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

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Abstract

Constructing a novel database on the real-estate holdings of public firms, we show that distressed firms sell their real-estate assets at a discount relative to healthy firms. We find that distress discount in real-estate assets is less pronounced for sellers with less liquidity-constrained industry peers and in machinery-heavy industries. We also document that asset redeployability and the availability of potential buyers are two important property-specific determinants of the distress discount. Additionally, firms' property portfolios that are less redeployable with less potential buyers exacerbate the negative impact of financial distress on the cost of borrowing.

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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 the value of all commercial and

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industrial loans made by domestic banks in the USA 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 can become a concern for the lender.

Using commercial aircraft transactions, Pulvino (1998) investigates the impact of capital constraints on the liquidation price and documents a 14% discount for the aircrafts sold by financially constrained airlines. Although aircrafts are a major asset type that airline companies invest in, it is not a typical asset for firms in other industries. Therefore, this paper focuses on commercial real estate, an asset class that is common to all firms regardless of their industries. For instance, according to Cvijanović (2014), 54% of Compustat firms reported some real-estate ownership on their balance sheet. Campello and Giambona (2013) document that between 1984 and 1996, an average nonfinancial firm has 11.8% of its total assets invested in land and buildings, which coincides with about 33% of its tangible assets. Hence, it is important to uncover the factors that affect the liquidation value of real-estate assets and understand whether those factors play any role in a firm's financing activities.

The primary objective of this paper is to investigate whether a firm's financial health affects the liquidation value of its real-estate assets. For this purpose, we assemble a unique dataset of real-estate portfolios of nonfinancial public firms to identify individual real-estate properties' location, type, and other property-specific features, such as whether the real estate can be used for alternative purposes.[1] Using this dataset, we investigate the extent to which specific property characteristics, as well as the seller's industry, moderate the relationship between the transaction price and the seller's financial health. Finally, we study whether the variation in a firm's property portfolio value affects its cost of borrowing.

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 be used for more general purposes and/or if there are multiple potential buyers from a seller's industry located or active in the property's state. Consistent with Shleifer and Vishny (1992), we also find that the impact of a firm's financial distress on the transaction price is exacerbated when the firm's industry peers are also liquidity-constrained. There is also considerable cross-industry variation in the distress discount: the distress discount in commercial real estate is less prominent in machinery-heavy industries. Moreover, our loan-level analysis suggests that lenders charge borrowers less if a borrower's real-estate portfolio has desirable redeployability characteristics that can increase the portfolio's liquidation value.

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 interest coverage ratio, leverage, and an indicator for highly levered firms with low current assets proposed by Pulvino (1998). We find that decreasing a firm's interest coverage ratio by one standard deviation corresponds to a 17% lower selling price after controlling for a battery of property and seller characteristics. Our findings are robust to using book leverage and a high leverage/low current asset dummy as alternative distress proxies and to various model specifications. Moreover, following Falato and Liang (2016), we use

1 Previous literature estimates the value of real-estate holdings based on the accumulated depreciation of buildings, which firms are no longer required to report after 1993 (Chaney, Sraer, and Thesmar, 2012; Cvijanović, 2014). Furthermore, because Compustat does not provide the geographic location of real-estate assets, the market value of real-estate holdings after 1993 are often approximated based on a firm's headquartered location.

violation of loan covenants as an alternative indicator of a seller's financial condition. Covenant violations are more common than payment defaults, and they allow the creditors to demand immediate repayment of the principal and terminate future lending commitments. Hence, violations can trigger financial distress without the borrower defaulting on payments and filing for bankruptcy. Our findings indicate that properties that are sold following a covenant violation fetch significantly lower prices, that is, the distress discount associated with a covenant violation is about 0.18 standard deviations.

An important concern about our analysis is the potential endogenous relationship between a firm's financial health and the transaction price of its property. In particular, an omitted variable that is correlated with both the firm's financial condition and the value of its property can drive our results. For instance, the quality of the management can be correlated with the quality of real-estate assets purchased or how well they are maintained by the management. While it is not straightforward to solve this type of endogeneity problem as quality is unobservable, we attempt to address the issue in two ways. First, we perform a regression discontinuity analysis. Following Chava and Roberts (2008), we limit our sample to firm-year observations that fall within a narrow range around a covenant threshold. We identify the impact of a covenant violation by comparing the transaction prices of sellers that breach a covenant by a small margin to those that do not breach a covenant but have accounting variables with values close to the covenant threshold. In this setup, we assume firm quality is similar around the threshold, at least with respect to accounting distress measures, and identify financial distress as when one firm violates a covenant while the other firm does not but is close to violating it. Although the discontinuity analysis substantially limits the sample size, we find a significant impact of financial distress on property prices. In our second analysis, we limit our sample to properties with repeated transactions. By tracking the changes in the transaction price of the same property over time, the impact of property quality on property value is significantly reduced. In line with this approach, we regress the differential price from repeated sales of the same property on our distress proxies. We show that firm distress measured by common financial indicators has a significantly negative impact on the differential price.

Another plausible explanation for our findings is that local economy-wide conditions can potentially drive firms into distress. At the same time, they can affect local real-estate prices, without a causal relation between distress and real-estate prices. Firms that are dependent on local markets, if they have concentrated real-estate assets in the same location, are more prone to such an omitted variable problem. To understand whether this scenario explains our results, we perform two tests. First, we include market-by-property type-by-year fixed effects in our specifications and find results consistent with our baseline specification. This particular fixed effect specification allows us to control for local economic factors that can simultaneously influence transaction prices and a firm's financial health. Second, as a more direct test of local dependency on our results, we divide industries into local and global industries, based on the amounts of their out-of-state shipments. We find that distress discount is less pronounced for local firms, indicating that our findings are not driven by local economic activity.

As real estate is a broader type of asset owned by firms from various industries, we further analyze whether there is heterogeneity in the distress discount related to property-specific and sellers' industry-specific characteristics. Past literature offers clues about potential factors that might affect the liquidation value of real-estate assets. We study two of these factors, namely asset redeployability and availability of potential buyers.

A distribution center with a specific layout can only be utilized by a buyer that has characteristics similar to those of the seller (e.g., in terms of industry, location, customer base, etc.). Conversely, an office space can be purchased and used by buyers both within and outside the seller's industry; hence, offices are more redeployable relative to distribution centers. We find that, unlike their more specialized counterparts, redeployable assets do not suffer large discounts when they are sold by financially distressed firms. More specifically, office properties receive up to a 50% lower price discount on average relative to more specialized industrial and retail properties.

Our data allow us to test whether the 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 seek transaction opportunities during times when the best potential users of the asset are also liquidity-constrained.[2] Since 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 potential buyers from the same industry as the seller located in the same state as the property. Our results indicate that an increased number of potential buyers alleviates the discount on distress sales up to 50%.

Next, we exploit the cross-industry variation in distress discount. First, following Shleifer and Vishny (1992), we investigate whether the magnitude of collateral discount depends on the financial health of potential buyers. Indeed, consistent with Shleifer and Vishny (1992), we find that real-estate assets are sold at a higher distress discount if industry peers of the seller are liquidity-constrained. Second, we differentiate between different types of tangible assets. We expect that machinery-heavy industries rely less on real estate as collateral. We also anticipate that firms in these industries are more likely to liquidate their machinery and equipment in case of distress. Our findings complement the results of Pulvino (1998) by showing that collateral discount in real estate is more pronounced for less machinery-heavy industries.

After establishing asset redeployability and the number of potential buyers as important determinants of the liquidation value, next we investigate whether a bank's pricing of a loan reflects these determinants. To do so, we first estimate the value of the real-estate asset holdings of the firms in our sample, and then calculate the fraction of assets with desirable redeployability characteristics. We then relate our portfolio redeployability and potential buyers measures to loan pricing. Our results show that a one-standard-deviation decrease in the interest coverage ratio is associated with a 0.15-standard-deviation increase in loan spreads for firms with below-median portfolio redeployability and potential buyers, whereas the impact of the interest coverage ratio is insignificant for those with above-median portfolio redeployability and potential buyers. Overall, our findings suggest that the property-specific factors that can affect collateral value are priced in debt markets.

Our paper contributes to several strands of the literature. To our knowledge, this is the first study that estimates the economic magnitude of the impact of a corporate seller's

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.

financial health on the transaction price of its commercial real-estate assets.[3] Second, our paper helps generalize the findings of Pulvino (1998) to a widely held asset class. Pulvino (1998) documents distress discount for an asset class specific to a single industry, whereas real-estate assets are commonly held and used as collateral by almost all public firms in a variety of industries. When we exploit the cross-industry variation in distress discount, we find that machinery-heavy industries rely less on real estate as collateral, which suggests that firms in these industries are more likely to liquidate their machinery and equipment rather than real property in case of distress.

