Likely and Unlikely Reasons for Selection into Securitization: Evidence from Commercial Mortgages*

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Abstract

We investigate differences in the characteristics and performance of securitized loans versus loans held on lenders' balance sheets using a unique data set of commercial mortgages. The main findings are as follows. First, consistent with risk-sharing being a likely reason for securitization, loan size strongly predicts the likelihood of securitization. The largest 10% of loans have a 44% chance of being securitized while the smallest 10% of loans have a less than 1% chance of securitization. Second, commercial loan performance (i.e., default) is not predictable by securitization, suggesting that CMBS loans are, *ex post*, not riskier. Third, we provide a stylized model that links the selection into securitization of a loan with its performance. Using this model, we find no evidence of adverse selection in the commercial mortgages market.

JEL classification: G21, G23, G20

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1 Introduction

From the early 1990s to 2007, securitization had become the usual financing structure for residential mortgages and was common in the market for corporate loans, credit card receivables, auto loans, and commercial mortgages. In principle, securitization offers lenders important benefits, such as liquidity and risk-sharing, relative to the alternative of holding individual loans on lenders' balance sheets. In the wake of the 2007-9 financial crisis, however, securitization has come under scrutiny in regulatory circles and academic articles.[1] Among the concerns surrounding securitization are that it was associated with an increase of credit supply in subprime markets (Mian and Sufi (2009)), that it may create difficulties in servicing and renegotiating loans[2], that it is used to achieve regulatory arbitrage (Acharya, Schnabl, and Suarez (forthcoming)), and that it creates "securitized banking" runs that FDIC insurance was not designed to prevent (Gorton and Metrick (2012)). Securitized markets may also suffer from adverse selection.[3] Most of the empirical work on securitization focuses on residential mortgages, which is understandable, given the recent turmoil in that market. However, it is unclear whether the conclusions drawn from the residential mortgage market are applicable to other asset classes and, if so, to what extent. Given the prevalence of securitized loans before the financial crisis, and their anemic recovery since, it is important to gather more facts about the incentives and performance in various markets.

In this paper, we provide new evidence on the selection into securitization by comparing securitized and non-securitized commercial real estate loans between 2005 and 2012. We are able to do that using a unique dataset that combines balance sheet and securitized loans of commercial properties (loans packaged into commercial mortgage backed securities, or CMBSs) from a large number of lenders in four markets: Boston, Las Vegas, Los Angeles,

[1] Several aspects of securitization were explicitly addressed in recent financial legislation. Subtitle D of the Dodd-Frank Act, passed by Congress in 2009 and titled "Improvements to the Asset-Backed Securitization Process," sets new policies on securitization. See Richardson, Ronen, and Subrahmanyam (2011) and Adrian and Ashcraft (2012) for discussions of the changes the Dodd-Frank Act proposes to the regulatory framework for securitization.

[2] See Cordell, Dynan, Lehnert, Liang, and Mauskopf (2009), Piskorski, Seru, and Vig (2010), Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff (2011), Ghent (2011), and Adelino, Gerardi, and Willen (2012).

[3] See Ambrose, Lacour-Little, and Sanders (2005), Downing, Jaffee, and Wallace (2009), Keys, Mukherjee, Seru, and Vig (2010), An, Deng, and Gabriel (2011), Elul (2011), Krainer and Laderman (2011), Agarwal, Chang, and Yavas (2012), and Benmelech, Dlugosz, and Ivashina (2012).

and New York. We use the dataset to address the following questions. First, what characteristics make some commercial loans more likely to be securitized? Provided that the likelihood of securitization is predictable by loan-, borrower-, and property-specific characteristics, our goal is to verify whether the evidence is consistent with the main benefits of securitization, i.e., risk-sharing and liquidity. Second, is the performance of securitized loans, namely, probability of default, different from that of balance sheet[4] loans? Literature from other asset classes has used this framework to investigate the presence of adverse selection in securitization. Since, in our context, a predictive regression cannot fully identify the economic reasons for why securitization might be correlated with default, the third question we ask is whether other data or market features allow us to test more concretely for adverse selection in the CMBS market.

With regards to the first question, we find that the likelihood of securitizing a commercial loan is predictable to a significant extent by loan characteristics that are known at origination. More specifically, we provide strong evidence that larger loans are much more likely to be securitized than are smaller loans. This finding is consistent with risk-sharing being a key motivation for securitization. The relationship between loan size and securitization can be seen in the following descriptive statistics: although only 19% of our loans are securitized, 7 of the 10 largest loans and none of the smallest 10 loans are securitized. Similarly, of the largest 100 loans, 46 are securitized, and of the smallest 100 loans, only 2 are securitized. The difference in size between securitized and balance sheet loans remains after controlling for other characteristics and performing numerous robustness checks. The relationship between loan size and the likelihood of securitization is strikingly monotonic. After controlling for other observable loan characteristics, the loans in the top decile of loans by loan amount have a 44% chance of being securitized while less than 1% of loans in the bottom decile of the loan amount distribution get securitized. These results indicate a desire on the part of balance sheet lenders to reduce their exposure to the idiosyncratic risk of a single large loan defaulting.

[4]We use the term balance sheet loan rather than portfolio loan to refer to non-securitized loans to avoid confusion. The term portfolio loan in the commercial mortgage market is sometimes used to refer to multi-property, as opposed to single-property, loans rather than to indicate a non-securitized mortgage. All of our loans are single-property loans.

Second, we find no evidence of differences in the risk of balance sheet and CMBS loans. More specifically, the securitization status of a loan does not increase its probability of default, which is our measure of risk. The fact that we do not observe that CMBS loans are riskier, *ex post*, suggests that adverse selection into the CMBS market is unlikely. We also do not observe any significant differences in loss given default across CMBS and balance sheet loans. The probability of default is predictable by other variables such as the loan-to-value ratio (positive coefficient) and loan size (positive coefficient). Failure to control for these determinants leads to omitted-variable bias and incorrect inference.

Third, we present a stylized model that links the performance of the loan with selection into securitization. This approach represents a more structural way of testing for adverse selection in the market for securitized commercial mortgages. Our stylized model disentangles the causal effect that securitization may have on loan performance from selection into securitization based on differences in risk. We estimate this model and find no evidence of adverse selection.

To our knowledge, ours is the first paper to study differences between balance sheet and securitized loans using data from the commercial mortgage market. There are several reasons to explore securitization in that market. First, commercial deals are typically very large in terms of the market value of the asset that is being financed and the absolute value of the loan. For instance, in our dataset, the largest loan is for $1.9 billion for a commercial development in Manhattan. The size of such deals makes it more likely that the risk-sharing incentives for securitization will be apparent. In terms of loan size, commercial loans are more like corporate loans and less like residential mortgages, auto, credit card, and other smaller loans.

Second, commercial loans are particularly suitable to isolate the differences in defaults between securitized and non-securitized contracts. Agarwal, Chang, and Yavas (2012) emphasize the importance of disentangling prepayment from default risk in testing for adverse selection in the residential market. In contrast to the residential market, commercial mortgages usually provide the lender with substantial prepayment protection[5] such that the main

[5]Such prepayment protection can take the form of a lockout period, a yield maintenance fee, defeasance, or a combination of the above. A lockout period is a contractual stipulation wherein the borrower cannot repay the loan within a specified period of time. A yield maintenance fee is a fixed fee the borrower must

risk to a commercial mortgage lender is default, not prepayment.

Third, the decision to securitize is overwhelmingly made at origination of the loan. While prior to 2000, some lenders chose to securitize commercial mortgages subsequent to origination, by 2001 the commercial mortgage market was dominated by conduit lenders, i.e., lenders who originate commercial mortgages with the express intent of selling them into a securitization (see An, Deng, and Gabriel (2011)). We find the same to be true in our sample: the originator of a securitized loan knows not only that the loan he is originating will be securitized but also which security it will be in. Non-securitized loans are originated by other financial institutions (e.g., regional banks, national banks, and insurance companies). This is different from other markets, such as residential mortgages and CLOs, where the decision to securitize is often made after loan origination. As such, the securitization status is predetermined for our predictive regressions.

Fourth, mortgages in this market are securitized without the presence of government-sponsored enterprises (GSEs) that distort incentives and eliminate credit risk for certain loans. The pervasive influence of the GSEs in particular may make it difficult to extrapolate findings from the residential mortgage market to asset classes with different institutional structures.

