Shuffling Through the Bargain Bin: Real Estate Holdings of Public Firms*

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Abstract

We construct a novel database on the real estate portfolio holdings for a comprehensive set of public firms between 2000 and 2013. We show that a distressed firm, on average, sells its real estate asset, most frequently used collateral type, at a discount of 22% relative to a healthy firm. We then identify asset deployability and the availability of potential buyers as two important determinants of the average price in a distress sale. Our loan level analysis indicates that bank loan spreads incorporate information on real estate assets' alternative uses and the availability of their potential buyers. We use surges of foreign investor demand from countries with increased policy uncertainty as plausibly exogenous shocks to commercial real estate prices. Our results show that the firms with real estate portfolios that experience this price appreciation enjoy lower bank rates that we attribute to increased collateral values.

1 Introduction

Collateral is an important part of debt contracts. 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 U.S. is secured by collateral (Leitner, 2006). When the borrower falls short on liquidity or defaults on its debt, asset-specific factors that determine the liquidation value of the collateral become a concern for the lender. In this study, we provide a comprehensive analysis of the factors that determine collateral values in distress and investigate whether lenders take these factors into consideration in their loan pricing decisions.

The type of collateral we focus on in this paper is commercial real estate, which is the most general form of collateral across publicly traded firms in the U.S. We start by documenting the property-specific factors that affect the liquidation value of firms' real estate assets. We then test whether these factors are priced in debt markets. Specifically, we test whether banks lend at higher rates due to anticipated losses in the liquidation value resulting from the borrower's assets not being deployable for alternative uses or from the existence of only a few firms that can pay for their best-use price. We find that financially troubled firms sell their real estate assets at a significant discount, but this effect is substantially reduced if the property can serve for more general purposes and/or if there are multiple potential buyers that might be interested in the property. Our loan-level analysis suggest that lenders charge borrowers less if their properties have such desirable characteristics that would positively affect their liquidation values.

Our paper contributes to the literature by providing direct evidence for the impact of collateral value on cost of financing, which was made possible by our novel dataset.[1] The most important advantage of our dataset is that it allows us to observe both the individual real estate assets owned by firms and their property-specific characteristics. Indeed, the previous literature estimates the value of real estate holdings based on the accumulated depreciation of buildings that firms are no longer required to report after 1993 (Cvijanovic, 2014 and Chaney, Sraer, and Thesmar, 2012). Furthermore, because Compustat does not provide data on the geographic location of real estate holdings, the market value of these assets after 1993 are approximated based on firms' headquarters location. By relying on the transaction price, geographic location and asset type information of individual real estate assets, our study identifies property-specific factors that generate variation in collateral values. Moreover, by linking this information to owners' characteristics, we can investigate whether changes in collateral value induced by these factors affect the borrowing rates.

We begin our empirical analysis by investigating the impact of a firm's financial distress on the selling price of its real estate properties. We use various proxies for financial distress such as leverage, industry-adjusted leverage, interest coverage ratio and an indicator for highly levered firms with low current assets proposed by Pulvino (1998). We find that increasing a firm's leverage from the lowest tercile to the highest tercile corresponds to 22% lower selling price after controlling for a battery of property and seller characteristics. Our analysis also reveal that these results cannot be explained by the property's quality measured by buyer intention, occupancy rate or tenancy status. To our knowledge this is the first study that estimates the economic magnitude of the impact of a seller's financial health on the transaction price of its real estate

[1] Although we focus on the impact of collateral on financing, our findings are also important for understanding the link between firms' financing and investment decisions. The existing evidence shows that collateral value has a significant impact on corporate investment. Using the breakdown of each industry's investment into different asset classes, Kim and Kung (2017) find that following an increase in uncertainty, firms with less deployable capital reduce investment more. In a related paper, Chaney, Sraer, and Thesmar (2012) test the sensitivity of investment to collateral values and find that constrained firms' investment is twice as sensitive to collateral value as unconstrained firms' investment.

assets. Pulvino (1998) documents a discount for aircrafts sold by financially constrained airlines. Our paper is unique in that it generalizes the findings of Pulvino (1998) to a broader asset class that is commonly held by all public firms from various industries.

Past literature offers clues about the potential factors that might affect the liquidation value of real estate assets. We study two of these factors, namely asset deployability and availability of potential buyers. A distribution center with a specific layout can only be utilized by a buyer that bears similar characteristics as the seller (e.g. industry, location, customer base, etc.). On the other hand, an office space can be purchased and used by several buyers both within and outside of the seller's industry; hence offices are more deployable relative to distribution centers. Consistent with our prior, we find that, unlike their more specialized counterparts, deployable assets do not suffer large discounts when the firms experience financial distress.

With our detailed data, we can also test whether number of potential buyers alleviates the discount on distress sales. Shleifer and Vishny (1992) suggest that significant discounts in asset prices can occur if a financially distressed seller is forced to look for transaction opportunities during times when the best users of the asset are also constrained.[2] Since the potential bidders operate in similar business lines as the distressed firm, they are subject to similar shocks as the seller. With the advantage of observing both seller characteristics and property location, we can identify the potential buyers for each property owned by firms from a broad set of industries. Our results indicate that the number of potential buyers alleviates the discount on distress sales significantly.

After we establish asset deployability and the number of potential buyers as important determinants of the liquidation value, next we investigate whether banks'

[2]Financial assets also result in deep discounts if sellers are motivated to unload them 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.

pricing of loans reflects these determinants. More specifically, we estimate how much a firm's real estate portfolio would lose value in a hypothetical state of the world where the firm is in financial distress. Our results show that a one-standard-deviation increase in our collateral discount measure is associated with a 9-to-16-basis-points (0.08-0.14 standard deviation) decrease in loan spreads. This suggests that any potential loss in the value of a collateral asset due to a distress sale as well as the collateral-specific factors that affect this loss are priced in debt markets.

Our paper is related to Benmelech and Bergman (2009) and Benmelech, Garmaise, Moskovitz (2005).[3] Using a data set of secured debt tranches issued by U.S. airlines, Benmelech and Bergman (2009) investigate the impact of aircraft characteristics on the cost of borrowing. They find that more redeployable aircraft is associated with lower credit spreads. Our paper differs from Benmelech and Bergman (2009) in two major ways. First, the type of collateral that we study is not specific to a single industry. Certainly, aircraft is a major asset type pledged as collateral by airline companies. However, it is not a typical collateral for firms in other industries. An average firm operating in nonfinancial industries invests significant amounts in commercial properties, which makes real estate the most common asset type across industries that serves as collateral.[4] Also, the industry-specific nature of aircrafts suggests that deployability would have a more pronounced effect on their collateral value compared to assets with more general use, mainly due to the limited number of potential buyers who could pay for their best-use price. Therefore, it is an empirical question whether there is an economically significant relationship between the value of more general assets and how easily they can be deployed. Second, different from Benmelech and Bergman (2009), our study estimates the discount

[3]Benmelech and Bergman (2011) relate airline bankruptcy to the cost of borrowing, but their focus is on the spillover effects on financially safe airlines. The cost of borrowing in their paper is the interest rate on securitized debt in the secondary markets, which is more liquid than bank loans.

[4]For instance, Campello and Giambona (2013) estimate that over the period 1984-1996, an average non-financial firm has 11.8% of its total assets invested in land and buildings, which coincides with about 33% of its tangible assets. In 1993, 54% of the Compustat firms reported some real estate ownership on their balance sheet (Cvijanovic, 2014).

in the transaction price due to the seller's distress and presents direct evidence for the price impact of deployability. Indeed, our findings indicate that office properties, an asset type that is deployable across different industries, do not lose significant value when they are sold by distressed owners.

Benmelech, Garmaise, Moskovitz (2005) investigate the impact of a property's zoning designation on the loan contract terms at the time of sale. They find that properties with more flexible zoning designations are associated with larger loans, longer loan maturities and durations and lower interest rates. Our setup allows us to identify the property owners and link them to their financial information on Compustat. This is important for various reasons. First, we can control for the seller's characteristics (such as industry and size) that might have confounding impact on the relationship between loan contract terms and deployability of real estate assets.[5] Second and more importantly, we can estimate the discount on the transaction price due to the seller's financial health and study the variation in this discount generated by collateral characteristics.

The determinants of collateral value (asset deployability and/or number of potential buyers of the real estate asset) can be correlated with unobserved firm characteristics. Therefore, a correlation between real estate discount and bank loan rates does not necessarily imply a causal relation. In order to understand whether our results reflect this particular form of endogeneity, we use significant surges of foreign demand from countries with increased policy uncertainty as an exogenous shock to commercial real estate prices in the U.S. Following an increase in economic and political uncertainty in a foreign country, the U.S. commercial real estate markets become more attractive to the investors in that country. We hypothesize that if the relationship between our collateral discount measure and loan spreads is driven by a factor that is unrelated to the collateral channel, then such demand shocks shouldn't have a differential impact on the

[5]Our focus is on the publicly traded industrial firms operating in the U.S., therefore our sample doesn't include any private firms or financial firms.

loan spreads of firms with high and low collateral discount. Consistent with our prior, we find that firms which happen to have assets in locations that experience this presumably exogenous demand shock enjoy lower loan rates. Furthermore, this finding is exacerbated for assets with high collateral discount, suggesting that our results are not likely to be driven by a channel other than collateral.

2 Data and Summary Statistics

We use the Real Capital Analytics (RCA) database to identify commercial real estate transactions. This database has tracked 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 more than $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 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) because they buy or sell real estate for investment purposes. Utility firms (SIC codes between 4900 and 4999) and government entities (SIC code between 9000 and 9999) are also excluded. Our matching procedure yields 327 unique public firms that were involved in 2,274 transactions. Because our interest lies in relative prices, we use the 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 property type 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 Table 1 we summarize the characteristics of the properties and of the sellers in our sample.[6] Panel A and Panel B report the summary statistics for the company-level and property-level variables, respectively. One of the most important differences between the sellers and an average Compustat firm is total asset size. Since the transactions in our sample exceed $2.5 million, our RCA sample is composed of medium and large 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.[7] Secondly, the median firm in the RCA sample is more profitable and has more tangible assets relative to the median firm in Compustat. In the Compustat universe, median *Tangibility* is 0.135 and median *ROA* is 0.054, whereas in our sample they are 0.397 and 0.150, respectively. Finally, *Book Leverage* and *Industry-Adjusted Book Leverage* are higher for sellers compared to the average firm in Compustat. The average property in our sample is about 22 years old and the average price per square foot, is $130. About 12% of the properties in our sample have been previously renovated and 33.4% of the sales are part of a portfolio transaction.

Panel D of Table 1 reports the distribution of sub-property types for *Industrial*, *Retail*

[6]Table A1 in the Appendix provides the details of variable construction.

[7]We have also employed a two-stage selection model in which we estimate the probability of a Compustat firm selling a real estate asset as a function of various firm characteristics. We find that firm selection does not have a significant impact on the selling price. These results are available upon request.

and *Office* properties. *Flex* denotes a property that is flexible in that it can be used for industrial or office activities. While 37.29% of the properties in our sample are industrial, retail properties constitute 44.28% and offices constitute 18.43% of our sample. Panel E of Table 1 shows 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.