Finally, the loan analysis in our paper is related to Benmelech, Garmaise, and Moskowitz (2005) and Benmelech and Bergman (2009).[4] Benmelech, Garmaise, and Moskowitz (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 setting allows us to identify property owners and link them to their financial information on Compustat. This information is not available in the data used by Benmelech, Garmaise, and Moskowitz (2005). It is important to study owner and property characteristics together for various reasons. First, we can control for various seller characteristics (such as industry and size) that might have a confounding impact on the relationship between loan contract terms and redeployability of real-estate assets. 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.[5]

The remainder of the paper is organized as follows: Section 2 describes the data and the summary statistics. Section 3 presents the results on the impact of financial distress on real-estate prices and discusses endogeneity concerns. Section 4 investigates the cross-sectional

3 Although we focus on the impact of asset characteristics 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 redeployable 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' investments are twice as sensitive to collateral value as unconstrained firms' investments.

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

5 Using a dataset of secured debt tranches issued by US airlines, Benmelech and Bergman (2009) investigate the impact of aircraft characteristics on the cost of borrowing. They find that more redeployable aircrafts are 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. Second, the industry-specific nature of aircrafts suggests that redeployability would have a more pronounced effect on their collateral value compared with 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 redeployed. Indeed, our findings indicate that office properties, an asset type that is redeployable across different industries, do not lose significant value when they are sold by distressed owners.

variation in distress discount by studying the factors that affect the distress discount and links those factors to the cost of borrowing. Section 5 concludes.

2. Data and Summary Statistics

We use the RCA database to identify commercial real-estate transactions. This database has tracked commercial property and portfolio sales in the USA of $2.5 million or greater since 2000. The data sources for RCA 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 USA-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, the year of property renovation, 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 a RCA market identifier, which is a RCA-defined metropolitan area.

We identify the seller 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.[6] Utility firms (SIC codes between 4900 and 4999) and government entities (SIC code between 9000 and 9999) are also excluded. Our matching procedure yields 322 unique public firms that were involved in 2,279 transactions over the period 2000–13. Because our interest lies in relative prices, we use the remaining transactions, whose sellers are not Compustat firms, to estimate the implied price of the properties in our sample. We obtain firm characteristics from Compustat Annual Files.

Our sample is composed of retail (44%), industrial (37%), and office (19%) properties. Industrial properties include warehouses (26%) and flex (10%) assets, where the property can be used for both industrial and office activities. Retail properties are composed of malls and other (39%) and strip centers (4%). Offices are divided into two subtypes based on their location as either CBD (3%) or suburban area (16%).

In Table I, we summarize the characteristics of the properties and of the sellers in our sample. In order to attenuate the possible impact of outliers on our results, we winsorize all ratio variables at the top and bottom 2.5%, although our results are robust to winsorizing the variables at the top and bottom 1%. The median transaction value in our sample is $6.6 million. The average value of the logarithm of price per square foot and the logarithm of property size in square feet are 4.42 and 11.44, respectively. The average property age in our sample is 22 years. The fraction of properties that were previously renovated is 12% and 33% of the sales are conducted within a portfolio transaction. About 5% of the properties in our sample are located in a CBD. “Office” is a dummy variable that takes one for offices and for properties that can be used for industrial or office activities which constitute 29% of our sample. Additionally, 28% of the properties in our sample were vacant at the

6 We also exclude real-estate investment trusts (REITs) (SIC code 6798) because they buy and sell real estate merely for investment purposes. Indeed, REITs are required to receive at minimum 75% of their gross income from rentals on real property, interest on mortgages that finance real property, or from real-estate sales.

Table I. Summary 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. Ln(Price) is the natural logarithm of price per square foot plus one. Ln(Square feet) is the natural logarithm of property size measured in square feet. Renovated Dummy equals one if there is non-missing data for the year that the property was renovated or expanded. Portfolio Dummy indicates that the sale is part of a portfolio transaction. CBD Dummy equals one if the property is located in a CBD or in the downtown of a city. Residual Price is estimated from the hedonic model given in Column (1) of Online Appendix Table A3. "Redevelopment/Renovation Dummy" 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 not occupied at the time of the sale. "Occupancy Rate" is defined as the percentage of floor space or units occupied by tenants when compared with the total leasable area of the building at the time of the sale. "Office Dummy" is an indicator variable that takes one for offices and for properties that can be used for both industrial and office activities. "Interest Coverage Ratio" is the ratio of income before depreciation divided by interest expense. The negative values of this ratio are normalized to zero and values above 50 are normalized to 50. "Book Leverage" is the ratio of total book debt to book value of assets. "High Leverage and Low Current Assets" indicates that the seller's leverage is above the industry median and its current assets are below the industry median. ROA is defined as operating income scaled by total assets, "Tangibility" is defined as the ratio of property, plant, and equipment (PPE) to total assets and "Market-to-Book Ratio" is the ratio between the market value and the book value of total assets. "Median Ind. Leverage" is determined based on the three-digit SIC codes. "Covenant Violation Dummy" is calculated using the data from Nini, Smith, and Sufi (2012) and equals one if the firm breaches at least one covenant in a given year prior to the property's sale. "Loan Spread" is all-in-drawn spread, which is the rate a borrower pays in basis points over LIBOR including any recurring annual fees on the loan. "Loan Maturity" is in months. All ratio variables are winsorized at the top and bottom 2.5%.

	Mean	SD	p25	Median	p75	N
Ln(Price)	4.42	0.96	3.78	4.49	5.09	2,279
Ln(Square feet)	11.44	1.29	10.71	11.51	12.29	2,279
Property age	22.17	18.38	9.00	18.00	31.00	2,279
Renovated dummy	0.12	0.32	0.00	0.00	0.00	2,279
Portfolio dummy	0.33	0.47	0.00	0.00	1.00	2,279
CBD dummy	0.05	0.23	0.00	0.00	0.00	2,279
Residual price	−0.16	0.60	−0.49	−0.13	0.20	2,133
Redevelopment/renovation dummy	0.11	0.31	0.00	0.00	0.00	2,273
Vacant dummy	0.28	0.45	0.00	0.00	1.00	1,957
Occupancy rate	0.78	0.40	0.85	1.00	1.00	1,647
Office dummy	0.29	0.46	0.00	0.00	1.00	2,279
Interest coverage ratio	16.00	15.75	4.50	9.28	22.55	2,279
Book leverage	0.27	0.16	0.16	0.26	0.35	2,279
High leverage and Low current assets	0.41	0.49	0.00	0.00	1.00	2,177
ROA	0.14	0.08	0.09	0.15	0.18	2,279
Tangibility	0.37	0.18	0.20	0.40	0.54	2,279
Market-to-book	1.43	0.89	0.85	1.24	1.68	2,279
Ln(Assets)	9.49	1.64	8.26	9.80	10.44	2,279
Median ind. leverage	0.20	0.12	0.11	0.19	0.29	2,279
Covenant violation dummy	0.07	0.26	0.00	0.00	0.00	1,221
Loan spread	119.35	117.96	30.00	75.00	175.00	1,220
Ln(Loan spread)	4.30	1.02	3.40	4.32	5.16	1,220
Ln(Loan maturity)	3.46	0.78	2.48	3.87	4.09	1,220
Ln(Loan amount)	20.10	1.15	19.34	20.03	20.91	1,220

time of the sale and the occupancy rate corresponds to 78% for an average property. About 11% of the buyers' main intention is redevelopment or renovation.

One of the most striking differences between the sellers in our sample and the firms in the Compustat universe is the size of their assets. 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 9.49, whereas Compustat median for the same time period is 5.35. Also, the median firm in the RCA sample is more profitable and has more tangible assets relative to the median Compustat firm. In the Compustat universe, median "Tangibility" is 0.14 and median "ROA" is 0.05, whereas in our sample they are 0.40 and 0.15, respectively.

We rely on three variables to proxy for the financial health of the sellers in our sample. "Interest Coverage Ratio" is the ratio of income before depreciation divided by interest expense. "Book Leverage" is the ratio of total book debt to book value of assets. "High Leverage & Low Current Assets" indicates that the seller's leverage is above the industry median and its current assets are below the industry median. The average "Interest Coverage Ratio" and "Book Leverage" are 16% and 27%, respectively. About 41% of the sellers in our sample simultaneously have leverage ratios above their industry median and current assets below their industry median. Alternative to our accounting measures, we also use covenant violation dummy to proxy financial distress using the data from Nini, Smith, and Sufi (2012). In 7% of the transactions in our sample, buyers breach at least one covenant in a given year prior to a property's sale.

For our cost of financing analysis, we obtain loan-level data from Loan Pricing Corporation's (LPC) Dealscan database, which contains detailed information about commercial (primarily syndicated) loans made to US corporations since the 1980s. According to Carey and Hrycray (1999), the Dealscan database covers between 50% and 75% of the value of all commercial loans in the USA during the early 1990s with increased coverage after 1995. Our initial sample contains all commercial loans denominated in US dollars. We link the Dealscan dataset to the Computstat database using the links provided by Chava and Roberts (2008). While each observation in the Dealscan database represents a facility (or a tranche), multiple facilities with similar loan terms and pricing are frequently packaged into deals. Following Hertzel and Officer (2012), we choose the largest facility in each deal as our unit of observation. We define the year of a loan based on its facility start date and each loan appears in our data only once. We require non-missing information on loan amount, loan maturity, loan type, and loan purpose.[7] 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 1,220 loans with a median (mean) spread of 75 (119) basis points.