Finally, the structure of the CMBS market is such that, prior to the implementation of the Dodd-Frank Act, there was no requirement that the sponsor of the CMBS or the sellers of the loans retain any portion of the risk of the loans. Therefore, studying the CMBS market over our sample period provides us with a unique opportunity to examine whether adverse selection necessarily arises in markets in which the originator of the security does not have any immediate financial stake in the performance of the security.

Our finding that securitization is used to diversify idiosyncratic risk provides evidence of an important benefit of securitization. Loutskina and Strahan (2009) and Loutskina (2011) also document benefits of securitization. Loutskina and Strahan (2009) show that securitization mitigates the impact of bank funding shocks on the availability of residential

pay the lender upon prepayment that compensates the lender for a lower reinvestment rate; the fee is proportional to the lender's assumed reinvestment rate. Finally, a defeasance clause requires a prepaying borrower to provide the lender with a set of US Treasury STRIPS that replicate the cash flows of the loan; see Dierker, Quan, and Torous (2005) for a detailed discussion of defeasance clauses.

mortgages. Loutskina (2011) shows that securitization enables banks to hold fewer liquid assets and expand their lending capacity.

Our results regarding the lack of adverse selection are consistent with the findings of Benmelech, Dlugosz, and Ivashina (2012) in the CLO market who focus their analysis on the securitization status of loans at origination. Agarwal, Chang, and Yavas (2012) find that securitized prime residential mortgages are less likely to terminate through default than prime mortgages retained by the originator; they suggest that the reason securitized mortgages default less is because of the dominance of the GSEs in the prime market. They also find no difference in the performance of securitized and portfolio mortgages in the subprime market. Ambrose, Lacour-Little, and Sanders (2005) also find no evidence of adverse selection in the residential mortgage market.

In contrast, Elul (2011) finds that securitized prime residential mortgages default more than balance sheet loans and interprets his results as consistent with adverse selection in the securitized market. Krainer and Laderman (2011) also present evidence that securitized residential loans are riskier. Downing, Jaffee, and Wallace (2009) find evidence of adverse selection in the Collateralized Mortgage Obligation (CMO) market. They find that the Freddie Mac participation certificates, mortgage backed securities themselves, that are re-securitized into CMOs carry greater prepayment risk. An, Deng, and Gabriel (2011) suggest that the decline of the balance sheet CMBS market (i.e., mortgages originated as balance sheet loans) owes to adverse selection from these originators into the CMBS market. Their methodology and empirical results rely exclusively on CMBS loans, whereas our data set includes both balance sheet and securitized loans. They also look at an earlier sample period of 1994-2000.

The remainder of the paper proceeds as follows. Section 2 describes our data set and documents the collapse of the CMBS market during our sample period. In Section 3, we discuss the motivations for securitization that are consistent with a predictive analysis of whether a loan is securitized as well as the relationship between loan performance and securitization. In Section 4, we present a simple econometric model to test for adverse selection. Section 5 concludes.

2 Data

We construct our data set from transactions of office property in the metropolitan statistical areas (MSAs) of Boston, Las Vegas, Los Angeles, and New York. Our data was provided to us by Real Capital Analytics (RCA), a leading provider of commercial property and mortgage data. We use two of RCA's databases in this study. The first product contains information on the properties financed by mortgages. The other product comes from RCA's troubled asset database which tracks distressed mortgages. We link the two datasets using the address of the property. All mortgages in our sample are single-property purchase mortgages (i.e., mortgages used to purchase a property rather than to refinance an existing mortgage) originated between January 1st, 2005 and May 1st, 2012.[6] The start of the sample coincides with the first date that RCA has comprehensive data on balance sheet mortgages. RCA specializes in transactions on property values of \$2.5 million and more such that we have comprehensive data for properties above this threshold.

The four cities for which data is available have diverse commercial real estate markets. New York (including Manhattan) is consistently the largest office property market by a considerable margin. Los Angeles was the third largest office property market, as measured by sales volume, in 2007, the second largest in 2008, but had fallen to seventh place in 2010. Boston was not a large office market during the boom years of 2005-2007, but it fared well throughout the downturn. Las Vegas, although a relatively small portion of the national office market, experienced a disproportionate share of distress. The cities in our sample represent between 30% and 40% of the national office market based on the dollar amount of sales transaction and approximately 25% of the national office market based on the number of sales.[7] They have differing shares of the national office property market over our sample and each one has experienced a somewhat different real estate cycle.

Securitized versus Balance Sheet Loans: The RCA collects data shortly after a commercial real estate transaction takes place. For transactions involving a loan, information about the financing is also available. If the loan is known to be from a conduit lender–a

[6] While we have detailed information on refinancings for securitized mortgages, such data is not comprehensive for balance sheet mortgages. To prevent a potential selection bias, we focus on purchase mortgages.

[7] Authors' calculations based on RCA aggregate sales data.

lender who originates mortgages with the sole purpose of securitizing them as soon as they are issued–RCA enters details of the security the loan will be packaged into. Many large loans that exceed industry norms for conduit deals are also originated into CMBSs. CMBS deals that include such large loans are typically referred to as "fusion" deals or "conduit/fusion" deals if the deal contains large loans as well as smaller conduit loans. It is also possible that a single loan may be originated as a CMBS deal. These loans are readily categorized as CMBS. The remaining mortgages are either balance sheet loans or were securitized at a date after origination. In principle, mortgages can be securitized at any point after issuance. In practice, however, the overwhelming majority of commercial real estate loans are securitized at origination or not at all. See An, Deng, and Gabriel (2011) for a similar finding from a sample ending in 2001.

Nevertheless, to prevent any misclassification of deals, we run a second check to verify whether a loan has been securitized at some point after issuance. We do so using the TREPP database, which contains comprehensive loan-level data for securitized mortgages in the US. The merged RCA-TREPP data allows us to ascertain that the loans we classify as balance sheet do not end up being securitized at a later point. After cross-referencing the portfolio loans in the RCA data with the TREPP data, we find that less than 3% of the mortgages that RCA codes as balance sheet loans are recorded in TREPP (as being securitized) confirming the rarity of non-conduit originations in CMBSs. For this study, a loan is categorized as CMBS if it is classified as securitized in the RCA data or if it is in the TREPP data. We define a dichotomous variable, CMBS, that equals one for securitized loans and zero for balance sheet loans.

Other Variables: The RCA data also contains information on other loan-, property-, and borrower-specific characteristics. For all mortgages, we have the loan amount, the loan to value (LTV) at origination, and the date of origination.[8] The property variables that we have available are: price at origination, price per square foot, the year the property was built, its square footage, the number of floors, whether the property has multiple buildings,

[8]As balance sheet loans are not subject to the same disclosure requirements as CMBS loans, we do not have comprehensive data on loan terms for balance-sheet loans. While we do have information on the interest rate, maturity, and other loan terms for the CMBS loans and for some of the balance sheet loans in our sample, there is likely to be a sample bias in the balance sheet loans for which we have such data. As a result, we do not make use of detailed information on loan terms.

and whether or not it is located in a central business district (CBD). In addition, we know whether the properties are located in Boston, Las Vegas, Los Angeles, or New York City.

Finally, the RCA keeps track of the borrower type, which it sorts into the following categories: Developer/Owner/Operator, Equity Fund, Corporate, REIT, Other/Unknown. The largest category by far is the Developer/Owner/Operator category which RCA defines as a non-traded privately held Development/Property Management/Owner/Operator firm. Regarding the definition of Equity Funds, RCA states the following: Equity Funds are "privately held and guided investment vehicles dedicated to commercial real estate investment. Equity Funds gather and commingle investment funds from investors in other categories and specific funds often focus their investments by location, property type or return profile i.e., opportunistic or value-add." RCA defines corporate borrowers as borrowers that use real estate primarily for corporate use. REITs are defined according to the tax code; we include both public and privately traded REITs under the same category as we have relatively few of each type.

Defaults: We classify all loans in our sample as either having defaulted or not having defaulted using indicators of distress that are observable for both securitized and balance sheet loans. As such, many loans that RCA codes as troubled we do not code as having defaulted. For example, RCA codes a loan that is transferred to the special servicer as troubled while we do not classify such a loan as having defaulted if that is the only indicator of distress. As Gan and Mayer (2007) discuss, there may be substantial differences in the timing of transfer to the special servicer and the distress event depending on the ownership of the various tranches in the security. The borrower itself may also request a transfer to the special servicer even if the loan is not in default. While a transfer to the special servicer definitely indicates distress, there is no comparable indication of trouble for balance sheet loans in the data.