3 Real Estate Asset Discount

3.1 Estimating the Discount

In this section, we investigate whether the average price of commercial real estate assets sold by distressed sellers is significantly lower than the average transaction price in the rest of the sample. Panel A of Table 2 reports the average property price, defined as the natural logarithm of price per square foot plus one. We split the sample into three equal-size groups depending on the seller's *Industry-Adjusted Leverage* (at 33$^{\text{rd}}$ and 67$^{\text{th}}$ percentiles of the sample). Average transaction prices for *Low*, *Medium* and *High Industry-Adjusted Leverage* groups are 4.698, 4.522 and 4.184, respectively. The univariate analysis shows a monotonically decreasing relationship between the average price and the seller's leverage. The results suggest that highly levered firms sell real estate assets at a significant discount compared to their low-leverage counterparts.

In order to control for the effect of confounding factors, we estimate a model where we regress the selling price on our distress measures and various property- and firm-specific controls. The property-specific controls include the natural logarithm of property size, dummy variables indicating the property's age, whether the property is renovated at any point in time, whether the property is purchased within a portfolio and whether the property is located in a central business district. Additionally, we include RCA market-fixed effects as physical location controls and year-quarter-fixed effects that indicate the quarter in which the transaction was completed. We also control for the seller's return on assets, tangibility, market-to-book and size.[8] Results in Table 2 Panel B reveal a strong negative relationship between the selling price and the seller's leverage ratio tercile. When all the control variables are included, an increase from the lowest leverage tercile to the highest leverage tercile leads to a 22.6% decrease in price with other variables held constant.[9] Overall, our results indicate that the seller's financial health has a significant impact on the transaction price and that the findings of Pulvino (1998) can be generalized to a broader asset class that is commonly held by all firms from various industries.

We conduct a battery of robustness tests for the baseline model in column (4) of Table 2, Panel B. First, we employ several alternative distress proxies, namely *Industry-Adjusted Leverage*, *Leverage*, *Leverage Tercile Dummies*, *High Leverage & Low Current Assets Dummy* and *Interest Coverage Ratio*. Panel A of Table A2 reports the results which point to the same conclusion: The price of commercial real estate assets sold by distressed sellers is significantly lower than the average transaction price in the rest of the sample. Second, we estimate our baseline model using several different specifications. Table A2, Panel B reports the results. In column (1), we restrict the sample to the period before 2007. In column (2), we include the seller's industry-fixed effects, where the industries are defined according to two-digit SIC codes. Column (3) focuses on the transactions that are not conducted as part of a portfolio sale. Finally, in the last column, we restrict the sample to properties that are located outside the seller's headquarters state. 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

[8]We define geographical market-fixed effects and year-quarter-fixed effects for each property type separately so that we can control for seasonal trends and time-invariant market-specific factors that affect property types differently. 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. Standard errors are clustered at the firm level. Results are robust to two-way clustering at the RCA market and quarter levels.

[9]Note that because the dependent variable equals the natural logarithm of 1 plus the transaction price, the discount is calculated by taking the exponent of the coefficient. For example, $1 - exp(\beta_2)$ is equal to the percentage change in 1+price when the seller's leverage increases from the lowest- to the highest-leverage tercile.

are not driven by the recent financial crisis, portfolio sales, or shocks to local economy. While controlling for industry-fixed effects decreases the economic significance of the coefficient estimates for our distress measures, they remain statistically significant at 1% and 5% levels.

The factors that force a firm to dispose assets at unfavorable prices might also reduce the quality of assets sold. Consequently, distressed sellers transacting at lower prices suggests that these properties may be of lower quality. Our data allow us to observe additional property characteristics that can serve as proxies for asset quality. Renovation and redevelopment as buyer intentions signal whether the buyer is willing to spend extra resources to make the asset more appealing or functional for future use. Hence, we expect properties whose buyers have such intentions to fetch lower prices. We can also observe the tenancy status and the occupancy rate of the property being sold. Vacant properties and those with low occupancy rates are relatively less well-maintained compared to the properties that are currently in use. Thus, future owners of such properties are likely to incur additional costs.

In Panel C.1 of Table 2 we regress the transaction price on each of the quality proxies, namely buyer purpose, tenancy status and occupancy rate. *Redevelopment/Renovation* is an indicator variable that equals one if the buyer's intention is to renovate or redevelop the property. *Vacant Dummy* indicates that the property is vacant at the time of the sale. *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 in columns (1)-(3) confirm our prior: transaction price is lower for the properties to be renovated after the purchase, vacant properties and properties with low occupancy rates. In columns (4)-(6) of Panel C.1, we regress the selling price on each of the quality proxies and the industry-adjusted leverage dummies to test whether quality accounts for the impact of leverage on prices. The coefficient estimates for the leverage dummies are significant and their magnitudes are similar to those in our baseline estimation, indicating that our financial distress proxies are not significantly related to the quality of the properties in our sample. In Panel C.2, we repeat the analysis for *High Leverage & Low Current Assets Dummy* and *Interest Coverage Ratio*. Overall, results suggest that asset quality cannot explain the distress discount that we document in Panel A and Panel B of Table 2.[10]

3.2 Determinants of the Discount

After documenting the existence of distress discount in real estate transactions, next we investigate the factors that affect the size of the discount. Our study is unique in that these factors are common to all public firms regardless of their industry affiliation. Therefore, our analyses provide the most general results in the literature.

The main prediction of Shleifer and Vishny (1992) is that an asset should sell for less if it is of use to fewer buyers. Our data set allows us to identify the properties that have less specific usage compared to others. For instance, office properties can be used by different firms from various industries. Similarly, *Flex* properties, which can be employed for both industrial or office activities, are also expected to attract a broader group of potential buyers. Our *Office Dummy* is an indicator variable that equals to unity for offices and flexible properties and zero otherwise.

In order to capture the incremental impact of asset deployability on prices, we estimate our baseline specification by including the interactions between *Office Dummy* and various distress proxies. We also control for the interactions between *Office Dummy* and other independent variables to account for the impact of offices on the transaction price through channels other than firm distress. The results are reported in Panel A of Table 3 which indicate that the impact of firm distress is significantly muted for offices and flexible properties. This suggests that generic assets command higher prices when they are sold by distressed sellers.

[10] We also estimate a regression equation where we regress asset quality on our distress proxies. Consistent with the results in Table 2, we find that the distress proxies do not have any explanatory power on asset quality.

The type of a property tells us how specific the property is in its use, but it doesn't measure the size of its buyer base. This is particularly important for real estate assets because of their non-movable nature. Even a generic asset, such as an office space, may not be sold very easily if there are a few potential buyers at its location. Almazan et al. (2010) argue that being located within an industry cluster increases the opportunities to make acquisitions, and to facilitate those acquisitions, firms within clusters maintain more financial slack. They find evidence that such firms indeed make more acquisitions, have lower debt ratios and larger cash balances than their industry peers located outside. Motivated by the prevalence of local factors in shaping financial transactions, we test whether the discount is less severe in properties surrounded by more potential buyers.

We use three different measures to capture the number of potential buyers. Our first 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. Although, this measure doesn't take the property's location into account, we expect it to be correlated with the number of potential buyers, particularly in geographically clustered industries. Second, we calculate the number of companies in the seller's three-digit SIC industry that mention the state of the property in their 10-Ks at least once during the transaction year (Garcia and Norli, 2012). Our last measure is the number of companies in the seller's three-digit SIC industry whose headquarters are located in the same state as the property's. We label the last two measures as *10-K Count* and *Headquarters Count*, respectively.[11]

Panel B of Table 3 presents the results. In columns (1), (4) and (7), the coefficient estimates for all three measures are positive and significant, indicating that average price is higher when there are more firms that might be interested in buying the property. Columns (2), (5) and (8) report the coefficient estimates for the number of potential

[11]Benmelech, Garmaise, Moskovitz (2005) use the zoning of a property as a proxy for the availability of potential buyers. We anticipate that the property having multiple usage is more important than the flexibility of its zoning unless it is purchased to be rebuilt immediately. Also, unlike Benmelech, Garmaise, Moskovitz (2005), we are able to observe both the seller's industry and the property's location, thereby we can determine property-specific measures for the number of potential buyers.

buyers proxies as well as for their interactions with the seller's leverage tercile. The coefficient estimates for the interactions 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 0.127 and the direct effect of high leverage is –0.430. This implies that a one-standard-deviation increase in the logarithm of the number of potential buyers (1.22) decreases the impact of high leverage from –0.430 to –0.275. Columns (3), (6) and (9) report the results for *Industry-Adjusted Leverage* included as a continuous variable. The interaction terms between *Industry-Adjusted Leverage* and all three potential buyer proxies have positive coefficient estimates that are significant at 5-10% level. Collectively, these results suggest that the discount is low or does not exist when there are more potential buyers.

Real estate assets can be considered as a composite good that can be reduced to its constituent parts. Hedonic models are often used to find the market values of those constituent parts. As a robustness test, we run a hedonic model in which we estimate the selling price as a function of a detailed set of property characteristics using a larger sample of transactions. Column (1) and (2) of Table A3 report the estimation results from the first-stage model. In these regressions, we include RCA market-year-fixed effects which control for market-wide events throughout the year. Results show that smaller properties, renovated properties and properties in central locations have higher values. Next, we calculate *Residual Price* as the difference between the transaction price and the price estimated based on the real estate property's observable characteristics. Columns (3)-(6) of Table A3 show that our leverage dummies and the residual price are negatively related. The economic significance of distress on prices is comparable to those estimated in Table 2: an increase from the lowest leverage tercile to the highest leverage tercile leads to a 22.1% decrease in the residual price.

In Table A5 and A6, we repeat our main tests reported in Tables 2C and Table 3 using residual prices estimated from the hedonic model. We find that our results are robust to this alternative methodology.

4 Real Estate Holdings and Loan Spreads

4.1 Collateral Discount

Our analysis in section 3 shows that, if we compare two identical sellers, the one that is financially less healthy gets a lower price for the same property. However, this negative effect is weakened if the asset is deployable and/or if the asset has a higher number of potential buyers. These findings provide insights about how the value of a healthy firm's collateral might change if the firm becomes distressed in the future. In this section, we investigate whether these potential risks associated with collateral characteristics are priced by the lenders, after controlling for the borrower's characteristics. Our methodology relies on the comparison between the current market value of a firm's real estate portfolio and the value of this portfolio in a hypothetical distress scenario. The ratio of these two values indicates how much discount that the firm will suffer if it becomes financially distressed.