3. Financial Distress and Real-Estate Prices

3.1 Univariate Results

In this section, we investigate whether there is a significant distress discount in the average price of commercial real-estate assets sold by distressed sellers. Table II reports the results

7 Loan types are indicators for term loans, revolver loans $<$ ($\geq$1 year), 364-day facility, and others. The primary purposes of the facilities in our sample are acquisition line, commercial paper (CP) backup, corporate purposes, debt repayment, takeover, or working capital.

Table II. Univariate results

This table reports the average Ln(Price) and Residual Price for each quintile of Interest Coverage Ratio and Book Leverage as well as for firms with High Leverage and Low Current Assets and others. In each year, observations are split into five quintiles based on the seller's lagged Interest Coverage Ratio and Book Leverage. Quintile 1 and Quintile 5 represent the lowest and the highest quintiles, respectively. Residual Price is estimated based on the regression model in Column (1) of Online Appendix Table A3.

	Coverage quintiles		Leverage quintiles		High Lev. and Low Cur. assets	
	Ln(Price) (1)	Residual price (2)	Ln(Price) (3)	Residual price (4)	Ln(Price) (5)	Residual price (6)
1	4.37	−0.20	4.79	−0.04		
2	4.07	−0.24	4.30	−0.19		
3	4.49	−0.19	4.38	−0.18		
4	4.54	−0.11	4.35	−0.24		
5	4.68	−0.02	4.15	−0.21		
Dif. (Q1−Q5)	−0.30***	−0.18***	0.64***	0.17***		
0					4.54	−0.10
1					4.31	−0.23
Dif. (0 − 1)					0.23***	0.14***

from our univariate analysis. For each year, we split the sample into quintiles based on our financial distress proxies, namely the seller's "Interest Coverage Ratio," "Book Leverage," and "High Leverage and Low Current Assets" dummy. Column (1) compares the average transaction price (Ln(Price)) between the highest and the lowest interest coverage ratio quintiles which reveals a significant discount of 0.3 (0.31 standard deviations) on properties sold by firms with low interest coverage ratios. We obtain similar results when we repeat our univariate analysis for the leverage ratio quintiles and "High Leverage and Low Current Assets" dummy in Columns (3) and (5), respectively. The difference between the average price in the lowest and the highest leverage ratio quintiles is around 0.64 (0.67 standard deviations). Similarly, the average price in "High Leverage and Low Current Assets" group is less than the average price in the rest of the sample by 0.23 (0.24 standard deviations). These univariate results suggest that an average firm in distress faces a significant discount in its real-estate property sales.

We also repeat our univariate analysis based on residual prices estimated from a hedonic model using a larger sample of transactions for which we do not necessarily have the seller's accounting variables. By using a larger sample, we aim to obtain more accurate estimates for the coefficients of the property characteristics. We calculate residual prices from the hedonic model reported in Column (1) of Online Appendix Table A3. Overall, the results on residual prices, as presented in Columns (2), (4), and (6) of Table II, suggest that the difference between the average "Residual Price" of the lowest and the highest financial distress groups is significant at the 1% level for all our measures.

3.2 Baseline Results

In order to control for the effect of confounding factors on our univariate results, we estimate a model where we regress the natural logarithm of the selling price on our distress measures and various property and firm characteristics. The property-specific controls include the natural logarithm of property size, dummy variables indicating the property's age, whether the property was renovated at any point in time, whether the sale is conducted within a portfolio transaction, and whether the property is located in a CBD. We also control for the seller's return on assets (ROA), tangibility, market-to-book, total assets, and industry leverage as well as its industry based on Fama and French 17 industry categories.[8] In all specifications, we control for year-fixed effects that are defined for each property type separately (i.e., year-by property type-fixed effects). We also include dummy variables for the property's RCA market identifier. Standard errors are clustered at both the firm and RCA market level.

Results are reported in Table III which reveal a strong positive relationship between the transaction price and the seller's "Interest Coverage Ratio." Comparing Columns (1) and (2) suggests that the coefficient estimate for the "Interest Coverage Ratio" is largely unaffected when we include industry-fixed effects and market-fixed effects. In Column (3), we include RCA market-by property type-by year-fixed effects to capture the omitted factors that are specific to a geographical market in a given year and a property type. While the number of observations decreases from 2,238 to 1,507, the coefficient estimate of the "Interest Coverage Ratio" remains unchanged. A one-standard-deviation decrease in "Interest Coverage Ratio is associated with a 17% decrease in price.[9] Finally, in Column (4), we include firm-fixed effects which decreases the number of observations further to 1,398. The coefficient estimate of "Interest Coverage Ratio" remains the same and is statistically significant at the 10% level. Overall, our results indicate that the seller's financial health has a significant impact on the transaction price. Furthermore, the findings of Pulvino (1998) can be generalized to a broader asset class that is commonly held by all firms from various industries.

In order to eliminate the impact of the outliers on our findings, we repeat our baseline analysis by replacing the continuous values of "Interest Coverage Ratio" with the quintile dummy variables. Online Appendix Table A1 reveals a monotonic relationship between the interest coverage ratio quintiles and the selling price. The results in Column (2) suggest a 0.36 (0.38 standard deviation) difference in the natural logarithm of per square foot selling price between the lowest and the highest "Interest Coverage Ratio" quintiles which is comparable to the univariate results in Table II.

Next, we repeat our baseline analysis using our alternative distress proxies, namely "Book Leverage" and "High Leverage and Low Current Assets Dummy." The results, as shown in Online Appendix Table A2, point to the same conclusion: 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. For instance, based on the results in Column (1), a one-standard-deviation increase in "Book Leverage" is associated with a 0.11-standard-deviation decrease in property prices. Similarly, on average, a property owned by a firm in "High Leverage and Low Current Assets Dummy" group is sold at a 0.2 standard deviations discount relative to others (Column (4)).

8 Our results are robust to inclusion of Fama and French 49 industry definitions.

9 Because the dependent variable equals the natural logarithm of the transaction price, the discount is calculated by taking the exponent of the estimated coefficient times standard-deviation of Interest Coverage Ratio.

Table III. Transaction price and firm distress

This table reports the results from the regression of Ln(Price) on Interest Coverage Ratio and various property and firm controls. The standard errors are clustered at both the market and firm level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: Ln(Price)			
	(1)	(2)	(3)	(4)
Interest coverage ratio$_{t-1}$	0.01***	0.01***	0.01***	0.01*
	(3.27)	(3.13)	(4.30)	(1.74)
ROA$_{t-1}$	−1.88***	−1.31***	−1.18*	0.16
	(−4.00)	(−3.00)	(−1.94)	(0.19)
Tangibility$_{t-1}$	0.07	−0.03	0.23	0.66
	(0.36)	(−0.22)	(1.29)	(0.96)
Market-to-book$_{t-1}$	−0.02	−0.02	−0.10*	−0.12
	(−0.49)	(−0.68)	(−1.95)	(−1.64)
Ln(Assets$_{t-1}$)	−0.00	−0.01	−0.02	−0.11
	(−0.03)	(−0.73)	(−0.80)	(−0.83)
Median ind. leverage$_{t-1}$	−0.01	0.14	0.17	0.79
	(−0.03)	(0.47)	(0.49)	(1.00)
Ln(Square feet)	−0.39***	−0.35***	−0.34***	−0.29***
	(−11.15)	(−10.46)	(−11.60)	(−8.20)
Age 11–20 years	−0.28***	−0.31***	−0.30***	−0.29***
	(−6.14)	(−9.82)	(−7.54)	(−5.91)
Age 21–30 years	−0.36***	−0.42***	−0.36***	−0.37***
	(−6.05)	(−10.29)	(−8.12)	(−8.69)
Age 31–40 years	−0.37***	−0.52***	−0.46***	−0.45***
	(−5.81)	(−10.40)	(−7.82)	(−7.16)
Age 41–50 years	−0.54***	−0.70***	−0.62***	−0.58***
	(−5.65)	(−9.07)	(−6.68)	(−6.14)
Age 50 or more years	−0.47***	−0.71***	−0.64***	−0.55***
	(−3.84)	(−7.40)	(−5.54)	(−4.70)
Renovated dummy	0.11	0.18***	0.19***	0.16**
	(1.50)	(2.98)	(2.74)	(2.05)
Portfolio dummy	−0.05	0.02	0.02	−0.03
	(−1.00)	(0.49)	(0.36)	(−0.55)
CBD dummy	0.59***	0.32***	0.40***	0.37***
	(3.12)	(2.91)	(2.65)	(3.98)
Year×Type FE	Yes	Yes	No	No
Market FE	No	Yes	No	No
Industry FE	No	Yes	Yes	No
Market×Type×Year FE	No	No	Yes	Yes
Firm FE	No	No	No	Yes
Observations	2,279	2,238	1,507	1,398
R-squared	0.48	0.59	0.60	0.62

3.3 Robustness Tests

We conduct a battery of robustness tests for our baseline specification in Column (3) of Table III. First, we regress residual prices obtained from a larger sample, as explained previously, on our distress proxies. The results presented in Online Appendix Table A3 indicate a positive relationship between the seller's financial health and residual prices.