We code a loan as having defaulted only if the loan has gone through foreclosure, if a foreclosure has been initiated, or if the borrower has declared bankruptcy. Consequently, the loans we code as having defaulted are quite troubled and almost all of our defaults result in the borrower losing control of the property. Our definitions of default also imply that the first time a loan gets dated as having defaulted in our database is late into distress rather than an early indicator of distress (e.g., the first missed payment). We use loan amounts at origination to calculate the amount of loans in distress although the figures are very similar if we use RCA's estimate of the outstanding balance at the first indication of distress. Although some of the loans in our sample are partly amortizing, many are development loans which typically have increases in balances over time.

Resolution after Default: Of our defaulted loans, most had not been resolved by the end of our sample in the sense of no longer being a troubled asset on the lender's balance sheet or, for securitized loans, the trust's. This is perhaps not surprising given the extent of the problems in the commercial property market since the loans defaulted. Of the 175 loans we identify as defaulted, 83 had been resolved by the end of our sample. The resolution almost always ends with the borrower losing control of the property: Of the 83 resolutions we observe, only 3 are resolved via a refinancing with no loss to the lender (recovery rate = 100%). Twelve loans are resolved via a purchase by another buyer before the foreclosure sale without any loss to the lender (recovery rate = 100%) and 3 of the loans are resolved by an assumption of the loan by a new property owner without any loss to the lender (recovery rate = 100%). Another 59 resolutions are resolved by a sale of the property either before or after the foreclosure sale with the lender taking a loss. We do not have sufficient information to ascertain recovery rates or exactly how the default was resolved for the remaining 6 loans that RCA indicates had been resolved by the end of our sample.

2.1 Summary Statistics

Table 1 provides summary statistics of the CMBS variable along with the other characteristics of the loans. There are 2236 purchase mortgages in the dataset 19% of which are CMBS loans (422 observations) and the remaining 1814 loans are held on the balance sheet of the lender. In addition to whether a loan is securitized, we display other loan-specific information. The average loan amount is $29M with a large standard deviation ($83M) and skewness 9.3. The heterogeneity in loan sizes in commercial deals is significant: the smallest loan in our database is only $0.2 million whereas the largest one is $1.9 billion (CMBS). The average loan-to-value ratio is 75% with a standard deviation of 46%. We have 214 loans with LTVs above 100% such as the maximum LTV of 973% shown in the table. 95% of the loans with LTVs above 100% are balance sheet loans. These are development or redevelopment loans wherein the lender provides the borrower with funds to develop the property in addition to funds to purchase the property. We investigate the sensitivity of our main results to excluding loans with LTVs above 100%.

We also have the origination date of each loan, the mean of which for our 2005-2012 sample is 2007. It is important to mention that the commercial real estate market has been affected by the financial crisis of 2008-2009. The entire securitization industry (RMBS, CMBS, CLOs, CDOs, etc.) was frozen during those years and is only now slowly recovering. We discuss this episode in detail below, correct for this time variation with year dummies throughout the paper, and conduct various robustness checks.

Regarding property-specific variables, the average price is $45M with a minimum deal of $1.60M and the largest deal of $2.95 billion. The price per square foot displays similarly large variation, from $11 to $4,933, with an average value of $328. The other property attributes and the geographical location variables capture the heterogeneity in the commercial real estate market. We observe that 40% of the properties are in NYC, 43% are in Los Angeles, while Boston and Las Vegas constitute a modest 13% and 4%, respectively.

The most likely borrowers, constituting about 65% of all commercial mortgages, fall in the Developer/Owner/Operator category. Equity funds, corporations, and REITs follow with about 8%, 6%, and 4% of all deals. The remaining 17% of loans are extended to various other entities or to borrowers of unknown category.

The aggregate numbers in Table 1 do not reveal the time-series properties of the data. While most of the analysis will be conducted with the pooled dataset, it is important to highlight two peculiarities of the sample period. First, to say that the financial crisis of 2007-2009 had a large impact on the commercial mortgage market is an understatement. The number of commercial loans issued dropped from 509 (market value of $19.6B) in 2007 to 244 ($4.9B) in 2008 and to 76 ($1.4B) in 2009. Since then, the market is improving but the numbers are not near their pre-crisis levels.

Second, the crisis hit the CMBS market particularly hard, resulting in its effective shutdown in 2008 and 2009. The number of CMBS loans plummeted from 126 in 2007 (with a market value of $7.9B) to zero in the subsequent two years. While the number of balance sheet commercial mortgages also declines significantly during this period–by about 36% between 2007 and 2008, and by about 69% between 2008 and 2009–the issuance of commercial mortgages did not come to a standstill. Stanton and Wallace (2012, Table 4) similarly report a collapse in the universe of CMBS loans in TREPP, from 5219 loans in 2007 to 53 loans in 2008. This finding parallels the collapse of the private label RMBS market during the financial crisis (see Calem, Covas, and Wu (2011) and Fuster and Vickery (2012)). There has also been a significant decline in the securitization rate of non-mortgage consumer credit. The securitization rate of non-mortgage consumer credit fell from 27% in 2007 to 2% in 2011, the lowest rate since the Federal Reserve began tracking pools of securitized consumer credit in 1989 (Federal Reserve Board of Governors, 2012).

To illustrate these facts, Figure 1 plots the number of CMBS and balance sheet loans originated each year in our sample. Figure 1 also plots the cumulative number and volume of loans that had defaulted in our sample. The first time we observe default of any of the loans in our sample is in 2008. During that year, 22 loans worth a combined $364 million defaulted. In 2009, another 50 loans with a combined total balance of $2.3 billion entered default, a larger amount than issuance of new loans in 2009. In 2010, another $2.7 billion worth of loans entered default. By the end of our sample, $6.6 billion worth of loans had entered default. In Figure 2 we plot the Moody's/RCA commercial property price index for office property at the national level. It is a repeat transaction index similar to the Case-Shiller and FHFA home price indices.[9] We can readily observe the dramatic effect of the crisis.

To check whether the crisis had a significant effect on the variables of interest, in the second panel of Table 1, we display summary statistics based on loans that were originated during the pre-crisis period of 2005-2007. We observe that pre-crisis, the ratio of CMBS loans was higher (27%). We also notice small differences in the average loan amount ($33M), but most other variables including LTV, price, price per square foot and other property and borrower characteristics are remarkably similar.

[9]The Moody's / RCA office property price indices are not available at the MSA level, because there are far fewer office property transactions than residential transactions.

2.2 Comparing CMBS and Balance Sheet Loans

As a first step in our analysis, we investigate differences between securitized and non-securitized loans. Systematic differences in their characteristics may provide insight behind the economic motivation for securitization. Such a comparison has not been done in the literature. It is worth mentioning that the characteristics that we investigate are all known at loan origination, and are pre-determined with respect to loan performance (i.e., default and loss given default).

In Table 2, we compute the averages of all characteristics in Table 1 for CMBS and balance sheet loans, separately. We then conduct univariate comparisons between the means using a simple t-test of differences in means where the null is that balance sheet loans are not statistically different from CMBS loans. Looking at the loan-specific characteristics, there are substantial differences. The most striking difference is that, unconditionally, securitized loans are more than twice larger than portfolio loans, a difference that is economically meaningful and statistically significant at the 1 percent level. Moreover, securitized mortgages are associated with properties with larger square footage, with a larger number of floors, and are comprised of multiple buildings. Some additional differences are that securitized deals are less likely to be extended to properties located in a central business district (0.27 versus 0.33). As far as geographical differences go, securitized loans are slightly less likely to finance transactions in Los Angeles but more likely to finance transactions in Las Vegas. Properties financed with securitized loans are about nine years younger on average than properties financed with portfolio loans. All of these differences are significant at the 1 percent level. Several important characteristics, such as LTV and price-per-square foot, are remarkably similar between securitized and balance sheet deals.

There are also substantial differences between the types of borrowers that finance themselves with securitized loans rather than with balance sheet loans. While by far the most common type of institution among our borrowers is the developer/owner/operator category, equity funds and REITs are much more likely to use securitized borrowing. Given that REITs often have extensive ties to lenders, it may be surprising that they rely on securitized mortgages. However, many REITs rely on general bank loans or unsecured debt rather than property-specific mortgages such that many of their property purchases will not be financed with a mortgage *per se*; see Giambona, Mello, and Riddiough (2012) for a discussion of REITs' financing strategies. Corporate borrowers are more likely to rely on balance sheet loans.

The picture that emerges from this comparison is that securitized loans tend to be issued on larger properties–properties with larger square footage, more floors, and multiplicity of buildings. Because the purchase of such buildings requires larger mortgages, we find that securitized deals tend to also be significantly larger, in dollar amount. However, we do not find significant differences in price-per-square-foot in the univariate analysis.