To execute this idea, we first construct the real estate portfolios of companies using all the transactions contained in the RCA database. These transactions help us identify the date when the property was acquired and when it was disposed. After constructing the real estate portfolios from transaction data, then we estimate the market value for each of the firm's properties twice first, assuming that the leverage equals the firm's current industry-adjusted leverage (*Current Portfolio Value*), and then assuming that the leverage is 25% higher than the industry median (*Hypothetical Portfolio Value*).[12]

In estimating the market values, we rely on the specifications in Panel A and B of Table 3 which report the positive impact of deployability and potential buyers on distress

[12] 25% refers to the 90th percentile value of the industry-adjusted leverage in our sample. We obtain similar results with 20% and 30% cutoff values.

discount. More specifically, we use the models in column (2) of Panel A and column (9) of Panel B, respectively. These specifications account for property characteristics, firm controls, RCA market-fixed effects and time-fixed effects as well as the direct effects of office dummy and the number of potential buyers. Notice that the contribution of these variables to the estimated values of *Current Portfolio Value* and *Hypothetical Portfolio Value* are the same. The difference between the two portfolio values mainly results from the direct impact of a firm's leverage and its interaction with asset deployability or with the number of potential buyers. Finally, we multiply the estimated values by the size of each property and sum over all properties to obtain the *Current Portfolio Value* and the *Hypothetical Portfolio Value.*

$$Current\ PV_t = \sum_{i}^{N} Size_i \times E[Ln(Price)|Current\ Leverage_{i,t}]$$

$$Hypothetical\ PV_t = \sum_{i}^{N} Size_i \times E[Ln(Price)|Hypothetical\ Leverage]$$

We define the expected collateral discount as follows[13]

$$Collateral\ Discount_t = Current\ PV_t/Hypothetical\ PV_t\ \text{-}\ 1$$

RCA only tracks transactions that are above a certain threshold (2.5 million USD), therefore our current and hypothetical portfolios are tilted toward large properties. Because our collateral discount measure is the ratio of the two portfolio values, we conjecture that *Collateral Discount* is neither overstated nor understated due to RCA's coverage choice.

To investigate whether loan spreads vary with expected collateral discount, we obtain loan-level data from Loan Pricing Corporation's (LPC) Dealscan database,

[13]In few instances where *Current PV* is less than *Hypothetical PV*, we normalize the ratio of *Current PV* to *Hypothetical PV* to unity.

which contains detailed information about commercial (primarily syndicated) loans made to U.S. corporations since the 1980s. According to Carey and Hrycray (1999), the Dealscan database covers between 50% and 75% of the value of all commercial loans in the U.S. during the early 1990s with increased coverage after 1995. Our initial sample contains all commercial loans denominated in U.S. dollars. We link the Dealscan data set 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 information on loan amount, loan maturity, loan type and loan purpose.[14] Following the literature, we evaluate loan prices using all-in-drawn spread, which is the rate a borrower pays in basis points over LIBOR including any recurring annual fees on the loan. Our final sample consists of 1,201 loans with a median (mean) spread of 75 (122) basis points.

Table 4 reports the results from the regression of loan spread on the *Collateral Discount*, and loan- and firm-level controls. In all regressions, we control for industry-adjusted leverage, which accounts for the direct impact of leverage on the estimated collateral discount. Thus, the variation in the *Collateral Discount* results from either the interaction of industry-adjusted leverage with the office indicator or with the number of potential buyers. In columns (1)–(3), we use deployability levels, and in columns (4)–(6) we use the number of potential buyers to estimate the wedge between the current and hypothetical portfolio values. Our results in columns (1) and (4) indicate a positive relationship between loan spreads and our collateral discount measure after controlling for firm leverage, industry-fixed effects and year-fixed effects. More specifically, a one-standard-deviation increase in expected collateral discount

[14] Loan types are indicators for term loans, revolver loans < (>=1 year), 364-day facility and others. The primary purposes of the facilities in our sample are acquisition line, CP backup, corporate purposes, debt repayment, takeover or working capital.

resulting from asset deployability (fewer potential buyers) is associated with about 9.39 (16.35) basis points higher loan spreads which translates into a 0.08 (0.14) standard deviation increase in loan spreads.

In columns (2) and (5) of Table 4, we control for the current value of real estate holdings so that we can account for the variation in *Collateral Discount* that is not related to the property values in a potential distress scenario. The coefficient estimates are very similar to those reported in columns (1) and (4), suggesting that our results are mainly driven by the portfolio value estimated for a distress scenario.

Strahan (1999) investigates the impact of non-price terms of loans on loan pricing and shows that secured loans 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 collateral. Consistent with the literature, we find that the average spread is higher for secured loans. In columns (3) and (6), we interact our collateral discount measure with the *Secured Loan Dummy*. The coefficient estimates of both the secured loan indicator and our collateral discount variable are positive, but the main effect of collateral discount is not statistically significant. The coefficient estimate of the interaction term between the secured loan indicator and the collateral discount measure is positive, suggesting 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 transaction price for such non-traded real estate assets, we perform the following analysis to gauge the importance of this issue on the measurement of collateral discount: Using a logit regression model, we estimate the likelihood of a property being sold in a given year as a function of the property's market liquidity, other property characteristics, firm controls, as well as RCA market- and year-fixed effects. We use *Annual Sales Volume* to measure the liquidity of a property's market, which is the dollar value of total sales defined for each property type separately. We also calculate the percentile rank of a property in the firm's portfolio based on *Annual Sales Volume* of its market and property type. Table A7 reports the coefficient estimates which indicate that a one-standard-deviation increase in *Ln(Annual Sales Volume)* results in a 0.152 standard-deviation increase in the log odds of a property being sold. These results suggest that firms choose to sell the assets that are less likely to be discounted in distress, and that collateral discount coefficient, if anything, is *underestimated*.

In our sample, the average ratio of the real estate portfolio value to tangible assets is 8.38%. Industry-fixed effects enable us to capture the cross-industry variation in the ratio of real estate properties to tangible assets. Moreover, we include the value of property, plant and equipment (scaled by total assets) to account for the effect of tangible assets on loan rates (see Acharya et al., 2013). In Table A8 we show that our results in columns (2) and (5) of Table 4 are robust to inclusion of additional controls, mainly the value of real estate holdings relative to tangible assets, median industry leverage ratio and fixed effects for the borrower's headquarters state.

To sum up, our findings suggest that when banks price collateral, they consider marketability of a borrower's real estate portfolio in case of a distress scenario. A borrower with assets that are not deployable for alternative uses borrows at higher rates after controlling for its current financial health. Likewise, a borrower faces a higher loan rate if its real estate assets are located in areas where only a few firms are able to pay for the best-use price. Overall, our findings reveal the link between a firm's real estate holdings, an asset type that is frequently used in almost all industries, and bank loan rates, the major source of short term financing for U.S. companies.

To our knowledge, our paper is the first to provide a complete analysis of the collateral channel. Previous studies either directly relate collateral proxies to borrowing rates (Benmelech and Bergman, 2009) or evaluate the relationship in the realized state of bankruptcy (Benmelech, Garmaise, Moskovitz, 2005). By relying on the transaction-level data, we first quantify the distress discount and document the variation in the discount due to various collateral characteristics. Then, using our model, we estimate the future discount in the collateral value for all firms after controlling for their financial health. Finally, we investigate the impact of the future discount on current borrowing rates. Hence, our comprehensive analysis provides a stage-by-stage investigation of the collateral channel.

4.2 Robustness: Foreign Investment as a Shock to Collateral Value

Our findings in the previous section suggest that capital markets price a potential decrease in the collateral value in a future distress state. An important concern about this result is that an unobserved factor might drive both loan rates and real estate prices when the two variables are not directly related to each other. For example, some of the determinants of collateral value (i.e., asset deployability and/or number of potential buyers of the real estate asset) can be correlated with unobserved firm characteristics that affect the cost of borrowing. Then, a correlation between collateral discount and bank loan rates would not necessarily imply a causal relation. To address this particular endogeneity issue, we need exogenous changes in collateral values that can not be attributed to firm characteristics.

We use significant surges in commercial real estate demand attributed to *foreign investors from countries with increased policy uncertainty* as an exogenous shock to commercial real estate prices.[15] Our conjecture is that political and economic uncertainty in other countries will cause some foreign investors to invest in the U.S. commercial real estate markets, and this demand will increase the values of firms'

[15]A similar identification strategy is utilized in Badarinza and Ramadorai (2015) for house prices. They show that in London areas with high densities of people originating from a particular country, house prices are 1.42 percentage points higher in the year following an episode of elevated political and economic risk in that country. Our setting differs from Badarinza and Ramadorai's in that we focus on commercial real estate properties rather than houses. Also, we measure foreign investment into different types of real estate separately, which allows us to identify significant surges in a specific property type and RCA market.

collateral.[16] If this conjecture is correct, following a heightened uncertainty in a given country, we would expect to see relatively higher real estate prices in areas where this particular form of foreign demand increases the level of real estate prices for certain property types.

In Table 5, we investigate the link between commercial real estate prices and foreign investment from countries with elevated uncertainty. We regress the natural logarithm of average price per square foot calculated for each property type in a given RCA market on *Investment from Countries with Increased Uncertainty* which is defined as the natural logarithm of total commercial real estate purchases of investors from countries with increased policy uncertainty (in million dollars) plus one. We obtain average real estate prices from RCA which are available for the 66 major RCA markets. In order to determine the countries with increased policy uncertainty, we use the annual average policy uncertainty index of Baker, Bloom, and Davis (2015) that is available for Australia, Canada, China, France, Germany, India, Italy, Japan, Netherlands, Russia, South Korea, Spain, UK. We assign a country to the increased uncertainty category if its policy uncertainty index is in the top quintile of its time-series distribution. Since average prices are defined at the property type and market level, we control for property type-fixed effects as well as year-quarter- and market-fixed effects. The results show that after controlling for various factors, increased foreign demand is accompanied by higher commercial real estate prices in the U.S. A 1% increase in foreign investment generates about 0.022% increase average prices assuming the specification given in column (5) which controls for the regional variation in property prices and foreign

[16] According to RCA statistics, foreign investment into U.S. commercial real estate markets increased from $10 billion to $40 billion between 2003 and 2007, and from $5 billion to $45 billion between 2009 and 2015. (`http://urbanland.uli.org/development-business/six-global-trends-commercial-real-estate-watch-2016/`) The amount of foreign investment is non-negligible given the $550 billion total transaction volume in commercial real estate markets in 2015. Results of 2017 AFIRE Foreign Investment Survey taken among the largest international institutional real estate investors in the world reveal that 60% of the participants chose the U.S. as the country providing the most stable and secure real estate investment. (`http://www.afire.org/content.asp?admin=Y&contentid=208`)

investment over time.

We also test whether the impact of abnormal commercial real estate demand of foreign investors from high policy uncertainty places is distinct from the impact of demand from other countries. More specifically, we regress *Investment from Countries with Increased Uncertainty* on *Investment from Other Countries* and various fixed effects. Column (6) of Table 5 reports the results which show that the amount of investment triggered by increased uncertainty cannot be explained by the investment from other countries, suggesting that the variation in investment from such countries is not likely to be driven by unobserved local factors that are common to all types of foreign investment.