Next, we control for additional property characteristics that can potentially capture the effect of demand-related factors. 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 these intentions to fetch lower prices. We can also observe the tenancy status and the occupancy rate of the properties. Vacant properties and those with low occupancy rates are arguably less well-maintained compared with properties that are currently in use. Thus, future owners of such properties are likely to incur additional costs and thereby sell at lower prices.

In Online Appendix Table A4, we regress the transaction price on each of the property-specific proxies for demand, namely buyer purpose, tenancy status, and occupancy rate, as well as on the set of control variables and "Interest Coverage Ratio."[10] Results confirm our expectations that the average transaction price is lower for vacant properties and properties with low occupancy rates. After controlling for these additional property characteristics, we continue to find a positive coefficient estimate for the "Interest Coverage Ratio."[11]

Next, we conduct two subsample analyses, the results of which are reported in Online Appendix Table A6. First, we repeat our baseline estimation for the subsample of transactions that were not conducted as part of a portfolio sale. Second, we restrict our sample to properties that are located outside the seller's headquarters state addressing the possibility of local economic conditions simultaneously affecting the real-estate prices and the seller's financial health. Our results continue to hold in these two subsamples, and the coefficient estimates of our distress proxies are comparable to the baseline specification.

Firms in our sample are larger, more profitable, and have more tangible assets compared with an average Compustat firm. In order to check whether firm selection affects our findings, we employ a two-stage regression model. In the first stage, we estimate the likelihood of a randomly selected Compustat firm appearing in our sample as a seller. Our findings suggest that firms are more likely to sell their real-estate assets when their financial health deteriorates. Next, we include the "Inverse Mill's Ratio" calculated from the first-stage probit model in our baseline specification. Overall, the results reported in Online Appendix Table A7 indicate that firm selection does not have a significant impact on the selling price and including the "Inverse Mill's Ratio" in our baseline specification leaves the coefficient estimates of our distress proxies largely unchanged.

10 "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 building's total leasable area.

11 In Online Appendix Table A5, we repeat the analysis for Book Leverage and High Leverage and Low Current Assets Dummy. Overall, the coefficient estimates are largely unaffected by the inclusion of the demand-related controls.

3.4 Alternative Explanations

Our findings based on financial indicators of distress demonstrate that the deterioration of a firm's financial health is associated with a discount in the selling price of its real-estate assets. However, this relationship is subject to various endogeneity concerns. An omitted variable that is correlated with both the financial health of a firm and the transaction price of the property that it sells can drive our findings. For instance, our distress proxies might be correlated with the firm's management quality. This can potentially determine the quality of the real-estate assets purchased and how well they are maintained.

Our first approach addresses the concerns related to time-varying omitted factors such as maintenance quality. We conduct a regression discontinuity analysis based on an important component of loan contracts, namely covenants. Our aim is to evaluate transaction prices following a distress event measured by a covenant violation and plausibly an immediate need for liquidity by those firms that breached a covenant.

Financial covenants, such as minimum net worth or current ratio, are important elements of loan contracts that shift the control rights to creditors upon their breach. Such transfers of control rights can take place even if the firm is not in financial default. Following Chava and Roberts (2008), who study the impact of covenant violations on firms' investment decisions, we exploit the discrete nature of covenant violations and perform a regression discontinuity analysis to identify the impact of distress on the liquidation value of real-estate assets.

Before we conduct the regression discontinuity analysis, we document the relationship between covenant violations and real-estate prices. For this purpose, we use the covenant violation data hand-collected by Nini, Smith, and Sufi (2012) which is available for the period between 2000 and 2008. We define a dummy variable (Covenant Violation Dummy) that takes one if the firm breaches at least one covenant within the year prior to the sale, and zero otherwise. In Table IV, we regress the transaction price on the "Covenant Violation Dummy" and the control variables. In three of the four specifications, we find a significant negative impact of covenant violations on the selling price. The results in Column (2), where we control for the market-by property type-by-year fixed effects, suggest that firms that breach a covenant prior to the sale are associated with about 6% lower prices relative to the sample mean.

We also test whether covenant violations provide any differential information about the financial health of the firm in comparison to "Interest Coverage Ratio." Online Appendix Table A8 repeats the analysis in Table IV this time by including "Interest Coverage Ratio" together with the "Covenant Violation Dummy." The coefficient estimates of "Covenant Violation Dummy" remain similar to baseline results after controlling for "Interest Coverage Ratio." More importantly, both "Covenant Violation Dummy" and "Interest Coverage Ratio" are significant in explaining transaction prices which suggests that they contain differential information about a firm's financial health.

Although the covenant violation data provided by Nini, Smith, and Sufi (2012) accurately detect the firms that actually breached a covenant, the data do not allow for measuring the distance from the violation threshold which is necessary for conducting a regression discontinuity analysis. We follow a similar approach to Chava and Roberts (2008); Falato and Liang (2016); and Ferreira, Ferreira, and Mariano (2018), and infer violations from the accounting data. We focus on two covenants, (tangible) net worth and current ratio

Table IV. Covenant violation analysis

This table reports the results from the regression of the transaction price on the covenant violation indicator. We use the covenant violation data hand-collected by Nini, Smith, and Sufi (2012). "Covenant Violation Dummy" equals one if the firm breaches at least one covenant in a given year prior to the property's sale. The sample period is between 2000 and 2008. The dependent variable in Columns (3) and (4) is the residual price estimated from the hedonic model given in Column (1) of Online Appendix Table A3. The standard errors are clustered at both the market and firm level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Ln(Price)		Residual price	
	(1)	(2)	(3)	(4)
Covenant violation dummy	−0.10	−0.28**	−0.24**	−0.28**
	(−0.95)	(−2.27)	(−2.45)	(−2.27)
ROA_{t-1}	−0.43	0.22	0.05	0.22
	(−0.96)	(0.22)	(0.13)	(0.22)
$Tangibility_{t-1}$	−0.06	0.13	−0.10	0.13
	(−0.39)	(0.56)	(−0.61)	(0.56)
Market-to-$book_{t-1}$	0.02	−0.06	−0.03	−0.06
	(0.64)	(−0.87)	(−1.19)	(−0.87)
Ln($Assets_{t-1}$)	−0.04***	−0.05**	−0.05***	−0.05**
	(−2.72)	(−2.17)	(−3.38)	(−2.17)
Median ind. $leverage_{t-1}$	−0.06	0.15	−0.10	0.15
	(−0.22)	(0.35)	(−0.44)	(0.35)
Ln(Square feet)	−0.33***	−0.32***	−0.11***	−0.15***
	(−8.96)	(−7.48)	(−3.23)	(−3.53)
Age 11–20 years	−0.36***	−0.36***	−0.08**	−0.12**
	(−8.73)	(−7.88)	(−2.08)	(−2.61)
Age 21–30 years	−0.47***	−0.43***	0.01	−0.03
	(−8.27)	(−7.49)	(0.23)	(−0.59)
Age 31–40 years	−0.51***	−0.48***	0.01	0.00
	(−5.31)	(−4.30)	(0.08)	(0.00)
Age 41–50 years	−0.64***	−0.69***	−0.16	−0.22
	(−5.64)	(−4.52)	(−1.50)	(−1.44)
Age 50 or more years	−0.77***	−0.86***	−0.33***	−0.39**
	(−7.43)	(−5.33)	(−3.52)	(−2.44)
Renovated dummy	0.21***	0.27***	0.05	0.15
	(3.07)	(2.87)	(0.76)	(1.59)
Portfolio dummy	0.09*	0.06	0.12***	0.08
	(1.77)	(0.99)	(2.88)	(1.15)
CBD dummy	0.29*	0.24	−0.04	−0.19
	(1.79)	(0.97)	(−0.34)	(−0.76)
Year×Type FE	Yes	No	Yes	No
Market FE	Yes	No	Yes	No
Industry FE	Yes	Yes	Yes	Yes
Market×Type×Year FE	No	Yes	No	Yes
Observations	1,221	816	1,143	816
R-squared	0.53	0.50	0.06	−0.02

covenants.[12] We calculate the "Distance to Violation" as the difference between the underlying covenant variable and its contractual limit as a fraction of the limit [(actual covenant variable/contractual limit)–1]. For our covenant sample, we find that 30% of the firm-year observations include a violation (86 firm-year observations out of 291) which is comparable to the percentage of covenant violations in the annual DealScan sample (34%) reported in Ferreira, Ferreira, and Mariano (2018).