3 The Characteristics and Performance of CMBS and Balance Sheet Loans

As a first step in the empirical analysis, we model the likelihood of securitizing a commercial loan using variables that are known at the time of loan origination.[10] In other words, we are predicting the probability of a loan being securitized, conditional upon its characteristics. We then investigate the performance of securitized and balance sheet loans. We model the likelihood of a loan defaulting by conditioning on the same observable characteristics and on whether it is securitized or not. We include the securitization status of the loan, since it is determined at origination. The question of whether securitization predicts future default, and the underlying reasons behind a potential relationship, have been hotly debated in the literature.

3.1 The Likelihood of Securitizing

The fact that there are significant differences between securitized and balance sheet loans suggests that their characteristics might predict whether a loan is securitized. Since many of the loan characteristics that we consider are correlated with one another, we would like to

[10]This mitigates the possibility of biases that stem from endogeneity and from the fact that, in a static probit estimated from an arbitrary starting date (other than origination), a loan could have been in distress (which is unobserved) several periods before going into default (Shumway (2001)).

know how to weigh them optimally in predicting the likelihood of securitization.

We model the discrete decision of whether to securitize a loan as an index function. The observable characteristics that influence such a decision are captured in a vector $x_{i,t-1}$ and enter linearly into the decision process $Y^*_{i,t}$, where

$$(1) \qquad Y^*_{i,t} = x_{i,t-1}\beta + u_{i,t}$$

and $u_{i,t}$ are the unobservable (to the econometrician) characteristics of loan i at time t. The loan characteristics in vector $x_{i,t-1}$ have a $t-1$ subscript because they are known before the loan is originated.

While the decision process itself is unobservable, its outcome–whether a loan is securitized–is observable. Hence, we construct a dichotomous variable $CMBS_{i,t}$ which equals to one if a loan is securitized and zero otherwise, which is related to $Y^*_{i,t}$ as $CMBS_{i,t} = 1$, if $Y^*_{i,t} > 0$ and zero otherwise. Thus, $P\left(CMBS_{i,t} = 1\right) = P\left(Y^*_{i,t} > 0\right) = F\left(x_{i,t-1}\beta\right)$, where F is the symmetric distribution of $u_{i,t}$. We assume that $F\left(.\right)$ is the normal distribution, denoted by Φ, and obtain the probit model:

$$(2) \qquad P\left(CMBS_{i,t} = 1\right) = \Phi\left(x_{i,t-1}\beta\right).$$

In Table 3, we report estimates of β, robust standard errors, and marginal probabilities averaged over all observations from estimating (2) for various specifications of $x_{i,t-1}$. We also report the pseudo-R^2 for each probit. In specification 1, the characteristics are the log loan amount, MSA dummies, and year of origination dummies. We use the log transformation of the loan amount to stabilize the variance of the series. Specifications 2-4 introduce progressively loan-to-value ratio, price-per-square-foot, other property characteristics (such as whether the property is located in a CBD), and borrower type. Finally, specification 5 replaces the log loan amount by nine loan amount decile dummies. We do so to better quantify the significance of loan size on the probability of securitization.

The results from Table 3 can be summarized as follows. The size of the loan is statistically significant (at the 1 percent level) in all specifications: larger loans have a higher likelihood of being securitized. Similar results (not displayed) obtain for other proxies for loan size, such as property price, square feet, and number of floors. Hence, the importance of loan size as a predictor of the likelihood of securitization is not only a novel but also a robust result.

In terms of economic magnitude, the marginal impact of log loan size, evaluated at the mean value of all conditioning variables, results in the probability of securitization increasing by about 9.2%. Simply controlling for the log loan amount, the MSA, and the year of origination explains about 22% of the variation in the data as captured by the pseudo-R^2. A better gauge of the economic importance of loan size on the probability of securitization is provided in Figure 3. Panel A of Figure 3 displays the probability of securitization estimated using coefficients of the nine size deciles from specification (5) of Table 3; Panel B of the figure displays the coefficients themselves. The probability of securitization is calculated for each observation using the coefficients from the probit model and varying only which decile of the loan amount the loan is in. The probabilities shown are the average probability of securitization for each decile using this calculation.

In Panel A, the loans in the lowest two size deciles, i.e., the smallest 20% of the loans, have about a one percent chance of being securitized. As the loan size increases, the probability of securitization also increases in a monotonic fashion. Remarkably, the largest loans, those in the top decile, have a 44 percent chance of being securitized. Hence, the difference in the probability of securitizing the largest versus the smallest loans is 43 percentage points. The finding that there is such a strong relation between loan size and future probability of securitization is consistent with the hypothesis that risk sharing is a likely reason for securitization in the commercial real estate market.

Several other variables in Table 3, such as loan-to-value ratio, price-per-square-foot, and CBD, are significant at the 1 percent level in almost all specifications. The overall explanatory power of the conditioning variables, captured by the pseudo-R^2, is between 22 and 33 percent, depending on the specification. Hence, the likelihood of securitizing a commercial real estate loan appears to be highly predictable by loan and property characteristics. A higher loan-to-value ratio decreases the likelihood that the loan is securitized suggesting that, on one key observable *ex ante* measure of risk, as we later demonstrate, CMBS loans are less risky than balance sheet loans. The predictive power of loan characteristics other than loan size and the relatively high pseudo-R^2 reveal that the probability of securitizing a commercial real estate loan is surprisingly predictable.

Although we have good information on the quality of the loan collateral, missing from regression (2) are variables that proxy for the quality (or riskiness) of the borrower. The vast majority of our borrowers are not public companies and therefore we do not have hard information on their credit-worthiness. Furthermore, even if we had financial statements from our borrowers, such that we could use key financial metrics like debt service coverage ratios in estimating (2), there remains the possibility that substantial differences in the soft information characteristics of balance sheet and CMBS borrowers is not available. Hence, we will later turn to a structural model that will enable us identify the role of unobservable differences in risk that might affect securitization.

Sensitivity analyses

We conduct several sensitivity analyses of our results regarding the *ex ante* differences between balance sheet and CMBS loans. First, we estimate the model using only originations from 2005 to 2007 since there are so few CMBS originations from 2008 onwards (see Figure 1). The results from estimating the model on this subsample are extremely similar to our benchmark case. Second, we drop all loans with LTVs above 100%. In these specifications, the coefficient on LTV decreases in magnitude and is no longer statistically significant suggesting that the significance of LTV is largely driven by development loans being more likely to be financed by balance sheet than CMBS loans. Third, we estimate the index model using a logit rather than a probit; we obtain nearly identical results to our benchmark specification. Finally, we estimate the model after dropping all loans in the bottom 2.5% and the top 2.5% of the distribution of the loan amount. The results from dropping the size outliers are extremely similar to our benchmark results. The robustness checks, available upon request, suggest that the relationship between loan size and the probability of securitization is a robust feature of our dataset.

3.2 Loan Performance

We model the likelihood of default using a probit model. Default is a discrete state captured by an index variable $D_{i,t+1}$ that equals 1 if the loan defaults, and zero otherwise. We estimate the probit

$$P(D_{i,t+1} = 1) = \Phi(\tilde{x}_{i,t-1}\theta + \tau CMBS_{i,t}) \tag{3}$$

where $\tilde{x}_{i,t-1}$ are the variables that are known at the origination of the loan. Hence, we are predicting the likelihood of default based on observable characteristics. Benmelech, Dlugosz, and Ivashina (2012) and Jiang, Nelson, and Vytlacil (2010) use similar models to predict defaults in CLOs and residential mortgages.

We address three questions with this probit. Is default in commercial real estate loans forecastable with variables that are observable at loan origination? If so, what variables in $\tilde{x}_{i,t-1}$ are significant predictors of default? The last question is whether CMBS loans are more likely to default than are balance sheet loans.

We estimate several specifications of equation (3) and present the results in Table 4. The specifications of $\tilde{x}_{i,t-1}$ are similar to those for the CMBS probits in Table 3. In the first specification, which includes the CMBS variable and year fixed effects, the estimate of τ is positive (0.22) and significant at the 5 percent level. However, when we control for the loan amount, the estimate of τ decreases to 0.07 and becomes insignificant. The τ estimate is biased upwards in the first specification, because, as we showed in Section 3.1, loan amount is positively correlated with the omitted CMBS variable. In specifications 3 and 4, we add LTV and price per square foot, as well as other building characteristics. We introduce borrower type dummies in specification 5, while specification 6 replaces the log loan amount with dummies for the loan amount decile. The results are consistent across all specifications: the estimate of τ is close to zero and statistically insignificant. Higher loan amounts increase the likelihood of default by about 2% when we average over the values of the other variables. Going from the lowest to the highest loan amount decile increases the probability of default by 9 percentage points, from 4% to 13% (not shown); the difference is statistically significant at the 1% level.