After establishing the link between property prices and foreign investment, we now turn our attention on sudden changes in investment from countries with increased policy uncertainty and loan spreads. In order to detect property types and markets that receive abnormal investments from countries with elevated uncertainty, we estimate the *Residual Investment* using the specification given in column (6) of Table 5. We assume that a property is exposed to abnormal foreign investment if the *Residual Investment* for its market and property type is in the top quintile of the distribution. The indicator variable *I(Abnormal Investment>0)* equals one if *at least one* of the properties of the firm is located in a market that received abnormal investment from increased uncertainty countries.[17] Table 6 reports the results from the regression of loan spreads on *I(Abnormal Investment>0)*, which indicate that firms with real estate properties that are located in areas with abnormal foreign investment pay about 18 basis points less on bank loan spreads relative to others.

Next, we analyze the differential impact of foreign investment on the loan spreads of firms with high collateral discount. We argue that if the relationship between our

[17] Alternatively, one can identify foreign investment induced by increased policy uncertainty by regressing total foreign investment on policy uncertainty index of each country and year-fixed effects using monthly index data. We obtain similar results if we determine abnormal investment based on the predicted values of foreign investment from this regression.

collateral discount measure and loan spreads is driven by a factor that is unrelated to collateral values, then such demand shocks shouldn't have a differential impact on the loan spreads of firms with different levels of collateral discount. If our conjecture is correct, then increased collateral values should lead to a reduction in loan spreads particularly for those firms with high collateral discount. In column (2), we interact *I(Abnormal Investment>0)* with our collateral discount measure. The main effect of the collateral discount measure is positive and significant. The interaction term between our collateral discount measure and *I(Abnormal Investment>0)* dummy has a negative coefficient estimate, suggesting that increased foreign investment reduces loan spreads more for firms with high collateral discount. In other words, firms that happen to have assets in locations experiencing this presumably exogenous price appreciation enjoy lower bank rates that we attribute to increased collateral values.

In column (3), we interact *I(Abnormal Investment>0)* dummy with the secured loan indicator to test whether the existence of a collateral backing up the loan can account for the effect of our collateral discount measure. This additional interaction term does not result in a significant change in the coefficient estimate of the interaction term between *I(Abnormal Investment>0)* and *Collateral Discount*, suggesting that our discount measure contains information beyond the existence of a collateral attached to the loan. In columns (4)-(6), we repeat the same analysis using *Collateral Discount* based on the number of potential buyers and find similar results.

Next, we explore the cross-sectional variation in the relationship between foreign investment and real estate prices using land-supply elasticity. More specifically, we expect the impact of abnormal foreign investment to be more prominent in areas where local supply of land is relatively inelastic such that increased demand for real estate cannot be absorbed by a simultaneous increase in the supply, which in turn raises real estate prices further (Saiz, 2010; Chaney, Sraer, and Thesmar, 2012).

In order to test whether the impact of foreign investment exposure is amplified for firms with real estate holdings mainly located in areas with low supply elasticity, we obtain housing supply elasticities from Saiz (2010), which are available for 95 MSAs with population over 500,000 in 2000. The estimated supply elasticities range between 0.60 and 5.45, the low values suggesting that the land supply is constrained. Saiz (2010) shows that estimated elasticities have a very strong correlation with both levels of and changes in house prices. We split the RCA markets into two equally sized groups with respect to their supply elasticities and determine the real estate properties that are located in areas with low supply elasticity. We define a dummy variable *I(Abnormal Investment - Low Elasticity > 0)* to indicate that a firm has *at least one* property located in an area with low supply elasticity and abnormal investment from countries with increased uncertainty.[18] In Table 7, we regress loan spreads on the interaction term between our collateral discount measure and this indicator variable. The interaction term's coefficient estimates in columns (1) and (2) are significantly larger than the coefficient estimates of the interaction term between *I(Abnormal Investment>0)* and *Collateral Discount* given in columns (3) and (6) of Table 6. This indicates that the impact of foreign investment exposure on the borrowing rate is amplified for firms with properties that are located in regions with low supply elasticity.

To sum up, using abnormal commercial real estate demand from countries with increased policy uncertainty and local land supply elasticity, we identify changes in collateral values that are likely to be attributed to exogenous factors. The evidence presented in Table 6 and Table 7 alleviate the concern that an unobserved factor drives both the loan rates and the real estate prices when these two variables are not directly related to each other. Furthermore, Table A8 shows that these results are robust to controlling for the value of real estate holdings relative to tangible assets, median industry leverage ratio and fixed effects for the borrower's headquarters state.

[18] We obtain similar results if we use a higher threshold for the number of properties to define the indicator variable, but the power of test goes down since the precision that comes with a higher threshold comes at the cost of low statistical power.

Conclusion

The existing studies on the collateral channel either focus on a single industry or investigate the role of deployability alone without taking firm distress into account. Our paper evaluates and documents the complete mechanism of the collateral channel in commercial real estate which is an asset type that is common to all firms regardless of their industries. After documenting the negative impact of seller distress on commercial real estate prices, next we study the role of deployability in distress sales. By relying on the variation in collateral characteristics, we estimate the discount in the value of a firm's real estate holdings due to a future distress scenario. Finally, we investigate the impact of this potential collateral discount on the pricing of bank loans.

We find that an average distressed firm can only sell its real estate assets at a discount of 22% relative to an average healthy firm. However, this discount is diminished or eliminated completely if the distressed firm sells a general asset with alternative uses or if the asset is located in areas with more potential buyers. Based on these findings and the hedonic model we develop, we estimate the discount in collateral value for each firm if they get distressed in the future. Our findings show that a one-standard-deviation increase in our collateral discount measure decreases loan spreads by 9-to-16 basis points. This indicates that any future loss in the value of a collateral asset that results from collateral-specific factors is priced in debt markets.

Using local land supply elasticity information and significant surges of foreign investor demand from countries with increased policy uncertainty as an exogenous shock to commercial real estate prices, we find that the firms which happen to have assets in locations that experience this presumably exogenous price appreciation enjoy lower bank rates that we attribute to increased collateral values. This confirms that our findings are robust to potential endogeneity problems due to omitted factors.

References

Acharya, Viral V, Heitor Almeida, and Murillo Campello, 2013, Aggregate risk and the choice between cash and lines of credit, *The Journal of Finance* 68, 2059–2116.

Adelino, Manuel, Antoinette Schoar, and Felipe Severino, 2015, House prices, collateral, and self-employment, *Journal of Financial Economics* .

Aghion, Philippe, and Patrick Bolton, 1992, An incomplete contracts approach to financial contracting, *The review of economic Studies* 59, 473–494.

Albuquerque, Rui, and Enrique Schroth, 2015, The value of control and the costs of illiquidity, *The Journal of Finance* 70, 1405–1455.

Almazan, Andres, Adolfo De Motta, Sheridan Titman, and Vahap Uysal, 2010, Financial structure, acquisition opportunities, and firm locations, *The Journal of Finance* 65, 529–563.

Almeida, Heitor, and Murillo Campello, 2007, Financial constraints, asset tangibility, and corporate investment, *Review of Financial Studies* 20, 1429–1460.

Badarinza, Cristian, and Tarun Ramadorai, 2015, Home away from home? foreign demand and london house prices, *Available at SSRN* Working Paper.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis, 2015, Measuring economic policy uncertainty, Working Paper 21633, National Bureau of Economic Research.

Benmelech, Efraim, and Nittai K Bergman, 2009, Collateral pricing, *Journal of Financial Economics* 91, 339–360.

Benmelech, Efraim, and Nittai K Bergman, 2011, Bankruptcy and the collateral channel, *The Journal of Finance* 66, 337–378.

Benmelech, Efraim, Mark J Garmaise, and Tobias J Moskowitz, 2005, Do liquidation values affect financial contracts? evidence from commercial loan contracts and zoning regulation, *The Quarterly Journal of Economics* 120, 1121–1154.

Berger, Allen N, and Gregory F Udell, 1990, Collateral, loan quality and bank risk, *Journal of Monetary Economics* 25, 21–42.

Bernanke, Ben S, and Mark Gertler, 1986, Agency costs, collateral, and business fluctuations, Technical report, National Bureau of Economic Research.

Bester, Helmut, 1985, Screening vs. rationing in credit markets with imperfect information, *The American Economic Review* 850–855.

Boot, Arnoud WA, and Anjan V Thakor, 1994, Moral hazard and secured lending in an infinitely repeated credit market game, *International Economic Review* 899–920.

Boot, Arnoud WA, Anjan V Thakor, and Gregory F Udell, 1991, Secured lending and default risk: equilibrium analysis, policy implications and empirical results, *The Economic Journal* 458–472.

Campello, Murillo, and Erasmo Giambona, 2013, Real assets and capital structure, *Journal of Financial and Quantitative Analysis* 48, 1333–1370.

Carey, Mark, and Mark Hrycray, 1999, Credit flow, risk, and the role of private debt in capital structure, *Unpublished working paper, Federal Reserve Board* .

Chan, Yuk-Shee, and Anjan V. Thakor, 1987, Collateral and competitive equilibria with moral hazard and private information, *The Journal of Finance* 42, 345–363.

Chaney, Thomas, David Sraer, and David Thesmar, 2012, The collateral channel: How real estate shocks affect corporate investment, *American Economic Review* 102, 2381–2409.

Chava, Sudheer, and Michael R Roberts, 2008, How does financing impact investment? the role of debt covenants, *The Journal of Finance* 63, 2085–2121.

Chu, Yongqiang, 2013, Asset fire sale and regulatory capital requirements: Evidence from commercial REO sales, *Available at SSRN 2178596* .

Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479–512.

Cvijanović, Dragana, 2014, Real estate prices and firm capital structure, *Review of Financial Studies* 27, 2690–2735.

Degryse, Hans, Moshe Kim, and Steven Ongena, 2009, *Microeconometrics of banking: methods, applications, and results* (Oxford University Press, USA).

Gan, Jie, 2007, Collateral, debt capacity, and corporate investment: Evidence from a natural experiment, *Journal of Financial Economics* 85, 709–734.

Garcia, Diego, and Øyvind Norli, 2012, Geographic dispersion and stock returns, *Journal of Financial Economics* 106, 547–565.

Granja, Joao, Gregor Matvos, and Amit Seru, 2015, Selling failed banks, *Journal of Finance* Forthcoming.

Hart, O, and J Moore, 1994, A theory of debt based on the inalienability of human capital, *Quarterly Journal of Economics* 109, 841–879.

Hart, Oliver, 1995, *Firms, contracts, and financial structure* (Oxford university press).

Hart, Oliver, and John Moore, 1998, Default and renegotiation: A dynamic model of debt, *The Quarterly Journal of Economics* .

Hertzel, Michael G, and Micah S Officer, 2012, Industry contagion in loan spreads, *Journal of Financial Economics* 103, 493–506.

John, Kose, Anthony W Lynch, and Manju Puri, 2003, Credit ratings, collateral, and loan characteristics: Implications for yield, *The Journal of Business* 76, 371–409.

Kim, Hyunseob, and Howard Kung, 2017, The asset redeployability channel: How uncertainty affects corporate investment, *Review of Financial Studies,* 30 (1), 245–280.

Kiyotaki, Nobuhiro, and John Moore, 1997, Credit chains, *Journal of Political Economy* 105, 211–248.