We further reduce firm heterogeneity by limiting our sample to firms whose covenant measures fall within a narrow range around the covenant threshold (discontinuity subsample). We focus on the subsample of firms that violate a covenant by a small margin and on the firms which do not violate any covenants but whose accounting variables have values close to the covenant threshold. Our objective here is to compare the transaction prices of real-estate assets sold by firms with similar unobservable characteristics, but with different statuses for breaching a covenant. We define three discontinuity subsamples based on bandwidths of 0.5, 0.45, and 0.4, respectively.

Columns (1)–(3) of Panel A in Table V report the results for three different bandwidths. In all subsamples, the "Covenant Violation Dummy" has a negative coefficient estimate with the magnitude increasing as the bandwidth shrinks. In Columns (4)–(6), we control for "Distance to Violation," its square, and their interactions with the "Covenant Violation Dummy." We continue to find a negative relationship between firms' financial health and the liquidation value of their real-estate assets. For instance, the results in Column (6) suggest that among firms that are around the covenant threshold, those that actually breach a covenant are associated with a selling price that is 15% below the average price in the full sample compared with those that do not breach a covenant.

We also check the robustness of our results in the full covenant sample. To do so, we split the sample into terciles based on the "Distance to Violation" within each covenant category. "Tight Covenant" indicates the tercile with the smallest values of this difference that is the group of firms that are the most distressed and the closest to breaching a covenant (or have already breached one). Similarly, "Loose Covenant" indicates the tercile with the largest values of "Distance to Violation" (i.e., furthest from the threshold).

Panel B of Table V reports the full-sample results for Ln(Price) (Columns (1)–(3)) and Residual Price (Columns (4)–(6)), respectively. In Column (1), we find that a one-standard-deviation (1.14) decrease in "Distance to Violation" is associated with a 0.07 standard deviations decrease in Ln(Price). In Column (2), we repeat the analysis for the "Tight Covenant" and "Loose Covenant" dummy variables. We find a 0.25 standard deviations discount for the "Tight Covenant" group relative to the middle tercile. The coefficient estimate for the "Loose Covenant" dummy is negative but not statistically significant. Column (3) reports the estimation results for "Covenant Violation Dummy" which suggest that firms that breach a covenant are associated with about a 0.18 standard deviation lower prices than others. We derive similar conclusions for "Residual Price."

Our second approach addresses the concerns related to time-invariant unobserved property characteristics. To do so, we analyze a subsample of properties that have been sold multiple times within our sample period. The repeated sales of the same unit are widely

12 We follow the literature in determining the types of covenants that we use. Current ratio and net worth covenants frequently lead to technical default. The definitions of the accounting variables used for these covenants are relatively more standardized and less ambiguous. Dichev and Skinner (2002) provide further discussion on various covenant types.

Table V. Implied covenant violation and regression discontinuity

This table reports the estimation results from the regression of transaction price on covenant violation variables. Our specification closely follows Chava and Roberts (2008). Distance to Violation is defined as the current value of the accounting variable minus its covenant threshold, normalized by the covenant threshold. Covenant Violation Dummy equals one if the firm breaches a (tangible) net worth or current ratio covenant within the year prior to the real-estate transaction. In Panel A, we restrict the sample to those firm-year observations that fall within a narrow range (±0.5, 0.45, or 0.4) whereas Panel B uses the full covenant sample. In each covenant category, we split the sample into terciles based on the Distance to Violation. Tight Covenant is a dummy variable that indicates the observations with the smallest values of Distance to Valuation and Loose Covenant indicates the tercile with the largest values of Distance to Violation. All regressions include property and firm controls but their coefficient estimates are not reported for brevity. The standard errors are clustered at firm level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: Ln(Price)					
Panel A: Discontinuity sample	$h=0.5$ (1)	$h=0.45$ (2)	$h=0.4$ (3)	$h=0.4$ (4)	$h=0.4$ (5)	$h=0.4$ (6)
Covenant violation dummy$_{t-1}$	−0.30	−0.87***	−1.14***	−0.70***	−0.71***	−0.71*
	(−1.61)	(−4.49)	(−4.49)	(−2.85)	(−3.09)	(−1.93)
Distance to violation$_{t-1}$				1.69**	1.67**	−0.35
				(2.49)	(2.39)	(−0.11)
(Distance to violation$_{t-1}$)^2					0.49	5.78
					(0.23)	(0.59)
Distance to violation$_{t-1}$						4.72
×Covenant violation dummy$_{t-1}$						(0.68)
(Distance to violation$_{t-1}$)^2						2.64
×Covenant violation dummy$_{t-1}$						(0.11)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	165	153	121	121	121	121
R-squared	0.67	0.71	0.72	0.73	0.73	0.72

	Dependent variable: Ln(Price)			Dependent variable: Residual price		
Panel B: Full sample	All (1)	All (2)	All (3)	All (4)	All (5)	All (6)
Distance to violation$_{t-1}$	0.06*			0.05		
	(1.87)			(1.64)		
Tight covenant$_{t-1}$		−0.24**			−0.23***	
		(−2.35)			(−2.96)	
Loose covenant$_{t-1}$		−0.11			−0.08	
		(−1.26)			(−1.02)	
Covenant violation dummy$_{t-1}$			−0.17*			−0.21**
			(−1.69)			(−2.64)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	291	291	291	258	258	258
R-squared	0.61	0.62	0.61	0.17	0.19	0.19

used in the real-estate literature particularly to form house price indices (e.g., Standard & Poor's Case-Shiller Home Price Indices). We argue that a differential price for the current transaction relative to the past (or future) transaction of the same property cannot be explained by time-invariant property characteristics. Hence, as long as unobserved characteristics do not change between the repeated transactions of the same property, we can attribute the price differential between two repeated sales to the variation in our distress proxies.

Columns (1)–(3) in Table VI report the results from the regression of the difference between the current selling price and the past or future transaction price of the same property on our financial distress proxies. We continue to find a significant coefficient estimate for two of our financial distress proxies, namely "Interest Coverage Ratio" and "High Leverage and Low Current Assets." Although the coefficient estimate for the "Book Leverage" is negative, it is not statistically significant. Results suggest that the distress discount that we have found in our baseline analysis cannot be explained by time-invariant property-specific characteristics. In Columns (4)–(6), we repeat the same analysis this time using the residual prices. The results are similar to those obtained using raw prices.

As local economic downturns drive firms into distress, they can also affect real-estate prices negatively. Hence, local economic factors can potentially drive our results. In our baseline regressions, we control for RCA market-by-property type-by-year-fixed effects which allows us to control for time-varying market-wide events. As an alternative to this approach, we perform a second test that distinguishes between industries that are local and global with respect to their customer base. We hypothesize that if the relationship between financial distress and real-estate prices is more pronounced in industries that depend on local markets, then our results can potentially be driven by omitted local economic factors.

In order to identify local and global industries, we use the 2012 Commodity Flow Survey (CFS) Public Use Microdata File available from the US Census Bureau. The database covers approximately 4.5 million shipments obtained from businesses included in the 2012 CFS and provides information on shipment-level characteristics such as the state of origin, destination, mode of transportation, value of shipment in dollars, and NAICS industry classification of the shipper.[13]

For each NAICS industry, we calculate the total dollar value of out-of-state freight shipments as a percentage of total freight shipments. Then, we split the sample into two as "Local" and "Global" based on the median value of out-of-state shipments in the sample. Table VII reports the estimation results for the interaction term between our distress proxies and the "Local Industry" and "Global Industry" dummy variables. In five out of six specifications, we find the coefficient estimate of the distress proxy to be larger and statistically significant for global industries, suggesting that our findings are not likely to be driven by firms that predominantly depend on the local economy for their sales.

4. Cross-Sectional Variation in the Distress Discount and Cost of Debt

4.1 Cross-Sectional Variation in the Distress Discount

After documenting the existence of distress discount in real-estate transactions, next we investigate the factors that generate variation in the magnitude of this discount. Because we

13 The 2012 CFS covers US businesses in mining, manufacturing, wholesale, and selected retail and services trade industries, namely, electronic shopping and mail-order houses, fuel dealers, and publishers.