Another important predictor of default is the loan-to-value ratio. The coefficient estimate on LTV is 0.19, which implies that a 10 percent increase in the LTV increases default by a modest 0.2%. While LTV is consistently a strong predictor of default in the residential mortgage literature, consistent with intuition regarding the importance of the default option value, previous studies using commercial mortgage data have seen mixed results regarding the LTV. An, Deng, and Gabriel (2011) find that an increase in the LTV actually lowers the risk of default. They attribute this finding to higher risk borrowers being unable to secure higher LTV loans. Ambrose and Sanders (2003) find no statistically significant relationship between the LTV and the loan amount.

Both of the above studies employ only data from CMBS loans. To investigate the difference in our results regarding the effect of LTV on default, we estimate the specifications of (3) shown in columns 4, 5, and 6 of Table 4 separately for CMBS loans and balance sheet loans. The coefficient on LTV is actually higher in the CMBS sample than in the balance sheet sample although the effect is not statistically significant due to the much smaller sample size. The difference in our findings regarding the effect of LTV on default is thus likely due to the differences in our sample period relative to the studies above. Over our sample period, commercial property prices fell substantially as shown in Figure 2.

The pseudo-R^2 of this regression is 11% which is surprisingly high, given the limited amount of borrower-specific financial information. To put this predictive performance in perspective, Campbell, Hilscher, and Szilagyi (2008) use a similar approach to predict bankruptcy and failure of US firms. Using a much larger dataset of more than a million observations and many variables that proxy for the financial condition of public companies, they report pseudo-R^2s in the range of 26% to 30%.

3.2.1 Sensitivity Analyses

We conduct sensitivity analyses for estimating equation (3) as we did for estimating the likelihood that a loan would be securitized. First, we perform two exercises to further disentangle the distinct roles of size and CMBS in default. It is possible that we do not find a significant relationship between default and securitization because of collinearity. The loan amount variable has much more variation in it than the dichotomous CMBS variable and yet it is highly correlated with CMBS. In our first alternative specification, we omit the size variable and estimate (3) using loans with loan amounts above the median loan amount. We find no significant effect of CMBS when we estimate the model only for these large loans and omit the loan amount variable. In the second specification, we include the loan amount only in quartiles. This specification also indicates that whether a loan is securitized is not a statistically significant predictor of default.

Third, we estimate (3) using only data on loans originated between 2005 and 2007. The results are very similar to our results from estimating the model on the full sample.

In our fourth sensitivity analysis, we exclude loans with LTVs above 100%. CMBS continues to have no predictive power when we exclude loans above 100%. The coefficient on LTV remains positive and statistically significant when we exclude loans with LTVs above 100% and increases in magnitude relative to our benchmark specification. The effect of LTV on default thus does not appear to be driven only by development and redevelopment loans. The age of the property is no longer a statistically significant predictor of default when we exclude loans with LTVs above 100% although the coefficients on these variables are similar to the coefficients we estimate in our benchmark specification.

Finally, instead of estimating a probit model for default, we estimate default using a proportional hazards model. We estimate proportional hazards models using only covariates known at origination as well as using dynamic information on MSA level employment and office property prices. The results from estimating proportional hazards models are very similar to those we find from estimating probit models and are available upon request.

3.2.2 Loss Given Default

Of course, investors care not only about whether a loan defaults but about what they recover in the event that the loan defaults. CMBS loans do not, however, have lower recovery rates than balance sheet loans. The mean recovery rates on CMBS and balance sheet loans are 72% and 70%; the univariate difference between the recovery rates is not statistically significant. We also run regressions of the recovery rate on the securitization status of the loan and controls such as the city the property is in, the year the loan was originated, the year the loan defaulted, and the length of time it took for the lender to resolve the default.

In no specification do we find the coefficient on CMBS to be close to statistically significant.

4 Identifying Adverse Selection: A Model

Although we do not find that securitization is a statistically significant predictor of default, the reduced form nature of equation (3) makes it difficult to infer whether CMBS borrowers are of lower quality than balance sheet borrowers. While the securitization status of our mortgages is overwhelmingly determined at origination, unlike in the CLO market and the residential mortgage market, the potential for adverse selection nevertheless exists. One can imagine a situation in which borrowers turn to the CMBS market only after having been repeatedly rejected by balance sheet lenders because of poor soft information. If CMBS investors will not invest in acquiring such soft information, the result will be that securitized loans are of lower quality than balance sheet loans with the same hard information characteristics. See Loutskina and Strahan (2011) for a discussion of the issue of soft information in loan performance. In this section, we model this adverse selection by identifying the role of soft information from default data.

4.1 The Model

To capture adverse selection, we provide more structure to the securitization decision in equation (1). In particular, we assume that

$$Y^*_{i,t} = x_{i,t-1}\beta + \gamma\varepsilon^{DISTRESS}_{i,t} + \varepsilon^{CMBS}_{i,t}. \quad (4)$$

The components $\varepsilon^{DISTRESS}_{i,t}$ and $\varepsilon^{CMBS}_{i,t}$ are orthogonal to each other and, unlike $u_{i,t}$ in (1), which is only a regression residual, they have a structural interpretation. Namely, $\varepsilon^{DISTRESS}_{i,t}$ captures unobservables that affect the likelihood that a loan will be in distress and at risk of default. In other words, $\varepsilon^{DISTRESS}_{i,t}$ represents soft information that cannot be captured by quantitative variables and hard information that is observable to the loan originator but not to the econometrician (such as the borrower's financial situation)[11].

To recover $\varepsilon_{i,t}^{DISTRESS}$, which is not directly observable from the data, we model the financial condition of the borrower. Suppose that $Z_{i,t+1}^{*}$ is the financial condition of the borrower which depends on observable characteristics $\tilde{x}_{i,t-1}$ and on the unobservable $\varepsilon_{i,t+1}^{DISTRESS}$. Hence, we write

$$Z_{i,t+1}^{*} = \tilde{x}_{i,t-1}\eta + \varepsilon_{i,t+1}^{DISTRESS}, \tag{5}$$

and we assume that the process for the unobserved risk of the loan is $\varepsilon_{i,t+1}^{DISTRESS} = \varepsilon_{i,t}^{DISTRESS} + v_{i,t+1}$, where $v_{i,t+1}$ is an independently and identically distributed zero-mean random variable. In other words, the distress state is persistent.

To illustrate how $\varepsilon_{i,t+1}^{DISTRESS}$ affects whether the loan is securitized, suppose that a loan has a high value of $\varepsilon_{i,t}^{DISTRESS}$. If $\gamma > 0$, the likelihood of securitization will increase. Therefore, for $\gamma > 0$, there is adverse selection into the CMBS market, i.e., the CMBS market has lower quality borrowers than the balance sheet market. If $\gamma < 0$, loans in the CMBS market are less likely to default than balance sheet loans. Hence, γ is the parameter that captures adverse selection that we want to estimate.

Securitization should not have a causal effect on whether a loan experiences distress. The key reasons that lead to a loan becoming distressed are the inability of the borrower to make the loan payments due to liquidity constraints and whether the default option is in the money in the sense of the property being worth less than the balance outstanding on the loan (for a discussion of the default option, see Deng, Quigley, and Van Order (2000)). Whether a particular loan is securitized affects neither the borrower's cash flow nor the price of the property.[12] Hence, the CMBS variable does not enter into expression (5). The assumption we make is equivalent to stating that, if we randomly assign half of a set of loans

[11] Borrower-specific variables, such as net operating income, net income to total assets, total liabilities to total assets, debt service ratio, and cash, have been shown to be good forecasters of default in the context of corporate debt (Shumway (2001) and Campbell, Hilscher, and Szilagyi (2008)). However, they are not observable in our dataset because the overwhelming majority of our borrowers are not publicly traded companies.

[12] It is, of course, possible that the availability of securitized financing may affect aggregate asset values. Indeed, Adelino, Schoar, and Severino (2012) show that homes that can easily be financed using a conforming loan have higher prices than homes that are difficult to finance in the conforming market. However, whether a property is *actually* financed using a securitized loan should not affect the individual property's value.

to securitization and the other half to balance sheet lenders, we do not expect securitization to affect the percentage of loans in each subset that experiences distress.