Knox, Kristin Elizabeth, 2005, *Essays in financial economics*, Ph.D. thesis, Harvard University.

Leitner, Yaron, 2006, Using collateral to secure loans, *Business Review* 9–16.

Mian, Atif, Kamalesh Rao, and Amir Sufi, 2013, Household balance sheets, consumption, and the economic slump, *The Quarterly Journal of Economics* .

Mian, Atif, and Amir Sufi, 2011, Consumers and the economy, part ii: Household debt and the weak us recovery, *FRBSF Economic Letter* 2.

Ortiz-Molina, Hernán, and Gordon M Phillips, 2014, Real asset illiquidity and the cost of capital, *Journal of Financial and Quantitative Analysis* 49, 1–32.

Pulvino, Todd C, 1998, Do asset fire sales exist? an empirical investigation of commercial aircraft transactions, *The Journal of Finance* 53, 939–978.

Rajan, Raghuram, and Andrew Winton, 1995, Covenants and collateral as incentives to monitor, *The Journal of Finance* 50, 1113–1146.

Saiz, Albert, 2010, The geographic determinants of housing supply, *The Quarterly Journal of Economics* 125, 1253–1296.

Schmalz, Martin C, David A Sraer, and David Thesmar, 2013, Housing collateral and entrepreneurship, Technical report, National Bureau of Economic Research.

Shleifer, Andrei, and Robert W Vishny, 1992, Liquidation values and debt capacity: A market equilibrium approach, *The Journal of Finance* 47, 1343–1366.

Strahan, Philip E, 1999, Borrower risk and the price and nonprice terms of bank loans, *FRB of New York Staff Report* .

Stulz, René M, and Herb Johnson, 1985, An analysis of secured debt, *Journal of financial Economics* 14, 501–521.

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 according to the three-digit SIC codes. *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. *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. *Ln(Price)* equals the natural logarithm of price per square foot 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 reports the summary statistics for bank loan analysis. *Loan Maturity* is in months. Panel D 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 both industrial or office activities. Panel E shows the distribution of properties by *Vacancy* and *Buyer Purpose*. *Single Tenant* is a property that is fully occupied by a single user. *Vacant* indicates that the property is not occupied at the time of the sale. *Occupancy* is a buyer's objective representing a property that is purchased for use by the buyer in the conduct of business.

Table 1 Cont.: Descriptive Statistics

Panel A: Company Characteristics	**Mean**	**St. Dev.**	**p25**	**Median**	**p75**	**N**
Leverage	0.262	0.161	0.155	0.258	0.353	2,274
Industry-Adjusted Leverage	0.059	0.174	-0.051	0.055	0.179	2,274
Interest Covarage Ratio	15.979	15.865	4.568	9.196	21.802	2,218
High Leverage & Low Current Assets Dummy	0.403	0.491	0	0	1	2,175
ROA	0.136	0.084	0.088	0.150	0.178	2,274
Tangibility	0.365	0.184	0.196	0.397	0.541	2,274
Market-to-Book	1.448	0.897	0.849	1.265	1.702	2,274
Ln(Assets)	9.473	1.629	8.219	9.786	10.421	2,274

Panel B: Property Characteristics	**Mean**	**St. Dev.**	**p25**	**Median**	**p75**	**N**
Ln(Price)	4.467	0.939	3.812	4.518	5.128	2,274
Ln(sqf)	11.414	1.298	10.659	11.501	12.268	2,274
Age	21.991	18.332	9	18	31	2,274
Renovated Dummy	0.120	0.325	0	0	0	2,274
Portfolio Dummy	0.334	0.472	0	0	1	2,274
CBD Dummy	0.051	0.219	0	0	0	2,274
Occupancy Rate	0.777	0.402	0.86	1	1	1,649

Panel C: Loan Characteristics	**Mean**	**St. Dev.**	**p25**	**Median**	**p75**	**N**
Loan Spread	122.231	119.905	30	75	175	1,201
Ln(Loan Maturity)	3.485	0.776	2.485	3.871	4.094	1,201
Ln(Loan Amount)	20.231	1.188	19.519	20.212	20.986	1,201
Collateral Discount based on						
Asset Deployability	0.110	0.093	0.039	0.092	0.162	1,201
Number of Potential Buyers	0.161	0.118	0.064	0.158	0.232	1,201

Table 1 Cont.: Descriptive Statistics

Panel D: Property Subtypes

Type	**Frequency**	**Percent**
	Industrial	
Flex	244	28.77
Warehouse	583	68.75
N/A	21	2.48
Total	848	
	Retail	
Mall	891	88.48
Strip	93	9.24
N/A	23	2.28
Total	1,007	
	Office	
CBD	63	15.04
Sub	345	82.34
N/A	11	2.63
Total	419	

Panel E: Vacancy and Buyer Purpose

Type	**Frequency**	**Percent**
	Vacancy	
Multi Tenant	262	13.48
Single Tenant	1,135	58.41
Vacant	546	28.10
Total	1943	
	Buyer Purpose	
Investment	1,711	75.44
Occupancy	316	13.93
Redevelopment/Renovation	241	10.63
Total	2,268	

Table 2: Transaction Price and Firm Distress

Panel A reports the average transaction 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 industry-adjusted leverage is between the 33rd and 67th (above the 67th) percentile of the sample. Panel B reports the results from the regression of *Ln(Price)* on industry-adjusted leverage dummies. Panel C investigates the impact of quality on *Ln(Price)*. *Redevelopment/Renovation* is an indicator variable that equals one if the buyer's intention is to renovate or redevelop the property. *Vacant Dummy* indicates that the property is vacant at the time of the sale. *Occupancy Rate* is defined as the floor space or units occupied by tenants as a percentage of the total leasable area of the building. Market-fixed effects and quarter-fixed effects are defined for each property type separately. Standard errors are clustered at the firm level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

Panel A: Univariate Analysis of Distress and Prices

Leverage Tercile	*Average Ln(Price)*	*N*		*Difference in Average Ln(Price)*	*t-stat*
Low Leverage	4.698	759	High-Low	-0.515	(10.72***)
Medium Leverage	4.522	752	High-Medium	-0.339	(7.35***)
High Leverage	4.184	763	Medium-Low	-0.176	(3.76***)

Panel B: Multivariate Analysis of Distress and Prices

	Ln(Price)			
	(1)	(2)	(3)	(4)
Medium Ind.-Adj. Leverage Dummy$_{t-1}$	-0.210**	-0.171**	-0.201**	-0.179**
	(-2.150)	(-2.428)	(-2.349)	(-2.465)
High Ind.-Adj. Leverage Dummy$_{t-1}$	-0.320***	-0.239***	-0.340***	-0.256***
	(-3.638)	(-2.937)	(-3.809)	(-2.996)
ROA$_{t-1}$			-0.879**	-0.583
			(-2.277)	(-1.629)
Tangibility$_{t-1}$			-0.139	-0.009
			(-0.853)	(-0.058)
Market-to-book$_{t-1}$			0.021	0.020
			(0.940)	(0.799)
Ln(Assets$_{t-1}$)			0.004	-0.002
			(0.192)	(-0.113)
Property Characteristics	✓	✓	✓	✓
Type X Year X Quarter FE		✓		✓
Type X Market FE			✓	✓
Adjusted R-squared	0.459	0.616	0.580	0.617
Observations	2,274	2,274	2,274	2,274

Table 2 Cont.: Transaction Price and Firm Distress

Panel C: Asset Quality and Price

	Ln(Price)					
Panel C.1	(1)	(2)	(3)	(4)	(5)	(6)
Redevelopment/Renovation$_t$	-0.097*			-0.082		
	(-1.767)			(-1.488)		
Vacant Dummy$_t$		-0.373***			-0.349***	
		(-6.484)			(-6.711)	
Occupancy Rate$_t$			0.320***			0.306***
			(5.515)			(5.684)
Medium Ind.-Adj. Leverage Dummy$_{t-1}$				-0.175**	-0.164**	-0.194**
				(-2.400)	(-2.067)	(-2.513)
High Ind.-Adj. Leverage Dummy$_{t-1}$				-0.250***	-0.219**	-0.266***
				(-2.902)	(-2.439)	(-2.907)
Property Characteristics	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
Type X Year X Quarter FE	✓	✓	✓	✓	✓	✓
Type X Market FE	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.609	0.615	0.606	0.617	0.621	0.615
Observations	2,268	1,949	1,649	2,268	1,949	1,649

Panel C.2	(1)	(2)	(3)	(4)	(5)	(6)
Redevelopment/Renovation$_t$	-0.092			-0.098*		
	(-1.635)			(-1.820)		
Vacant Dummy$_t$		-0.375***			-0.329***	
		(-6.807)			(-6.519)	
Occupancy Rate$_t$			0.322***			0.283***
			(5.754)			(5.319)
High Leverage & Low Current Assets Dummy$_{t-1}$	-0.150**	-0.132*	-0.175**			
	(-2.215)	(-1.900)	(-2.307)			
Interest Coverage Ratio$_{t-1}$				0.009***	0.007**	0.007**
				(3.048)	(2.498)	(2.229)
Property Characteristics	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
Type X Year X Quarter FE	✓	✓	✓	✓	✓	✓
Type X Market FE	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.602	0.615	0.607	0.607	0.609	0.596
Observations	2,169	1,884	1,587	2,212	1,904	1,605

Table 3: Asset Deployability and Potential Buyers

This table investigates the impact of asset deployability (Panel A) and the number of potential buyers (Panal B) on distress discount. *Office Dummy* is an indicator variable that takes one for offices and for properties that can be used for both industrial or office activities. The number of potential buyers is measured by one of the following three variables: (i) *1-Herfindahl Index* is the Herfindahl Index of sales based on the firm's three-digit SIC industry, (ii) *10-K Count* is the number of companies in the seller firm's three-digit SIC industry who mentions the state of the property in its 10-Ks at least once during the year preceding the transaction (Garcia and Norli, 2012), (iii) *Headquarters count* is the number of companies in the seller firm's three-digit SIC industry whose headquarters are located in the same state as the property. Market-fixed effects and quarter-fixed effects are defined for each property type separately. Standard errors are clustered at the firm level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

Panel A: Asset Deployability

	Ln(Price)			
	(1)	(2)	(3)	(4)
Medium Ind.-Adj. Leverage Dummy$_{t-1}$	-0.183**			
	(-2.132)			
X Office Dummy	0.110			
	(1.039)			
High Ind.-Adj. Leverage Dummy$_{t-1}$	-0.314***			
	(-3.226)			
X Office Dummy	0.244**			
	(2.099)			
Industry-Adjusted Leverage$_{t-1}$		-0.607***		
		(-3.404)		
X Office Dummy		0.395*		
		(1.681)		
Interest Coverage Ratio$_{t-1}$			0.010***	
			(3.265)	
X Office Dummy			-0.009**	
			(-2.413)	
High Leverage & Low Current Assets Dummy$_{t-1}$				-0.210***
				(-2.672)
X Office Dummy				0.197**
				(2.056)
Property Characteristics	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Office Interactions	✓	✓	✓	✓
Type X Year X Quarter FE	✓	✓	✓	✓
Type X Market FE	✓	✓	✓	✓
Adjusted R-squared	0.638	0.636	0.629	0.625
Observations	2,274	2,274	2,218	2,175