Table VI. Repeated sales sample analysis

This table reports the results from the regression of the difference between the current transaction price and past (or future) selling price of the same property on our financial distress proxies. The standard errors are clustered at both the market and firm level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Ln(Price)−Ln(Past price)			Residual price−Past residual price		
	(1)	(2)	(3)	(4)	(5)	(6)
Interest coverage ratio$_{t-1}$	0.01***			0.01***		
	(3.92)			(2.75)		
Book leverage$_{t-1}$		−0.20			−0.38	
		(−0.67)			(−1.25)	
High leverage and Low current assets$_{t-1}$			−0.26**			−0.33***
			(−2.24)			(−2.80)
ROA$_{t-1}$	−0.07	0.52	0.21	−0.28	0.28	0.15
	(−0.16)	(1.13)	(0.47)	(−0.55)	(0.53)	(0.28)
Tangibility$_{t-1}$	0.24	0.10	0.14	0.43	0.30	0.37
	(0.70)	(0.30)	(0.42)	(1.32)	(0.94)	(1.19)
Market-to-book$_{t-1}$	−0.14**	−0.09	−0.09*	−0.08	−0.02	−0.06
	(−2.65)	(−1.65)	(−1.68)	(−1.07)	(−0.29)	(−0.76)
Ln(Assets$_{t-1}$)	−0.07**	−0.06*	−0.04	−0.05*	−0.04	−0.02
	(−2.24)	(−1.80)	(−1.25)	(−1.81)	(−1.43)	(−0.60)
Median ind. leverage$_{t-1}$	0.90**	0.83**	0.42	1.21***	1.19**	0.71
	(2.51)	(2.20)	(1.15)	(2.69)	(2.54)	(1.62)
Ln(Square feet)	0.02	0.01	0.01	0.03	0.02	0.02
	(0.42)	(0.19)	(0.19)	(0.65)	(0.44)	(0.52)
Age 11–20 years	0.03	−0.04	−0.01	0.07	0.00	0.03
	(0.25)	(−0.40)	(−0.12)	(0.64)	(0.03)	(0.34)
Age 21–30 years	−0.14	−0.18	−0.17	−0.06	−0.10	−0.07
	(−1.03)	(−1.42)	(−1.29)	(−0.37)	(−0.66)	(−0.50)
Age 31–40 years	−0.21	−0.24*	−0.23*	−0.11	−0.14	−0.16
	(−1.56)	(−1.79)	(−1.70)	(−0.72)	(−0.84)	(−0.96)
Age 41–50 years	−0.07	−0.13	0.00	−0.02	−0.10	0.05
	(−0.34)	(−0.65)	(0.02)	(−0.11)	(−0.45)	(0.26)
Age 50 or more years	0.14	0.13	0.25*	0.12	0.13	0.23
	(1.11)	(1.06)	(1.91)	(0.64)	(0.74)	(1.43)
Renovated dummy	0.23	0.23	0.19	0.16	0.15	0.13
	(1.56)	(1.50)	(1.19)	(0.91)	(0.80)	(0.64)
Portfolio dummy	−0.13	−0.11	−0.23*	−0.10	−0.10	−0.23
	(−1.27)	(−1.00)	(−1.83)	(−0.92)	(−0.76)	(−1.60)
CBD dummy	0.26	0.25	0.19	0.15	0.12	0.04
	(1.18)	(1.17)	(0.98)	(0.62)	(0.52)	(0.17)
Year×Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Past (or future) transaction year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	272	272	266	254	254	248
R-squared	0.08	0.06	0.07	0.05	0.02	0.06

Table VII. Local economic conditions

This table reports the results for the interaction of our distress proxies with the value of out-of-state domestic freight shipments (as % of total value of shipments) in the seller's industry. We split the sample into two as "Local" and "Global" industries based on the percentage of out-of-state shipments. All regressions include property and firm controls as well as their interactions with Local and Global dummy variables but their coefficient estimates are not reported for brevity. The standard errors are clustered at the firm level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Dependent variable: Ln(Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
Global industry dummy	–0.06	–1.40	0.03	–1.12	0.11	–1.18
	(–0.08)	(–0.80)	(0.04)	(–0.66)	(0.12)	(–0.61)
Interest coverage × Local industry dummy	0.00	0.01				
	(1.02)	(1.26)				
Interest coverage × Global industry dummy	0.01***	0.01				
	(2.61)	(1.60)				
Book leverage × Local industry dummy			–0.27	–0.47		
			(–1.33)	(–1.43)		
Book leverage × Global industry dummy			–0.83***	–0.93*		
			(–2.92)	(–1.91)		
High leverage and Low current assets × Local industry dummy					0.02	0.01
					(0.24)	(0.09)
High leverage and Low current assets × Global industry dummy					–0.23***	–0.39***
					(–2.70)	(–3.44)
Year × Type FE	Yes	No	Yes	No	Yes	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Market × Type × Year FE	No	Yes	No	Yes	No	Yes
Observations	847	472	847	472	767	400
R-squared	0.44	0.60	0.45	0.61	0.44	0.58

have substantial cross-sectional variation in property types and industry characteristics, we can study the heterogeneity in the distress discount. As real estate is a broader asset type that firms from different industries hold, our analysis can offer a better understanding of heterogeneity in the distress discount related to asset-specific and sellers' industry-specific characteristics.

To examine heterogeneity related to asset-specific characteristics, we follow Shleifer and Vishny (1992). The main argument of Shleifer and Vishny (1992) is that an asset should sell for less if there are fewer buyers who can utilize it. Our dataset allows us to identify the properties that have less specific usage compared with 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 redeployability on prices, we estimate our baseline specification by allowing for the coefficient estimates of various distress proxies to vary between office and non-office properties. We also control for the interactions between "Office Dummy" and other independent variables to account for the impact of redeployability on the transaction price through channels other than firm distress. The results, as reported in Table VIII, indicate that the impact of firm distress is significantly muted or weaker for offices and flexible properties. For instance, in Column (1) while a one-standard-deviation decrease in the "Interest Coverage Ratio" is associated with a 0.16-standard-deviation decrease in the price of non-office properties, the effect is insignificant for offices and flex properties. The coefficient estimate for non-office properties is marginally significant after controlling for market-by-property type-by-year fixed effects (Column (2)). Columns (3) and (4) repeat the analysis using "Book Leverage" which yields higher coefficient estimates in absolute terms for non-office properties but the difference is less significant compared with Columns (1) and (2). Finally, in Columns (5) and (6), we interact our redeployability proxy with "High Leverage and Low Current Assets Dummy" which shows that the negative impact of the seller's distress on the transaction price is doubled for non-office properties relative to offices. These results suggest that generic assets command higher prices when they are sold by distressed sellers.[14]

The type of property tells us how specific the property is in its use, but it does not 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 easily if there are only a few potential buyers nearby. Almazan *et al.* (2010) argue that being located within an industry cluster increases the opportunities to make acquisitions. 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. 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.

Benmelech, Garmaise, and Moskowitz (2005) use the zoning of a property as a proxy for the availability of potential buyers. We anticipate that the property's multiple usage would have a more significant impact on its price than the flexibility of its zoning unless it is purchased to be rebuilt immediately. Unlike Benmelech, Garmaise, and Moskowitz (2005), we are able to observe the seller's industry and link the regional focus of other firms in the same industry with the property's location.

We measure the number of potential buyers based on the 10-K counts following Garcia and Norli (2012). More specifically, 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. We then divide the sample into low, medium, and high terciles based on the number of potential buyers. In Table IX, we estimate the impact of financial distress on the selling price separately for each tercile of the number of buyers. While a one-standard-deviation decrease in "Interest Coverage Ratio" is associated with a discount of 0.16 standard deviations in the low and medium terciles, the discount is insignificant in the high tercile (Column (1)). The coefficient estimate of the interaction between high tercile dummy and "Interest Coverage Ratio" is marginally significant after controlling for market-by property type-by-year fixed effects (Column (2)). The results in Columns (3) and (4) show that distress discount decreases monotonically from the lowest tercile of the

14 In untabulated results, we repeat the analysis for "Residual Price" and continue to find weaker effects for office properties.

Table VIII. Asset redeployability

This table investigates the impact of asset redeployability on distress discount. “Office Dummy” is an indicator variable that takes one for offices and for properties that can be used for both industrial and office activities. All regressions include property and firm controls as well as their interactions with Office Dummy but their coefficient estimates are not reported for brevity. The standard errors are clustered at both the market and firm level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Dependent variable: Ln(Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
Office dummy	−2.04***	−1.24*	−2.29***	−1.64**	−2.41***	−1.92**
	(−2.99)	(−1.72)	(−3.44)	(−2.08)	(−3.46)	(−2.43)
Interest coverage × Office	0.00	0.01*				
	(1.16)	(1.91)				
Interest coverage × Non-office	0.01***	0.02***				
	(2.86)	(3.87)				
Book leverage × Office			−0.52***	−0.69**		
			(−2.83)	(−2.03)		
Book leverage × Non-office			−0.63***	−0.83***		
			(−3.35)	(−4.05)		
High leverage and Low current assets × Office					−0.09	−0.18**
					(−1.33)	(−2.27)
High leverage and Low current assets × Non-office					−0.22**	−0.35***
					(−2.31)	(−3.70)
Year × Type FE	Yes	No	Yes	No	Yes	No
Market FE	Yes	No	Yes	No	Yes	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Market × Type × Year FE	No	Yes	No	Yes	No	Yes
Observations	2,238	1,507	2,238	1,507	2,136	1,423
R-squared	0.61	0.61	0.61	0.60	0.60	0.59

number of potential buyers to the highest tercile when we use “Book Leverage” as our distress measure. Table IX also reports the results for “High Leverage and Low Current Assets Dummy.” While properties with the lowest number of potential buyers are associated with a 0.28 standard deviation discount in the transaction price, the discount is only 0.09 standard deviations for the highest number of potential buyers group (Column (5)). Overall, our findings demonstrate that the discount is more evident for properties with a lower number of potential buyers.[15]

The evidence reported in Tables VIII and IX suggests that redeployability and the number of potential buyers are property-specific characteristics that affect the magnitude of distress discount. In Tables X and XI, we turn our attention to cross-industry analysis. According to Shleifer and Vishny (1992), asset prices can be significantly affected if a

15 As an alternative to 10-K counts, we also use the number of firms with headquarters in the same state as the property being sold provided that the firms operate in the same three-digit SIC industry as the seller. Our findings continue to hold with this alternative proxy.