It is tempting to model default as an index function, i.e., $D_{i,t+1} = 1$ if $Z^*_{i,t} > 0$ and zero otherwise. If distress were directly observable, then we could specify $P\left(D_{i,t+1} = 1\right) = P\left(Z^*_{i,t+1} > 0\right) = F\left(\tilde{x}_{i,t-1}\eta\right)$, and under a functional form assumption of $F(.)$, we could estimate the parameters of this model with a probit or a logit. However, we do not observe distress. We observe when a loan is in default as we define in Section 2. Using conditioning, and the fact that a loan must be distressed in order to default, we can write

$$\begin{aligned}(6) \qquad P\left(D_{i,t+1} = 1\right) &= P(D_{i,t+1} = 1|Distress_{i,t+1} = 1) * P\left(Distress_{i,t+1} = 1\right) \\ &= p_{i,t+1}P\left(Z^*_{i,t+1} > 0\right)\end{aligned}$$

The probability that a distressed loan actually defaults, $p_{i,t+1}$, has a natural interpretation. It complement, $1 - p_{i,t+1} = P(D = 0|Distress = 1)$, is the probability that the loan does not default, given that it was in distress. This can happen for a variety of reasons. The cash flow of the borrower may improve following favorable changes in market, industry, or firm-specific conditions or the value of the collateral can increase. In such cases, there is no difference in $p_{i,t+1}$ between CMBS and non-CMBS loans and we can let $p_{i,t+1} = p_t$.

However, securitization may influence whether a distressed loan experiences a default due to agency issues. In particular, securitization may make it more difficult to renegotiate distressed loans in such a way as to avoid a default. Several papers discuss the role of securitization in residential mortgage renegotiation[13]. Although CMBS loans have special servicers that are designed to mitigate the sorts of agency problems that arise from dispersed ownership and interest, the presence of special servicers may not entirely eliminate agency problems in distressed loan renegotiation. Indeed, Gan and Mayer (2007) and Ambrose, Sanders, and Yavas (2009) identify the potential for agency issues in renegotiating CMBS loans.

To incorporate this important channel into our model, we let $p_{i,t+1}$ be a function of

[13]See Cordell, Dynan, Lehnert, Liang, and Mauskopf (2009), Piskorski, Seru, and Vig (2010), Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff (2011), Ghent (2011), and Adelino, Gerardi, and Willen (2012).

whether a loan has been securitized or not, or $p_{i,t+1} = f\left(CMBS_{i,t}; \alpha\right)$ and α is a parameter. We adopt the simple function

$$p_{i,t+1} = \begin{cases} 1 & CMBS_{i,t} = 1 \\ \alpha & CMBS_{i,t} = 0 \end{cases} \tag{7}$$

where we have normalized the probability that a loan defaults conditional on it being distressed to 1 for CMBS loans.[14] Given this normalization, $\alpha < 1$ implies that the probability that a CMBS loans transitions from a state of distress to a state of default is higher (and the renegotiation rate is lower) than that of a balance sheet loan. Unfortunately, we do not have enough data to reliably estimate α. Hence, we estimate the model for a range of values of α.

4.2 Estimation Results

Based on the structure of equations (4)-(7), we first estimate $P\left(D_{i,t+1} = 1\right)$ assuming normality using maximum likelihood, for a given α. Second, we extract an estimate of $\varepsilon_{i,t}^{DISTRESS}$, denoted by $\hat{\varepsilon}_{i,t+1}^{DISTRESS}$, using generalized residuals (Chesher and Irish (1987) and Greene (2000), pp. 916-917). The estimate $\hat{\varepsilon}_{i,t+1}^{DISTRESS}$ is analogous to the usual regression residual, with the exception that here we are working with a probit rather than a linear model. Third, we estimate (4) assuming $F(\cdot)$ is the standard normal distribution and compute standard errors using a nonparametric bootstrap. Simply estimating a probit model with the given data and with $\hat{\varepsilon}_{i,t+1}^{DISTRESS}$ in place of $\varepsilon_{i,t}^{DISTRESS}$ would yield incorrect standard errors, because the uncertainty associated with estimating $\hat{\varepsilon}_{i,t+1}^{DISTRESS}$ is not taken into account; see Pagan (1984). We carry out this estimation for $\alpha = 0.6$, $\alpha = 0.7$, $\alpha = 0.8$, $\alpha = 0.9$, and $\alpha = 1$. The appendix details the derivation and estimation of the generalized residuals.

Table 5 presents the results from estimating equation (4) for $\alpha = 1$. We consider the same

[14] We verify that our results are robust to this normalization by also considering $p_{i,t} = p$ for CMBS loans and $p_{i,t} = \alpha p$ for balance sheets and estimating the model for various values of p. The results for $p = 0.75$ and $p = 0.5$ are available in an appendix. When p is quite small, for example 0.25, it becomes difficult to estimate the standard errors via the bootstrap procedure because the likelihood function is close to flat. Intuitively, the likelihood function loses its curvature because the information about a loan's default status contains little information about the loan's distress status.

specifications as we do when we estimate the reduced form of the CMBS selection equation (1). In each specification, we use the same conditioning variables $\tilde{x}_{i,t-1}$ as in section 3. In all specifications, the sign of γ is positive but statistically insignificant. The coefficients on all the other variables are nearly identical to what we found in Table 3, which is not surprisingly given that $\hat{\varepsilon}_{i,t+1}^{DISTRESS}$ is orthogonal to $\tilde{x}_{i,t-1}$. Including $\hat{\varepsilon}_{i,t+1}^{DISTRESS}$ also does not significantly increase the pseudo-R^2 in Table 3. The conclusion from Table 3 is that for $\alpha = 1$, i.e., for the case of no difference in renegotiation between CMBS and balance sheet loans, there is no evidence of adverse selection.

In Table 6, we present the results of estimating the structural model with different assumptions regarding differences in renegotiation as captured by α using the most complete set of covariates (specification 4 in Table 5). For all values of α, the γ estimate is either positive and insignificant or negative. For $\alpha = 0.6$, γ is in fact negative and significant at the 5% level, indicating that CMBS borrowers are actually higher quality borrowers than are balance sheet borrowers. Jiang, Nelson, and Vytlacil (2010) report a similar finding that "loans remaining on the bank's balance sheet are, ex post, of worse quality than sold loans." The coefficients on all the other predictors remain the same as for the case of $\alpha = 1$.

In Table 7, we present the estimates from the first-stage equation (5) for different values of α. For brevity, we only show the results from specification 4 in Table 5 which was also used in Table 6; the results from estimating specification 5 in Table 5 for different values of α are available in the appendix. The coefficient estimates of all of the covariates in the table are very similar to those we report in Table 4. In particular, for $\alpha = 1$, the coefficient on LTV (0.18) is slightly lower in the structural model and the standard errors are slightly larger. As we lower α, the coefficient on LTV rises, although the standard errors also increase. The coefficient remains significant at the 10% level or better. Hence, LTV seems to be a robust determinant of default in the data. The coefficients on the remaining covariates are very similar across different values of α but the standard errors increase. The standard errors increase because decreasing α lowers the amount of information that default provides you regarding distress in balance sheet loans. As such, there is less information about the quality of the loan from whether or not it defaults.

To summarize, we find very little evidence of adverse selection in the CMBS market.

CMBS loans do not appear to be of lower quality than balance sheet loans. Rather, our results indicate that the key motivation for securitization is a desire on the part of lenders to reduce their exposure to the risk of a large loan defaulting. Since each loan carries a substantial amount of idiosyncratic risk, securitization thus provides lenders with a risk management tool. Of course, this benefit may come at the cost of greater difficulties in renegotiating loans that do enter into distress. Our finding of a lack of adverse selection in the CMBS market suggests that the conduit lender model may be an effective way to mitigate the potential for adverse selection in other asset classes.

5 Conclusions

In this paper, we investigated differences in the characteristics and the performance of securitized and balance sheet commercial mortgages. By far the most important determinant of whether a loan is securitized is the size of the loan. Securitization of large loans allows lenders to manage risk by diversifying the idiosyncratic risk of a large potential default. The importance of the loan size thus underscores the benefits of securitization in financial markets. We saw no difference in the default rates or loss given default of securitized versus balance sheet loans. In a structural model, we found no evidence of an adverse selection problem whereby securitized loans have a higher risk based on unobservable characteristics than balance sheet loans.