Table 3 cont.: Asset Deployability and Potential Buyers

Panel B: Potential Buyers

	Ln(Price)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1-Herfindahl Index	0.562***	0.233	0.437***						
	(3.962)	(1.400)	(3.519)						
10-K Count				0.050***	0.029	0.050***			
				(3.038)	(1.254)	(3.159)			
Headquarters Count							0.061***	0.014	0.063***
							(3.195)	(0.522)	(3.278)
Medium Ind.-Adj. Leverage Dummy$_{t-1}$		-0.263*			-0.166*			-0.212**	
		(-1.692)			(-1.710)			(-2.458)	
X Number of Buyers		0.105			-0.007			0.033	
		(0.530)			(-0.238)			(1.008)	
High Ind.-Adj. Leverage Dummy$_{t-1}$		-0.664***			-0.482***			-0.430***	
		(-3.916)			(-4.153)			(-4.469)	
X Number of Buyers		0.590***			0.096***			0.127***	
		(2.802)			(2.799)			(3.669)	
Industry-Adjusted Leverage$_{t-1}$			-1.442***			-0.953***			-0.827***
			(-2.730)			(-4.068)			(-4.083)
X Number of Buyers			1.171*			0.159**			0.162**
			(1.852)			(2.100)			(2.031)
Property Characteristics	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Type X Year X Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Type X Market FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.618	0.627	0.625	0.611	0.623	0.620	0.611	0.625	0.621
Observations	2,274	2,274	2,274	2,274	2,274	2,274	2,274	2,274	2,274

Table 4: Loan Spreads and Collateral Discount

This table reports the results from the regression of loan spreads on *Collateral Discount*, which is defined as the ratio of current real estate portfolio value (*Current PV*) to its hypothetical value (*Hypothetical PV*). *Current PV* is the sum of the predicted values of the properties in a firm's portfolio. *Hypothetical PV* is the estimated portfolio value assuming that the firm has an industry-adjusted leverage ratio that equals to the 90th percentile of its sample distribution. Portfolio values are estimated twice based on two different models. In particular, we use the specifications in Panel A and B of Table 3 which report the positive impact of deployability and potential buyers on distress discount, respectively. *Loan 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 1. Standard errors are clustered at the firm level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Loan Spread					
	Asset Deployability			*Number of Potential Buyers*		
	(1)	(2)	(3)	(4)	(5)	(6)
Collateral Discount$_t$	100.999**	105.740**	26.732	138.530***	143.279***	86.646
	(2.125)	(2.160)	(0.466)	(2.746)	(2.839)	(1.645)
Ind.-Adj. Leverage$_{t-1}$	106.127***	109.405***	114.849***	146.901***	151.623***	162.641***
	(4.284)	(4.241)	(4.427)	(5.157)	(5.308)	(5.447)
Secured Loan Dummy$_t$=Yes	74.703***	74.415***	56.472***	73.063***	72.748***	48.054***
	(8.744)	(8.639)	(4.240)	(8.578)	(8.488)	(3.441)
X Collateral Discount$_t$			153.550**			148.474***
			(2.318)			(2.711)
Secured Loan Dummy$_t$=Missing	2.876	3.009	-7.644	2.709	2.889	-5.752
	(0.627)	(0.656)	(-0.973)	(0.592)	(0.631)	(-0.640)
X Collateral Discount$_t$			91.454			48.552
			(1.553)			(1.080)
Ln(Portfolio Value$_t$)		1.841	1.448		2.055	1.742
		(0.629)	(0.496)		(0.719)	(0.615)
ROA$_{t-1}$	-346.388***	-344.106***	-340.648***	-349.975***	-347.512***	-344.645***
	(-5.626)	(-5.572)	(-5.580)	(-5.602)	(-5.556)	(-5.633)
Tangibility$_{t-1}$	26.698	24.657	24.956	23.605	21.183	20.816
	(1.500)	(1.335)	(1.431)	(1.313)	(1.136)	(1.201)
Market-to-book$_{t-1}$	-3.834	-3.967	-3.888	-3.434	-3.542	-3.186
	(-1.197)	(-1.240)	(-1.224)	(-1.080)	(-1.115)	(-1.022)
Ln(Assets$_{t-1}$)	-4.123	-4.794	-4.745	-3.715	-4.445	-4.425
	(-1.222)	(-1.377)	(-1.359)	(-1.080)	(-1.239)	(-1.225)
Ln(Loan Maturity$_t$)	-3.294	-3.340	-3.282	-3.913	-3.970	-4.507
	(-0.334)	(-0.338)	(-0.334)	(-0.402)	(-0.408)	(-0.472)
Ln(Loan Amount$_t$)	-11.175***	-11.226***	-11.590***	-11.447***	-11.511***	-11.914***
	(-3.134)	(-3.135)	(-3.255)	(-3.178)	(-3.184)	(-3.331)
Loan Type Dummy	✓	✓	✓	✓	✓	✓
Loan Purpose Dummy	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.678	0.678	0.679	0.680	0.680	0.682
Observations	1,201	1,201	1,201	1,201	1,201	1,201

Table 5: Foreign Investment and Commercial Real Estate Prices

This table investigates the impact of foreign investment on commercial real estate prices. We regress quarterly *Ln(Average Price)*, defined as the natural logarithm of average price per square foot for industrial properties, offices, retail properties and apartments, on *Investment from Countries with Increased Uncertainty*. We assume that a country has increased policy uncertainty if the annual average policy uncertainty index (Baker, Bloom, and Davis, 2015) for that country is in the top quintile of its time-series distribution. *Investment from Countries with Increased Uncertainty* is the natural logarithm of total real estate purchases of countries with increased policy uncertainty (in million dollars) plus one, defined at the RCA market and property type level. In columns (5) and (6), we control for regional variation in property prices and foreign investment over time by including dummy variables for the U.S. regions (Mid-Atlantic, Midwest, Northeast, Southeast, Southwest and West) and their interactions with time-fixed effects. Standard errors are clustered at the market level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Ln(Average Price)					*Investment from Countries with Increased Uncertainty*
	(1)	(2)	(3)	(4)	(5)	(6)
Investment from Countries with Increased Uncertainty	0.066***	0.061***	0.028***	0.016**	0.0218***	
	(4.253)	(3.426)	(3.844)	(2.091)	(3.364)	
Investment from Other Countries						-0.00868
						(-1.618)
Property Type FE	✓	✓	✓	✓		
Year X Quarter FE		✓		✓		
Market FE			✓	✓		
Type X Market FE					✓	✓
Type X Year X Quarter FE					✓	✓
Region X Year X Quarter FE					✓	✓
Adjusted R-squared	0.331	0.366	0.637	0.678	0.724	0.175
Observations	13,962	13,962	13,962	13,962	13,962	13,962

Table 6: Loan Spreads and Foreign Investment

This table reports the results from the regression of loan spreads on a firm's exposure to the markets that received abnormal investments from countries with increased policy uncertainty. In order to detect property types and markets with abnormal investment, we first estimate the residuals from the regression of *Investment from Countries with Increased Uncertainty* on *Investment from Other Countries.* A property is subject to abnormal foreign investment if the predicted residual for its type and market is in the top 10% of the distribution. *I(Abnormal Investment>0)* is a dummy variable that equals one if at least one of the properties of the firm is located in a market that received abnormal investment from increased uncertainty countries in year t. Standard errors are clustered at the firm level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Loan Spread					
	Asset Deployability			*Number of Potential Buyers*		
	(1)	(2)	(3)	(4)	(5)	(6)
I(Abnormal Investment > 0)	-18.818**	7.920	14.010	-18.622**	25.423	29.619
	(-2.492)	(0.625)	(0.993)	(-2.483)	(1.207)	(1.378)
X Collateral Discount$_t$		-195.514**	-178.129**		-228.156**	-206.314*
		(-2.323)	(-2.042)		(-2.027)	(-1.772)
X Secured Dummy$_t$=Yes			-17.669			-16.995
			(-1.128)			(-1.092)
X Ind.-Adj. Leverage$_{t-1}$		-140.073***	-124.905**		-197.798**	-176.156**
		(-2.605)	(-2.299)		(-2.369)	(-2.052)
Collateral Discount$_t$		113.973**	110.909**		154.081***	150.611***
		(2.242)	(2.149)		(2.873)	(2.809)
Ind.-Adj. Leverage$_{t-1}$	72.917***	120.136***	118.148***	73.131***	164.058***	161.312***
	(3.949)	(4.584)	(4.422)	(3.947)	(5.499)	(5.351)
Secured Dummy$_t$=Yes	73.593***	74.297***	78.149***	73.706***	73.120***	76.802***
	(8.422)	(8.686)	(8.366)	(8.454)	(8.654)	(8.385)
Secured Dummy$_t$=Missing	2.749	3.535	5.153	2.782	3.154	4.862
	(0.602)	(0.777)	(0.983)	(0.610)	(0.699)	(0.937)
X I(Abnormal Investment > 0)			-7.915			-8.372
			(-0.689)			(-0.722)
Firm Controls	✓	✓	✓	✓	✓	✓
Loan Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.678	0.681	0.681	0.678	0.682	0.682
Observations	1,201	1,201	1,201	1,201	1,201	1,201

Table 7: Loan Spreads and Land Supply Elasticity

We obtain land supply elasticities from Saiz (2010), which are available for 95 MSAs, and range between 0.60 and 5.45. We split the RCA markets into two equally sized groups with respect to their land elasticities, and then determine the real estate properties located in areas with below-median supply elasticity. Next, we calculate the percentage of a firm's real estate portfolio value that is located in an inelastic market *and* received abnormal investment from countries with increased uncertainty. *I(Abnormal Investment-Low Elasticity > 0)* is an indicator variable that equals one if a firm has *at least one* property located in an area with low supply elasticity and abnormal investment from countries with increased uncertainty. Standard errors are clustered at the firm level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Loan Spread	
	Asset Deployability	*Number of Potential Buyers*
	(1)	(2)
I(Abnormal Investment-Low Elasticity > 0)	26.669	60.595
	(1.139)	(1.645)
X Collateral Discount$_t$	-301.558**	-391.623**
	(-2.103)	(-2.086)
X Secured Dummy$_t$=Yes	21.681	25.798
	(0.725)	(0.810)
X Ind.-Adj. Leverage$_{t-1}$	-192.977**	-294.373**
	(-2.139)	(-2.329)
Collateral Discount$_t$	115.275**	156.230***
	(2.344)	(3.041)
Ind.-Adj. Leverage$_{t-1}$	115.750***	162.271***
	(4.482)	(5.576)
Secured Dummy$_t$=Yes	73.138***	71.287***
	(8.174)	(8.053)
Secured Dummy$_t$=Missing	3.681	3.561
	(0.762)	(0.744)
X I(Abnormal Investment-Low Elasticity > 0)	-7.717	-8.323
	(-0.511)	(-0.532)
Firm Controls	✓	✓
Loan Controls	✓	✓
Year FE	✓	✓
Industry FE	✓	✓
Adjusted R-squared	0.678	0.680
Observations	1,201	1,201

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. All ratio variables in this panel are winsorized at the 2.5% and 97.5%. 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 C presents the definitions of loan-level variables from Dealscan.