Table IX. Potential buyers (10-K count)

This table investigates the impact of the number of potential buyers on distress discount. "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). In each year, we split the observations into terciles with the lowest (highest) tercile representing the observations with the lowest (highest) 10-K Count. All regressions include property and firm controls as well as their interactions with tercile dummy variables but their coefficient estimates are not reported for brevity. The standard errors are clustered at both the market and firm level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Dependent variable: Ln(Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
Medium 10-K count	−0.30	−1.35**	−0.24	−1.41**	−0.29	−1.55**
	(−0.63)	(−2.44)	(−0.50)	(−2.21)	(−0.56)	(−2.16)
High 10-K count	−1.78***	−1.39*	−2.07***	−1.96**	−2.33***	−1.90**
	(−2.69)	(−1.93)	(−3.03)	(−2.50)	(−3.76)	(−2.49)
Interest coverage × Low 10-K count	0.01***	0.02***				
	(3.10)	(4.21)				
Interest coverage × Medium 10-K count	0.01***	0.02***				
	(2.84)	(3.31)				
Interest coverage × High 10-K count	0.00	0.01*				
	(1.66)	(1.81)				
Book leverage × Low 10-K count			−0.76***	−1.06***		
			(−4.79)	(−3.12)		
Book leverage × Medium 10-K count			−0.62**	−0.89***		
			(−2.58)	(−3.88)		
Book leverage × High 10-K count			−0.58**	−0.70**		
			(−2.62)	(−2.41)		
High leverage and Low current assets × Low 10-K count					−0.27***	−0.33***
					(−3.55)	(−3.71)
High leverage and Low current assets × Medium 10-K count					−0.19*	−0.36***
					(−1.84)	(−3.20)
High leverage and Low current assets × High 10-K count					−0.09	−0.20**
					(−1.16)	(−2.22)
Year × Type FE	Yes	No	Yes	No	Yes	No
Market FE	Yes	No	Yes	No	Yes	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Market × Type × Year FE	No	Yes	No	Yes	No	Yes
Observations	2,238	1,507	2,238	1,507	2,136	1,423
R-squared	0.60	0.61	0.60	0.60	0.59	0.59

financially distressed seller is forced to seek transaction opportunities when its industry peers are also liquidity-constrained. In order to test the impact of financial health of the best users on the distress discount, we split our sample into terciles based on the lagged median value of current ratio in the seller's three-digit SIC industry, and define a dummy

Table X. Illiquidity in the seller's industry

This table reports the results for the interaction of our distress proxies with the median current ratio in the seller's industry. We split the observations into two subsamples based on the lagged median value of current ratio in the seller's three-digit SIC industry. "High Median Current Ratio Dummy" equals one if the median current ratio is in the highest tercile and zero otherwise. All regressions include property and firm controls as well as their interactions with High Median Current Ratio Dummy but their coefficient estimates are not reported for brevity. The standard errors are clustered at both the market and firm level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Dependent variable: Ln(Price)			
	(1)	(2)	(3)	(4)
High median current ratio dummy	–0.31	–0.47	–0.70	–0.82
	(–0.50)	(–0.52)	(–1.04)	(–0.83)
Interest coverage × Low median current ratio dummy	0.01***	0.02***		
	(3.21)	(3.70)		
Interest coverage × High median current ratio dummy	0.00	0.01*		
	(1.18)	(1.86)		
Book leverage × Low median current ratio dummy			–0.84***	–1.04***
			(–4.40)	(–4.64)
Book leverage × High median current ratio dummy			–0.35	–0.42
			(–1.51)	(–1.10)
Year × Type FE	Yes	No	Yes	No
Market FE	Yes	No	Yes	No
Industry FE	Yes	Yes	Yes	Yes
Market × Type × Year FE	No	Yes	No	Yes
Observations	2,238	1,507	2,238	1,507
R-squared	0.59	0.60	0.59	0.60

variable, "High Current Ratio Dummy," which takes a value of one if the median current ratio is in the highest tercile, and zero otherwise. Table X reports the results. We find that in three out of four specifications, the coefficient estimates of the distress proxies are insignificant for the highest median industry current ratio group. This suggests that the liquidation value of an asset depends on whether the industry peers have the financial capacity to pay the best-use price as predicted by Shleifer and Vishny (1992).

In our second cross-industry analysis, we investigate whether the discount varies with the seller's industry characteristics. To do so, we exploit the variation in the types of tangible assets that can be used as collateral. In machinery- and equipment-heavy industries such as mining, airline, and automobile, real estate constitutes a smaller fraction of firms' tangible assets. When a firm needs to shrink operations, we expect machines and equipment to be liquidated first rather than real-estate properties. Hence, the distress discount on real-estate transactions should be less pronounced in these industries. To test this prediction, we calculate "Machinery-to-Tangible Assets" as the industry average of machinery and equipment (as percent of total tangible assets) from 1984 to 1996 based on three-digit SIC

Table XI. Type of tangible assets

This table reports the results for the interaction of our distress proxies with the percentage of machinery and equipment in total tangible assets. “Machinery-to-Tangible Assets” is the industry average of machinery and equipment over the period between 1984 and 1996 calculated based on three-digit SIC industries. We split the observations into two as “High” and “Low” based on this average. All regressions include property and firm controls as well as their interactions with High and Low dummy variables but their coefficient estimates are not reported for brevity. The standard errors are clustered at both the market and firm level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Dependent variable: Ln(Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
High machinery-to-tangible assets	–1.55**	–2.15**	–2.14***	–3.07***	–1.89***	–2.41**
	(–2.25)	(–2.35)	(–3.18)	(–3.42)	(–2.78)	(–2.54)
Interest coverage×Low machinery-to-tangible assets	0.01***	0.02***				
	(3.32)	(4.48)				
Interest coverage×High machinery-to-tangible assets	0.00	0.01*				
	(1.36)	(1.68)				
Book leverage×Low machinery-to-tangible assets			–1.08***	–1.51***		
			(–3.02)	(–3.97)		
Book leverage×High machinery-to-tangible assets			–0.38***	–0.43**		
			(–2.69)	(–2.01)		
High leverage and Low current assets ×Low machinery-to-tangible assets					–0.32**	–0.43***
					(–2.52)	(–4.00)
High leverage and Low current assets ×High machinery-to-tangible assets					–0.08*	–0.15**
					(–1.66)	(–2.17)
Year×Type FE	Yes	No	Yes	No	Yes	No
Market FE	Yes	No	Yes	No	Yes	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Market×Type×Year FE	No	Yes	No	Yes	No	Yes
Observations	2,238	1,507	2,238	1,507	2,136	1,423
R-squared	0.60	0.61	0.60	0.61	0.59	0.59

industries.[16] We split the observations in “High” and “Low” groups based on the average “Machinery-to-Tangible Assets.” Table XI shows that the distress discount on real-estate prices is significantly less pronounced for firms in machinery-heavy industries. This result provides an interesting contrast between the types of assets that can be sold when firms are distressed and the discount they may face. Pulvino (1998) finds a significant discount in the aircraft sales in airline industry which is a machinery-heavy industry. In contrast, our results suggest that firms in machinery-heavy industries do not face a similar discount in real-estate sales.

16 The sample period that we use to calculate Machinery-to-Tangible Assets is determined by data availability. Campello and Giambona (2013) provide further discussion on the decomposition of tangible assets.

4.2 Heterogeneity in Real-Estate Portfolios and Cost of Debt

After establishing the relationship between asset liquidation value and property-specific factors such as asset redeployability and the number of potential buyers, we test whether those property-specific factors are priced in the corporate loan markets. To do so, we first construct real-estate portfolios of companies using all the transactions contained in the RCA database. These transactions help us identify the date the property was acquired and when it was disposed. After constructing real-estate portfolios from transaction data, we define two variables that measure the average redeployability of the portfolios. Each year, observations are split into two groups based on (i) the fraction of office properties in the portfolio and (ii) the fraction of properties that are located in the states with above-median number of potential buyers. "Low Office Fraction Dummy" denotes real-estate portfolios with below-median fraction of offices. Similarly, "Low Buyer Fraction Dummy" indicates that the real-estate portfolio is comprised of properties that are located in states that were mentioned by many firms in their 10-Ks (provided that they operate in the same three-digit industry as the owner). In order to control for the market value of the real-estate portfolio, we define two variables, "Portfolio Value (Office)" and "Portfolio Value (Buyer)" which represent the estimated values of a real-estate portfolio based on the specifications reported in the first column of Table VIII and IX, respectively.