Importantly, the institutional structure of the CMBS market is such that CMBS issuers and the sellers of loans to CMBS issuers do not need to retain any portion of the loan's risk. Issuers do not generally have "skin in the game" in the sense of directly bearing the costs of bad loans. Moreover, the securitization of commercial loans occurs almost exclusively at origination. The institutional structure of the market thus differs substantially from the CLO market that Benmelech, Dlugosz, and Ivashina (2012) study where lenders have a direct stake in the performance of the loan and where loans are frequently securitized after origination. Our finding regarding the lack of adverse selection thus indicates that, to avoid a lemons problem, it is not always necessary that securitizers retain some of the risk of the loan. Rather, the security issuer may care about its reputation so that it can issue more securities in the future. It is also possible that the conduit lending model that has evolved in that market forces lenders to incorporate all hard information into their choices and leaves little room for soft information.

We also documented the collapse of the CMBS market since 2008. In contrast, the balance sheet commercial mortgage market has recovered somewhat since 2008 and never came to a standstill the way the CMBS market did. Our finding that CMBS and balance sheet loans experienced similar defaults during the recent financial crisis indicates that there are reasons other than poor loan performance for the collapse of securitization in the aftermath of the financial crisis. Interestingly, the pattern of commercial mortgage securitization that we observe bears a sharp resemblance to the pattern that Goetzmann and Newman (2010) document in the 1920s and 1930s. They find that many skyscrapers built during that period were financed using large CMBS loans. The loan sizes at the time were larger than what balance sheet lenders were accustomed to making for a single property. In the 1930s, the CMBS market collapsed completely and did not return on any substantial scale until the 1990s. While our results provide insights into the loan-level differences between securitized and balance sheet borrowing, we hope future research can explain differences over time in securitization rates. We can only hope that the sharp contraction in securitized transactions does not persist for another 60 years.

Table 1: Summary Statistics

Characteristic	Mean	SD	Skew	Min	Max	No. Obs.
	Entire Sample: Jan 2005 - Apr 2012 Originations					
CMBS	0.19	0.39	1.6	0	1	2236
Loan-Specific:						
Loan Amount ($M)	29	83	9.3	0.2	1,900	2236
Loan-to-Value (LTV)	0.75	0.46	8.5	0.03	9.73	2235
Origination Year	2007.16	1.99	0.9	2005	2012	2236
Property-Specific:						
Property Price ($M)	45	144	9.2	1.6	2,950	2235
Price / Square Foot ($)	328	328	5.3	11	4,933	2234
Year Built	1963.95	32.77	-1.0	1732	2011	2176
Square Feet ($\times 10^3$)	122.91	234.18	5.2	0.90	2,961.07	2234
Floors	6.43	8.47	3.4	1	77	1836
Multiple Building	0.07	0.25	3.5	0	1	1965
Central Business District (CBD)	0.32	0.47	0.8	0	1	2236
NYC Metro	0.40	0.49	0.4	0	1	2236
LA Metro	0.43	0.49	0.3	0	1	2236
Boston Metro	0.13	0.33	2.2	0	1	2236
Las Vegas Metro	0.04	0.20	4.5	0	1	2236
Borrower-Specific:						
Developer/Owner	0.65	0.48	-0.6	0	1	2236
Equity Fund	0.08	0.27	3.1	0	1	2236
Corporate	0.06	0.24	3.7	0	1	2236
REIT	0.04	0.20	4.7	0	1	2236
Unknown	0.09	0.28	2.9	0	1	2236
	Sub-Sample: Jan 2005- Dec 2007 Originations					
CMBS	0.27	0.44	1.05	0	1	1526
Loan-Specific:						
Loan Amount ($M)	33	92	9.3	0.2	1,900	1526
Loan-to-Value (LTV)	0.76	0.44	8.5	0.03	9.73	1525
Origination Year	2006.01	0.81	0.0	2005	2007	1526
Property-Specific:						
Property Price ($M)	48	154	9.4	2	2,950	1525
Price / Square Foot ($)	324	289	4.0	13	3,449	1524
Year Built	1964.69	32.06	-1.2	1732	2008	1483
Square Feet ($\times 10^3$)	128.18	235.08	4.9	3.00	2,840.00	1524
Floors	6.45	8.28	3.3	1	70	1216
Multiple Building	0.07	0.25	3.5	0	1	1309
Central Business District (CBD)	0.31	0.46	0.8	0	1	1526
NYC Metro	0.39	0.49	0.4	0	1	1526
LA Metro	0.43	0.50	0.3	0	1	1526
Boston Metro	0.13	0.33	2.3	0	1	1526
Las Vegas Metro	0.05	0.22	4.0	0	1	1526
Borrower-Specific:						
Developer/Owner	0.66	0.48	-0.7	0	1	1526
Equity Fund	0.09	0.28	3.0	0	1	1526
Corporate	0.04	0.20	4.6	0	1	1526
REIT	0.04	0.20	4.6	0	1	1526
Unknown	0.10	0.30	2.6	0	1	1526

Notes: The table contains summary statistics of the data consisting of all purchase office commercial mortgages in Boston, Las Vegas, Los Angeles, and New York from January 2005 to April 2012. The dichotomous variable "CMBS" denotes whether a loan is securitized. The other characteristics of the loan are defined in section 2.

Table 2: Balance Sheet and Securitized Loans

	Balance Sheet			Securitized (CMBS)			Difference
Characteristic	Mean	SD	Skew	Mean	SD	Skew	in Means
Loan-Specific:							
Loan Amount ($M)	23	72	12.8	58	118	4.6	-35***
LTV	0.75	0.50	7.9	72%	0.17	0.8	0.03
Origination Year	2007.40	2.07	0.7	2006.16	1.15	2.0	1.25***
Property-Specific:							
Property Price ($M)	34	121	12.5	91	210	5.0	-57***
Price / Square Foot ($)	331	350	5.3	317	210	2.0	14
Year Built	1962.16	33.15	-0.8	1971.47	30.03	-2.2	-9.30***
Square Feet	99,480	201,537	6.1	223,509	321,936	3.5	-124,028***
Floors	5.88	7.83	3.9	8.90	10.57	2.3	-3.01***
Multiple Building	0.05	0.22	4.0	0.12	0.33	2.3	-0.07***
CBD	0.33	0.47	0.7	0.27	0.44	1.0	0.06**
NYC Metro	0.39	0.49	0.4	0.44	0.50	0.3	0.04
LA Metro	0.44	0.50	0.2	0.37	0.48	0.5	0.07***
Boston Metro	0.13	0.34	2.2	0.13	0.33	2.3	0.00
Las Vegas Metro	0.04	0.19	4.9	0.07	0.25	3.5	-0.03***
Borrower-Specific:							
Developer/Owner	0.66	0.47	-0.7	0.62	0.49	-0.5	0.04
Equity Fund	0.07	0.25	3.5	0.14	0.34	2.1	-0.07***
Corporate	0.07	0.26	3.4	0.02	0.13	7.6	0.05***
REIT	0.03	0.16	5.8	0.09	0.29	2.8	-0.07***
Unknown	0.10	0.30	2.7	0.05	0.22	4.0	0.05***

Notes: Summary statistics of the January 2005 to April 2012 sample, which is split into balance sheet and securitized (CMBS) loans. The exact definition of the variables can be found in section 2. The difference in the means of loan characteristics is reported in the last column. *** and ** denote that the difference between balance sheet and CMBS loans is significant at the 1% and 5% level.

Table 3: Probit Estimation of Loan Securitization

	(1)	(2)	(3)	(4)	(5)
Constant	-3.10***	-2.40***	-2.36***	-2.34***	-2.72***
	(0.15)	(0.18)	(0.22)	(0.22)	(0.29)
Log Loan Amount	0.37***	0.48***	0.51***	0.49***	
	(0.03)	(0.03)	(0.03)	(0.04)	Deciles
	7.8%	9.5%	9.5%	9.2%	
LTV		-0.93***	-0.99***	-0.98***	-1.18***
		(0.12)	(0.14)	(0.14)	(0.16)
		-19%	-18%	-18%	-21%
Price per Square Foot		-1.09***	-0.50***	-0.48***	-0.23
		(0.20)	(0.19)	(0.18)	(0.14)
		-0.022%	-0.009%	-0.009%	-0.004%
CBD			-0.69***	-0.68***	-0.58***
			(0.15)	(0.15)	(0.15)
			-13%	-13%	-10%
Multi-building			0.22	0.22	0.24
			(0.15)	(0.15)	(0.15)
			4.1%	4.1%	4.4%
Property built before 1960			-0.014	-0.015	-0.101
			(0.17)	(0.17)	(0.17)
			-0.3%	-0.3%	-1.8%
Property built 1960 to 1980			-0.021	-0.022	-0.037
			(0.16)	(0.16)	(0.16)
			-0.4%	-0.4%	-0.7%
Property built 1980 to 2000			0.23*	0.22	0.18
			(0.14)	(0.14)	(0.14)
			4.2%	4.1%	3.2%
Equity Fund				0.055	0.105
				(0.139)	(0.135)
				1.0%	1.9%
Corporate				-0.24	-0.18
				(0.22)	(0.23)
				-4.4%	-3.2%
REIT				0.13	0.19
				(0.17)	(0.16)
				2.4%	3.5%
Unknown Borrower Type				-0.036	0.230
				(0.160)	(0.180)
				-0.7%	4.2%
Year Dummies (2005, 2006, and 2007)	Yes	Yes	Yes	Yes	Yes
MSA Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	2236	2233	1962	1962	1962
Pseudo-R^2	22%	26%	30%	30%	33%