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**
Interest Coverage	Operating Income / Interest Expense	**oibdp / xint**
Ind.-Adj. Leverage	Leverage - Median Industry Leverage	
Median Industry Leverage	Calculated based on 3-digit SIC industry. If there are less than 5 firms in the 3-digit SIC industry, Fama-French 49 industries or 2-digit SIC industry definitions are used.	
Herfindahl Index	Sum of squared market shares of all firms in the same three-digit SIC industry	

Panel B: Property Variables

Variable	Definition
Ln(Price)	Ln[(Transaction price / square feet) + 1]
Size	Ln(square feet)
Age	Six categories: $\leq$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
Ln(Average Price)	Natural logarithm of average price per square foot for property types Apartment, Industrial, Office and Retail

Panel C: Loan Variables

Variable	Definition
Spread	All-in-drawn spread winsorized at the 2.5% and 97.5%
Loan Amount	Loan amount in dollars
Loan Maturity	Loan maturity period in months
Loan Type	An indicator with one of the following values: term loan, revolver loan $<$ 1 year, revolver loan $\geq$ 1 year, 364-day facility and others
Loan Purpose	An indicator with one of the following values: acquisition, corporate purposes, CP backup, debt repayment, takeover and others

Table A2: Robustness Tests

Panel A reports the estimation results for the specification in column (4) of Table 2 (baseline model) using alternative distress proxies. Panel B reports the results from the robustness tests of the baseline model for different specifications and subsamples. Column (1) estimates the baseline model for the subsample before 2007. Column (2) includes two-digit SIC industry-fixed effects. The sample in column (3) is restricted to sales that are not part of a portfolio transaction. Column (4) restricts the sample to properties that are located in a different state than the seller's headquarters. Standard errors are clustered at the firm level. Market-fixed effects and quarter-fixed effects are defined for each property type separately. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Ln(Price)				
Panel A	(1)	(2)	(3)	(4)	(5)
Industry-Adjusted Leverage$_{t-1}$	-0.551***				
	(-3.393)				
Leverage$_{t-1}$		-0.659***			
		(-4.638)			
Medium Leverage Dummy$_{t-1}$			-0.181**		
			(-2.428)		
High Leverage Dummy$_{t-1}$			-0.229***		
			(-3.270)		
High Leverage & Low Current Assets Dummy$_{t-1}$				-0.155**	
				(-2.310)	
Interest Coverage Ratio$_{t-1}$					0.009***
					(3.075)
Property Characteristics	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Type X Year X Quarter FE	✓	✓	✓	✓	✓
Type X Market FE	✓	✓	✓	✓	✓
Adjusted R-squared	0.615	0.617	0.614	0.601	0.606
Observations	2,274	2,274	2,274	2,175	2,218

Table A2 Cont.: Robustness Tests

	Ln(Price)			
Panel B	(1)	(2)	(3)	(4)
Medium Ind.-Adj. Leverage Dummy$_{t-1}$	-0.192***	-0.121**	-0.190***	-0.234**
	(-2.913)	(-2.486)	(-3.199)	(-2.488)
High Ind.-Adj. Leverage Dummy$_{t-1}$	-0.208**	-0.165***	-0.276***	-0.341***
	(-2.336)	(-3.118)	(-3.738)	(-3.208)
Adjusted R-squared	0.520	0.646	0.645	0.618
Observations	1,097	2,274	1,515	1,785
Industry-Adjusted Leverage$_{t-1}$	-0.457**	-0.392***	-0.650***	-0.705***
	(-2.594)	(-3.296)	(-4.559)	(-3.390)
Adjusted R-squared	0.520	0.647	0.645	0.615
Observations	1,097	2,274	1,515	1,785
High Leverage & Low Current Assets Dummy$_{t-1}$	-0.197***	-0.099**	-0.170***	-0.188**
	(-3.244)	(-2.512)	(-2.745)	(-2.200)
Adjusted R-squared	0.509	0.638	0.627	0.598
Observations	1,057	2,175	1,454	1,701
Interest Coverage Ratio$_{t-1}$	0.006**	0.004**	0.010***	0.011***
	(2.236)	(2.356)	(3.756)	(3.019)
Adjusted R-squared	0.505	0.634	0.627	0.605
Observations	1,067	2,218	1,461	1,741
Property Characteristics	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Type X Year X Quarter FE	✓	✓	✓	✓
Type X Market FE	✓	✓	✓	✓
Industry FE		✓		

Table A3: Hedonic Model and Firm Distress

Columns (1)-(2) report the estimation results of the hedonic model where we regress *Ln(Price)* on various observable property characteristics. In column (2), we include property characteristics as well as their interactions with property type indicators. The reported coefficient estimates are for the reference property type (*Apartment*). Columns (3)-(6) report the coefficient estimates from the regression of the residuals estimated in column (2) on leverage tercile dummies and firm characteristics. In columns (1) and (2), standard errors are clustered at the RCA market level and in columns (3)-(6) at the firm level. Market-fixed effects and quarter-fixed effects are defined for each property type separately. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Ln(Price) (First Stage)		*Residual Price (Second Stage)*			
	(1)	(2)	(3)	(4)	(5)	(6)
Property Size	-0.180***	-0.047**				
	(-15.833)	(-2.101)				
Age Group 1	-0.241***	-0.291***				
	(-21.243)	(-13.986)				
Age Group 2	-0.401***	-0.473***				
	(-24.121)	(-14.259)				
Age Group 3	-0.476***	-0.548***				
	(-19.413)	(-13.576)				
Age Group 4	-0.487***	-0.458***				
	(-15.398)	(-6.472)				
Age Group 5	-0.468***	-0.569***				
	(-15.137)	(-9.422)				
Renovated	0.132***	0.087***				
	(9.066)	(2.974)				
Portfolio	0.002	-0.032				
	(0.121)	(-1.196)				
Central Business District	0.373***	0.347***				
	(4.804)	(4.094)				
Medium Ind.-Adj. Leverage Dummy$_{t-1}$			-0.192***	-0.180**	-0.184**	-0.165**
			(-2.657)	(-2.266)	(-2.397)	(-2.120)
High Ind.-Adj. Leverage Dummy$_{t-1}$			-0.224***	-0.267***	-0.211**	-0.250**
			(-2.777)	(-2.940)	(-2.373)	(-2.549)
ROA$_{t-1}$			-0.482*	-0.422	-0.560*	-0.374
			(-1.883)	(-1.320)	(-1.778)	(-1.080)
Tangibility$_{t-1}$			-0.029	0.011	-0.070	-0.031
			(-0.222)	(0.067)	(-0.434)	(-0.175)
Market-to-book$_{t-1}$			0.041	0.022	0.047*	0.029
			(1.615)	(0.844)	(1.843)	(1.086)
Ln(Assets$_{t-1}$)			-0.022	-0.019	-0.018	-0.021
			(-1.426)	(-1.171)	(-1.013)	(-1.284)
Type X Year X Quarter FE	✓	✓		✓		✓
Year X Market FE	✓	✓				
Property Type Interactions		✓				
Type X Market FE					✓	✓
Adjusted R-squared	0.565	0.587	0.034	0.052	0.073	0.084
Observations	30,310	30,310	2,274	2,274	2,274	2,274

Table A4: Robustness Tests (Residual Price)

Panel A reports the estimation results for the specification in column (6) of Table A3 using alternative distress proxies. Panel B reports the results from the robustness tests of the baseline model for different specifications and subsamples. Column (1) estimates the baseline model for the subsample before 2007. Column (2) includes two-digit SIC industry-fixed effects. The sample in column (3) is restricted to sales that are not part of a portfolio transaction. Column (4) restricts the sample to properties that are located in a different state than the seller's headquarters. Standard errors are clustered at the firm level. Market-fixed effects and quarter-fixed effects are defined for each property type separately. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Residual Price				
Panel A	(1)	(2)	(3)	(4)	(5)
Industry-Adjusted Leverage$_{t-1}$	-0.506***				
	(-2.705)				
Leverage$_{t-1}$		-0.572***			
		(-3.648)			
Medium Leverage Dummy$_{t-1}$			-0.195**		
			(-2.126)		
High Leverage Dummy$_{t-1}$			-0.187**		
			(-2.320)		
High Leverage & Low Current Assets Dummy$_{t-1}$				-0.166**	
				(-2.179)	
Interest Coverage Ratio$_{t-1}$					0.009***
					(2.838)
Firm Controls	✓	✓	✓	✓	✓
Type X Year X Quarter FE	✓	✓	✓	✓	✓
Type X Market FE	✓	✓	✓	✓	✓
Adjusted R-squared	0.078	0.080	0.077	0.074	0.093
Observations	2,274	2,274	2,274	2,175	2,218

Table A4 Cont.: Robustness Tests (Residual Price)

	Residual Price			
Panel B	(1)	(2)	(3)	(4)
Medium Ind.-Adj. Leverage Dummy$_{t-1}$	-0.163***	-0.096**	-0.189***	-0.205*
	(-2.731)	(-2.039)	(-3.004)	(-1.918)
High Ind.-Adj. Leverage Dummy$_{t-1}$	-0.171*	-0.135***	-0.280***	-0.326**
	(-1.930)	(-2.650)	(-3.125)	(-2.498)
Adjusted R-squared	0.043	0.169	0.082	0.085
Observations	1,097	2,274	1,515	1,785
Industry-Adjusted Leverage$_{t-1}$	-0.388**	-0.320***	-0.640***	-0.644**
	(-2.291)	(-2.748)	(-3.704)	(-2.503)
Adjusted R-squared	0.042	0.169	0.080	0.077
Observations	1,097	2,274	1,515	1,785
High Leverage & Low Current Assets Dummy$_{t-1}$	-0.206***	-0.077**	-0.188**	-0.206**
	(-3.275)	(-2.032)	(-2.567)	(-1.983)
Adjusted R-squared	0.043	0.172	0.065	0.072
Observations	1,057	2,175	1,454	1,701
Interest Coverage Ratio$_{t-1}$	0.006**	0.004**	0.010***	0.012***
	(2.314)	(2.206)	(3.137)	(2.716)
Adjusted R-squared	0.050	0.162	0.088	0.092
Observations	1,067	2,218	1,461	1,741
Firm Controls	✓	✓	✓	✓
Type X Year X Quarter FE	✓	✓	✓	✓
Type X Market FE	✓	✓	✓	✓
Industry FE		✓		

