-1.865)
High Ind.-Adj. Leverage Dummy$_{t-1}$	-0.218***	-0.258***	-0.218***	-0.163***	-0.306***
	(-2.909)	(-3.043)	(-2.987)	(-3.492)	(-3.133)
ROA$_{t-1}$	-0.284	0.031	-0.244	-0.124	-0.144
	(-0.768)	(0.098)	(-0.853)	(-0.425)	(-0.336)
Tangibility$_{t-1}$	-0.136	-0.137	-0.116	-0.033	-0.202
	(-0.829)	(-0.828)	(-0.866)	(-0.196)	(-1.143)
Market-to-book$_{t-1}$	0.024	0.014	0.024	0.015	0.021
	(0.824)	(0.524)	(1.064)	(0.725)	(0.681)
Ln(Assets$_{t-1}$)	-0.044***	-0.032**	-0.028**	-0.023*	-0.025
	(-2.998)	(-1.985)	(-2.113)	(-1.689)	(-1.396)
Industry FE				Included	
Quarter FE	Included	Included	Included	Included	Included
Market FE	Included	Included	Included	Included	Included
Observations	1,099	1,542	2,295	2,295	1,803
R-squared	0.095	0.063	0.036	0.147	0.087

Table A6: Transaction Prices and Firm Distress - Matched Sample Analysis

This table shows the estimation results for the baseline model using an alternative definition for the independent variable. We obtain propensity scores from a logistic regression of a dummy variable that takes one if the transaction is a corporate sale and zero if the seller is not a corporation, on the logarithm of the property size, CBD dummy, quarter fixed effects and RCA market fixed effects. Using the propensity scores, we determine three and five best-matched properties for each corporate sale. We calculate propensity scores separately for each property type, so the matches are restricted to the property type of each corporate sale. Then, we calculate the mean of the residual prices estimated using the hedonic model (Table **??** column (4)). Finally, we calculate the difference of residuals by subtracting the mean of the residual prices of the matched properties from the residual price of each sale in our sample. All regressions include RCA Market fixed effects and year-quarter fixed effects. Standard errors are clustered at the firm level. Heteroskedasticity-robust t-statistics are reported in parentheses under coefficient estimates. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	First stage residual - Mean residual of best 3 match	First stage residual - Mean residual of best 5 match	Baseline
Medium Ind.-Adj. Leverage Dummy$_{t-1}$	-0.147***	-0.138**	-0.122**
	(-2.643)	(-2.466)	(-2.145)
High Ind.-Adj. Leverage Dummy$_{t-1}$	-0.285***	-0.279***	-0.260***
	(-3.395)	(-3.339)	(-3.146)
ROA$_{t-1}$	-0.229	-0.369	-0.373
	(-0.639)	(-1.003)	(-1.126)
Tangibility$_{t-1}$	-0.228	-0.165	-0.142
	(-1.434)	(-1.057)	(-0.942)
Market-to-book$_{t-1}$	0.020	0.032	0.032
	(0.666)	(1.074)	(1.155)
Ln(Assets$_{t-1}$)	-0.023	-0.022	-0.031**
	(-1.423)	(-1.390)	(-2.049)
Quarter FE	Included	Included	Included
Market FE	Included	Included	Included
Observations	2,287	2,287	2,295
R-squared	0.087	0.087	0.080