Table XII reports the results from the regression of loan spread on the "Interest Coverage Ratio," its interactions with property portfolio fraction measures, and loan- and firm-level controls as given in the following regression equation:

$$\begin{aligned}\text{Loan Spread}_{i,j,t} = \alpha + \beta_1\text{Loan Controls}_{i,j,t} + \beta_2\text{Firm Controls}_{i,t} + \delta_t + \text{Ind}_i \\ +\gamma_2\text{Interest Coverage Ratio}_{i,t} \times \text{Low Office Fraction Dummy}_{i,t} \\ +\gamma_3\text{Interest Coverage Ratio}_{i,t} \times \text{High Office Fraction Dummy}_{i,t} \\ +\gamma_4\text{High Office Fraction Dummy}_{i,t} + \epsilon_{i,j,t},\end{aligned} \tag{1}$$

where i denotes the firm, j denotes the loan, and t denotes the year in which the loan facility started.

The results are presented in Table XII. Column (1) reports the results for the direct effect of "Interest Coverage Ratio" on loan spreads alone which suggest a negative relationship between the loan spreads and the "Interest Coverage Ratio" that is significant at the 5% level. In Columns (2) and (3), we estimate the coefficient of "Interest Coverage Ratio" separately for firms with different real-estate portfolio characteristics. On the one hand, the coefficient estimates for the direct effects of high redeployability and high fraction of potential buyers are both insignificant, which suggests that such asset characteristics are not incorporated in loan prices when the borrower is not financially constrained.

On the other hand, real-estate portfolio characteristics generate a significant variation in the impact of financial distress on loan spreads. For instance, while the coefficient estimate of "Interest Coverage Ratio" for firms that are heavily invested in offices is negative (–0.0035) and insignificant, the corresponding coefficient estimate for other firms is two times larger (–0.0082) and statistically significant at the 5% level. Similarly, the impact of distress on the loan price is more evident if the firm has a higher fraction of its properties located in areas with a large number of potential buyers (Column (3)) with coefficient estimates of –0.0078 and –0.0034 for low and high buyer groups, respectively.

In Columns (4)–(6), we repeat our analysis this time using "Book Leverage" as our distress proxy. The difference between the two groups is less significant in this case but the

Table XII. Loan spreads and real-estate portfolio value

This table reports the results from the regression of loan spreads on real-estate portfolio characteristics. In each year, observations are split into two based on (i) the fraction of office properties in the portfolio and (ii) the fraction of properties that are located in the states with the highest number of potential buyers (i.e., High 10-K Count). "Low Office Fraction Dummy" denotes real estate portfolios with below-median fraction of offices. Similarly, "Low Buyer Fraction Dummy" indicates the fraction of properties with a low (below-median) number of potential buyers. "Portfolio Value (Office)" and "Portfolio Value (Buyer)" represent the real-estate portfolio value estimates based on the specifications in column (1) of Table VIII and IX, respectively. "Ln(Loan Maturity)" is the natural logarithm of loan maturity in months. The standard errors are clustered at both the firm and year level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Dependent variable: Ln(Loan spread)					
	(1)	(2)	(3)	(4)	(5)	(6)
Interest coverage ratio$_{t-1}$	−0.01**					
	(−2.27)					
Interest coverage × Low office fraction dummy		−0.01***				
		(−2.68)				
Interest coverage × High office fraction dummy		−0.00				
		(−1.10)				
Interest coverage × Low buyer fraction dummy			−0.01**			
			(−2.56)			
Interest coverage × High buyer fraction dummy			−0.00			
			(−1.07)			
Book leverage$_{t-1}$				0.71***		
				(4.24)		
Book leverage × Low office fraction dummy					0.89***	
					(3.82)	
Book leverage × High office fraction dummy					0.63***	
					(2.95)	
Book leverage × Low buyer fraction dummy						0.88***
						(4.27)
Book leverage × High buyer fraction dummy						0.53**
						(2.55)
High office fraction dummy		−0.03			0.10	
		(−0.45)			(0.95)	
High buyer fraction dummy			0.02			0.17*
			(0.32)			(1.96)
Portfolio value (Office)		0.02			0.03	
		(0.71)			(1.00)	
Portfolio value (Buyer)			0.01			0.02
			(0.45)			(0.72)
ROA$_{t-1}$	−2.06***	−1.96***	−1.99***	−2.36***	−2.27***	−2.29***
	(−3.94)	(−3.65)	(−3.66)	(−4.97)	(−4.72)	(−4.72)
Tangibility$_{t-1}$	−0.05	−0.06	−0.06	−0.09	−0.12	−0.11
	(−0.24)	(−0.28)	(−0.26)	(−0.46)	(−0.59)	(−0.52)

(continued)

Table XII. Continued

	Dependent variable: Ln(Loan spread)					
	(1)	(2)	(3)	(4)	(5)	(6)
Market-to-book$_{t-1}$	−0.10***	−0.11***	−0.11***	−0.11***	−0.12***	−0.12***
	(−3.01)	(−3.21)	(−3.00)	(−3.51)	(−3.61)	(−3.53)
Median ind. leverage$_{t-1}$	−0.01	−0.02	−0.02	−0.16	−0.16	−0.19
	(−0.03)	(−0.06)	(−0.05)	(−0.49)	(−0.49)	(−0.56)
Ln(Assets$_{t-1}$)	−0.10***	−0.11***	−0.10***	−0.10***	−0.11***	−0.11***
	(−3.79)	(−3.67)	(−3.68)	(−3.95)	(−3.99)	(−3.87)
Ln(Loan maturity)	−0.12*	−0.12*	−0.12*	−0.11*	−0.12*	−0.12*
	(−1.83)	(−1.87)	(−1.88)	(−1.77)	(−1.78)	(−1.82)
Ln(Loan amount)	−0.13***	−0.13***	−0.13***	−0.14***	−0.14***	−0.14***
	(−4.72)	(−4.85)	(−4.76)	(−4.98)	(−5.02)	(−5.04)
Loan type	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes
Secured dummy	Yes	Yes	Yes	Yes	Yes	Yes
Seniority	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,220	1,220	1,220	1,220	1,220	1,220
R-squared	0.72	0.72	0.72	0.72	0.72	0.72

coefficient estimates for “Book Leverage” are smaller for firms with more liquid real-estate portfolios. Financial distress has a less significant impact on the loan spreads of firms with more redeployable real-estate assets and potential buyers of these assets. These results suggest that commercial loans are priced not only based on the financial health of borrowers but also the redeployability and liquidity characteristics of their assets.[17]

Overall, our findings suggest that a borrower’s real-estate portfolio that is not redeployable for alternative uses exacerbates the impact of financial distress on the cost of borrowing. Moreover, we find that there is substantial heterogeneity in real-estate portfolios across industries, which is one of the major types of collateral assets that is frequently used in almost all industries and that, this heterogeneity affects loan terms.

5. Conclusion

We evaluate the economic magnitude of the impact of a seller’s financial health on the transaction price of its real-estate assets. Previous evidence on this subject comes from Pulvino (1998), who studies the distress discount for aircrafts sold by financially constrained airlines. Our paper generalizes the findings of Pulvino (1998) to an asset class that is commonly held and used as collateral by all public firms in various industries. We show that there is substantial heterogeneity in the properties of real-estate portfolios and then study how this heterogeneity affects both the distress discount and the loan terms.

17 Our results are robust to calculating the value-weighted averages of offices and high potential buyer properties.

The uniqueness of our dataset helps us observe property-specific characteristics of real-estate assets of public firms. By relating firms' financial characteristics to property-specific attributes, we test whether financial distress of a seller affects real-estate prices. Our findings demonstrate that there is a significant distress discount in the sales of commercial real-estate assets. We find that a one-standard-deviation decrease in "Interest Coverage Ratio" is associated with a 17% decrease in price. This finding is robust to alternative measures of distress and various model specifications.

We also exploit the heterogeneity in the distress discount across industries and find that distress discount is more pronounced for sellers whose industry peers are liquidity-constrained. We also show that location of properties matter. The distress discount is less evident when there are multiple potential buyers. Furthermore, our findings suggest that machinery-heavy industries are less prone to distress discount in real-estate assets as they potentially rely more on their machinery and equipment as collateral. These findings complement and extend the results in Pulvino (1998) to a broader group of industries.

In conclusion, the magnitude of real-estate asset liquidation values we document in this paper suggests firms face significant discount when they are in distress. This discount is especially prevalent in some industries. We expect our findings be useful in explaining why some firms maintain a conservative capital structure and whether anticipation of such distress discount leads to disincentive to invest.

Supplementary Material

Supplementary data are available at *Review of Finance* online.

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