Table A5: Residual Prices and Quality Proxies

This table reports the results from the regression of *Residual Price* on each of the quality proxies. *Redevelopment/Renovation* is an indicator variable that equals one if the buyer's intention is to renovate or redevelop the property. *Vacant Dummy* indicates that the property is vacant at the time of the sale. *Occupancy Rate* is defined as the floor space or units occupied by tenants as a percentage of the total leasable area of the building. Market-fixed effects and quarter-fixed effects are defined for each property type separately. Standard errors are clustered at the firm level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Residual Price					
Panel A.1	(1)	(2)	(3)	(4)	(5)	(6)
Redevelopment/Renovation	-0.196***			-0.181***		
	(-3.385)			(-3.157)		
Vacant Dummy		-0.354***			-0.335***	
		(-5.612)			(-6.078)	
Occupancy Rate			0.289***			0.284***
			(5.140)			(5.280)
Medium Ind.-Adj. Leverage Dummy$_{t-1}$				-0.161**	-0.159*	-0.164**
				(-2.091)	(-1.825)	(-1.998)
High Ind.-Adj. Leverage Dummy$_{t-1}$				-0.238**	-0.225**	-0.249**
				(-2.435)	(-2.172)	(-2.499)
Firm Controls	✓	✓	✓	✓	✓	✓
Type X Year X Quarter FE	✓	✓	✓	✓	✓	✓
Type X Market FE	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.073	0.124	0.100	0.090	0.138	0.117
Observations	2,268	1,949	1,649	2,268	1,949	1,649

Panel A.2	(1)	(2)	(3)	(4)	(5)	(6)
Redevelopment/Renovation	-0.181***			-0.181***		
	(-3.056)			(-3.463)		
Vacant Dummy		-0.356***			-0.303***	
		(-6.056)			(-5.971)	
Occupancy Rate			0.293***			0.248***
			(5.365)			(4.671)
High Leverage & Low Current Assets Dummy$_{t-1}$	-0.157**	-0.149*	-0.171**			
	(-2.063)	(-1.858)	(-2.074)			
Interest Coverage Ratio$_{t-1}$				0.009***	0.008**	0.007*
				(2.799)	(2.349)	(1.939)
Firm Controls	✓	✓	✓	✓	✓	✓
Type X Year X Quarter FE	✓	✓	✓	✓	✓	✓
Type X Market FE	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.080	0.136	0.115	0.099	0.139	0.108
Observations	2,169	1,884	1,587	2,212	1,904	1,605

Table A6: Asset Deployability and Potential Buyers (Residual Prices)

This table reports the results from the regression of residual prices on firm distress with asset deployability interactions (Panel A) and with the number of potential buyer interactions (Panal B). *Office Dummy* is an indicator variable takes one for offices and for properties that can be used for both industrial or office activities. The number of potential buyers is measured by one of the following three variables: (i) *1-Herfindahl Index* is the Herfindahl Index of sales based on the firm's three-digit SIC industry, (ii) *10-K Count* is the number of companies in the seller firm's three-digit SIC industry that mentions the state of the property in its 10-Ks at least once during the year preceding the transaction (Garcia and Norli, 2012), (iii) *Headquarters count* is the number of companies in the seller firm's three-digit SIC industry whose headquarters are located in the same state as the property. Standard errors are clustered at the firm level. Market-fixed effects and quarter-fixed effects are defined for each property type separately. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

Panel A: Asset Deployability

	Residual Price			
	(1)	(2)	(3)	(4)
Medium Ind.-Adj. Leverage Dummy$_{t-1}$	-0.185*			
	(-1.785)			
X Office Dummy	0.100			
	(0.843)			
High Ind.-Adj. Leverage Dummy$_{t-1}$	-0.349***			
	(-2.762)			
X Office Dummy	0.293**			
	(2.142)			
Industry-Adjusted Leverage$_{t-1}$		-0.663***		
		(-2.730)		
X Office Dummy		0.473*		
		(1.694)		
Interest Coverage Ratio$_{t-1}$			0.012***	
			(3.175)	
X Office Dummy			-0.011***	
			(-2.653)	
High Leverage & Low Current Assets Dummy$_{t-1}$				-0.245**
				(-2.400)
X Office Dummy				0.226**
				(1.983)
Firm Controls	✓	✓	✓	✓
Office Interactions	✓	✓	✓	✓
Type X Year X Quarter FE	✓	✓	✓	✓
Type X Market FE	✓	✓	✓	✓
Adjusted R-squared	2,274	2,274	2,218	2,175
Observations	0.108	0.101	0.120	0.099

Table A6 Cont.: Asset Deployability and Potential Buyers (Residual Prices)

Panel B: Potential Buyers

	Residual Price								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1-Herfindahl Index	0.582***	0.272*	0.467***						
	(3.871)	(1.700)	(3.792)						
10-K Count				0.046***	0.031	0.049***			
				(2.989)	(1.390)	(3.192)			
Headquarters Count							0.049**	0.013	0.053***
							(2.562)	(0.465)	(2.763)
Medium Ind.-Adj. Leverage Dummy_{t-1}		-0.229			-0.166			-0.189**	
		(-1.507)			(-1.523)			(-1.969)	
X Number of Buyers		0.082			0.002			0.024	
		(0.443)			(0.068)			(0.667)	
High Ind.-Adj. Leverage Dummy_{t-1}		-0.628***			-0.427***			-0.397***	
		(-3.301)			(-3.201)			(-3.400)	
X Number of Buyers		0.556**			0.074**			0.106***	
		(2.555)			(2.215)			(2.907)	
Industry-Adjusted Leverage_{t-1}			-1.299**			-0.840***			-0.733***
			(-2.218)			(-3.139)			(-3.043)
X Number of Buyers			1.056			0.128*			0.131
			(1.575)			(1.738)			(1.637)
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Type X Year X Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Type X Market FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.090	0.109	0.103	0.070	0.095	0.089	0.069	0.097	0.087
Observations	2,274	2,274	2,274	2,274	2,274	2,274	2,274	2,274	2,274

Table A7: Liquidity and Asset Selection

This table reports the coefficient estimates from the logit regression of *Sold Asset Indicator* that equals one if a property was sold in a given year and zero otherwise, on our liquidity proxies as well as various property characteristics and firm controls. *Ln(Annual Sales Volume)* is the natural logarithm of annual sales volume in a given RCA market, defined for each property type separately. *Portfolio Volume Rank* represents the portfolio (percentile) ranking of a property's RCA market with respect to its *Annual Sales Volume*. Standard errors are clustered at the firm level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Sold Asset Indicator			
	(1)	(2)	(3)	(4)
Ln(Total Sales Volume)	0.176***		0.224***	
	(4.420)		(5.309)	
Portfolio Volume Rank		0.272**		0.196
		(2.194)		(1.319)
Property Size	0.028	0.036	-0.004	0.005
	(0.831)	(1.053)	(-0.092)	(0.122)
Age Group 1	0.135	0.146	0.098	0.104
	(0.967)	(1.021)	(0.585)	(0.621)
Age Group 2	-0.004	0.005	-0.011	-0.006
	(-0.026)	(0.031)	(-0.066)	(-0.035)
Age Group 3	-0.131	-0.123	-0.186	-0.175
	(-1.048)	(-0.975)	(-1.235)	(-1.163)
Age Group 4	-0.039	-0.034	-0.114	-0.108
	(-0.262)	(-0.232)	(-0.597)	(-0.565)
Age Group 5	-0.003	0.005	-0.050	-0.030
	(-0.023)	(0.031)	(-0.281)	(-0.173)
Renovated	0.153	0.156	0.263**	0.265**
	(1.406)	(1.447)	(2.256)	(2.295)
Central Business District	-0.216	-0.221	-0.243	-0.251
	(-1.285)	(-1.312)	(-1.338)	(-1.392)
Office	-0.122	-0.009	-0.136	0.006
	(-1.133)	(-0.094)	(-1.021)	(0.043)
Retail	-0.201*	-0.158	0.001	0.074
	(-1.790)	(-1.409)	(0.005)	(0.462)
Portfolio	0.704***	0.717***	0.934***	0.939***
	(3.766)	(3.821)	(3.148)	(3.144)
Ind.-Adj. Leverage$_{t-1}$	1.015**	1.035**	1.551	1.574
	(2.066)	(2.101)	(1.155)	(1.181)
ROA$_{t-1}$	-2.590**	-2.676***	-4.568**	-4.518**
	(-2.541)	(-2.671)	(-2.139)	(-2.124)
Tangibility$_{t-1}$	-0.755***	-0.784***	-3.064*	-3.230**
	(-2.946)	(-3.046)	(-1.940)	(-2.039)
Market-to-book$_{t-1}$	-0.052	-0.042	0.160	0.166
	(-0.625)	(-0.504)	(1.484)	(1.531)
Ln(Assets$_{t-1}$)	0.065	0.062	-0.419	-0.413
	(1.600)	(1.526)	(-1.628)	(-1.613)
Year FE	✓	✓	✓	✓
Market FE	✓	✓	✓	✓
Firm FE			✓	✓
Observations	20,588	20,588	19,671	19,671

Table A8: Loan Spreads and Collateral Discount (Robustness Tests)

This table reports the results from robustness tests of the specifications in Table 4, 6 and 7. *Portfolio Value/PPE* is the ratio of real estate portfolio value to total propererty, plant and equipment. *Median Industry Leverage* is the median book leverage ratio of a firm's three-digit SIC industry. All regressions include fixed effects for firm headquarters state. Standard errors are clustered at the firm level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Loan Spread					
	Asset Deployability			*Number of Potential Buyers*		
	(1)	(2)	(3)	(4)	(5)	(6)
Collateral Discount$_t$	86.578*	95.310*	97.500**	118.850**	131.332**	131.203**
	(1.759)	(1.880)	(1.972)	(2.252)	(2.372)	(2.450)
I(Abnormal Investment > 0)		5.262			25.372	
		(0.415)			(1.179)	
X Collateral Discount$_t$		-179.880**			-232.103**	
		(-2.178)			(-2.058)	
X Ind.-Adj. Leverage$_{t-1}$		-130.837**			-200.397**	
		(-2.436)			(-2.350)	
I(Abnormal Investment-Low Elasticity > 0)			29.338			62.577*
			(1.255)			(1.809)
X Collateral Discount$_t$			-293.200**			-380.985**
			(-2.000)			(-2.285)
X Ind.-Adj. Leverage$_{t-1}$			-191.841**			-288.866***
			(-2.117)			(-2.625)
Ind.-Adj. Leverage$_{t-1}$	119.935***	129.050***	125.928***	152.193***	165.041***	162.057***
	(4.698)	(4.979)	(5.015)	(5.311)	(5.576)	(5.612)
Portfolio Value/PPE$_t$	-29.809	-32.081	-32.579	-27.983	-30.960	-30.492
	(-0.556)	(-0.628)	(-0.601)	(-0.505)	(-0.583)	(-0.549)
Median Industry Leverage$_{t-1}$	73.118*	65.600*	71.224*	58.096	54.938	58.787
	(1.948)	(1.716)	(1.876)	(1.484)	(1.377)	(1.506)
Firm Controls	✓	✓	✓	✓	✓	✓
Loan Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
HQ State FE	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.680	0.682	0.680	0.681	0.683	0.681
Observations	1,200	1,200	1,200	1,200	1,200	1,200