Notes: The table contains estimates of a probit where the dependent variable takes a value of 1 if the loan is securitized and 0 otherwise (equation (2) in the text). The estimates are obtained from a pooled dataset of all loans in our January 2005 to April 2012 sample. In all five specifications, the first entry for each variable is the coefficient, the second entry (in parentheses) is the robust standard error, and the third entry is the effect of a 1 unit change in the independent variable (the other characteristics are held fixed at their actual values). In all specifications, we include year and MSA fixed effects. In the specification presented in column 5, the loan amount is included in deciles rather than as a continuous variable; the coefficients and significance on each of the size deciles are reported in Figure 3. *** and ** denote significance at the 1% and 5% levels. Coefficients and standard errors shown on Price per Square Foot are $\times 10^3$.

Table 4: Probit Estimation to Predict Default

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-2.10***	-2.52***	-2.62***	-2.47***	-2.44***	-2.45***
	(0.11)	(0.14)	(0.14)	(0.19)	(0.20)	(0.25)
CMBS	0.22**	0.07	0.10	0.05	0.06	0.04
	(0.09)	(0.10)	(0.10)	(0.11)	(0.11)	(0.11)
	3.0%	1.0%	1.4%	0.7%	0.8%	0.5%
Log Loan Amount		0.16***	0.15***	0.16***	0.16***	
		(0.03)	(0.03)	(0.04)	(0.04)	Deciles
		2.1%	2.0%	2.0%	2.1%	
LTV			0.19***	0.19***	0.19***	0.17**
			(0.06)	(0.07)	(0.07)	(0.07)
			2.5%	2.5%	2.4%	2.1%
Price per Square Foot			-0.063	-0.047	-0.038	0.027
			(0.15)	(0.18)	(0.18)	(0.16)
			-0.0008%	-0.0006%	-0.0005%	0.0003%
CBD				0.011	0.006	0.047
				(0.158)	(0.158)	(0.155)
				0.1%	0.1%	0.6%
Multi-building				-0.15	-0.14	-0.14
				(0.19)	(0.19)	(0.19)
				-1.9%	-1.8%	-1.8%
Property built before 1960				-0.28*	-0.30*	-0.33**
				(0.17)	(0.17)	(0.17)
				-3.6%	-3.8%	-4.1%
Property built 1960 to 1980				-0.28*	-0.30*	-0.28*
				(0.17)	(0.17)	(0.17)
				-3.6%	-3.8%	-3.6%
Property built 1980 to 2000				-0.25*	-0.26*	-0.25*
				(0.15)	(0.14)	(0.15)
				-3.2%	-3.3%	-3.2%
Year Dummies (2005, 2006, and 2007)	Yes	Yes	Yes	Yes	Yes	Yes
MSA Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Type Dummies	No	No	No	No	Yes	Yes
Number of Observations	2236	2236	2233	1962	1962	1962
Pseudo-R^2	6%	8%	9%	11%	11%	12%

Notes: The table contains estimates of a probit where the dependent variable takes a value of 1 if the loan defaults before May 1, 2012 and 0 otherwise (equation (3) in the text). The estimates are obtained from a pooled dataset of all loans in our January 2005 to April 2012 sample. In all six specifications, the first entry for each variable is the coefficient, the second entry (in parentheses) is the robust standard error, and the third entry is the effect of a 1 unit change in the independent variable (the other characteristics are held fixed at their actual values). In all specifications, we include year and MSA fixed effects. In the specification presented in column 6, the loan amount is included in deciles rather than as a continuous variable; the coefficients and significance on each of the size deciles are not reported. *** and ** denote significance at the 1% and 5% levels. Coefficients and standard errors shown on Price per Square Foot are $\times 10^3$.

Table 5: Probit Estimation of Loan Securitization from Structural Model (α=1)

	(1)	(2)	(3)	(4)	(5)
Constant	-2.60***	-2.43***	-2.39***	-2.37***	-2.87***
	(0.20)	(0.18)	(0.22)	(0.22)	(0.62)
Log Loan Amount	0.38***	0.48***	0.51***	0.50***	
	(0.03)	(0.03)	(0.03)	(0.04)	Deciles
LTV		-0.94***	-1.00***	-0.99***	-1.21***
		(0.12)	(0.14)	(0.14)	(0.16)
Price per Square Foot		-1.09***	-0.51***	-0.50***	-0.23
		(0.20)	(0.19)	(0.19)	(0.15)
CBD			-0.69***	-0.68***	-0.58***
			(0.15)	(0.15)	(0.15)
Multi-building			0.22	0.22	0.24
			(0.16)	(0.17)	(0.16)
Property built before 1960			-0.010	-0.015	-0.100
			(0.17)	(0.17)	(0.18)
Property built 1960 to 1980			-0.024	-0.029	-0.042
			(0.16)	(0.16)	(0.17)
Property built 1980 to 2000			0.22	0.22	0.18
			(0.14)	(0.14)	(0.14)
Equity Fund				0.056	0.110
				(0.152)	(0.149)
Corporate				-0.29	-0.23
				(0.23)	(0.25)
REIT				0.13	0.19
				(0.18)	(0.17)
Unknown Borrower Type				-0.059	0.217
				(0.163)	(0.192)
$\varepsilon_{i,t}^{DISTRESS}$	0.053	0.061	0.036	0.037	0.018
	(0.059)	(0.060)	(0.066)	(0.067)	(0.068)
Year Dummies (2005, 2006, and 2007)	Yes	Yes	Yes	Yes	Yes
MSA Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	2236	2233	1962	1962	1962
Pseudo-R^2	23%	27%	31%	31%	33%

Notes: The table contains estimates of a probit where the dependent variable takes a value of 1 if the loan is securitized and 0 otherwise (equation (4) in the text). The independent variables $x_{i,t-1}$ are the same as in Table 3. We identify the distress variable $\varepsilon_{i,t}^{DISTRESS}$ using default rates of the loans (see section 4) under the assumption that $\alpha = 1$, i.e. no difference in the likelihood of distressed CMBS loans entering into default relative to balance sheet loans. The estimates are obtained from a pooled dataset of all loans in our January 2005 to April 2012 sample. In all five specifications, the first entry for each variable is the coefficient, the second entry (in parentheses) is the robust standard error, and the third entry is the effect of a 1 unit change in the independent variable (the other characteristics are held fixed at their actual values). Standard errors are estimated using nonparametric bootstrap with 500 replications to take into account the fact that $\varepsilon_{i,t}^{DISTRESS}$ was estimated rather than observed. In all specifications, we include year and MSA fixed effects. In the specification presented in column 5, the loan amount is included in deciles rather than as a continuous variable; the coefficients of the size deciles are not reported. *** and ** denote significance at the 1% and 5% levels. Coefficients and standard errors shown on Price per Square Foot are $\times 10^3$.

Table 6: Probit Estimation of Loan Securitization from Structural Model, Different Values of α

	α=1.0	α=0.9	α=0.8	α=0.7	α=0.6
Constant	-2.37***	-2.37***	-2.37***	-2.38***	-2.38***
	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
Log Loan Amount	0.50***	0.50***	0.50***	0.50***	0.50***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
LTV	-0.99***	-0.99***	-0.98***	-0.98***	-0.98***
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Price per Square Foot	-0.50***	-0.50***	-0.50***	-0.50***	-0.51***
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
CBD	-0.68***	-0.68***	-0.68***	-0.68***	-0.68***
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Multi-building	0.22	0.22	0.22	0.22	0.23
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Property built before 1960	-0.015	-0.014	-0.012	-0.010	-0.008
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Property built 1960 to 1980	-0.029	-0.028	-0.028	-0.027	-0.026
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
Property built 1980 to 2000	0.22	0.22	0.22	0.22	0.23
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Equity Fund	0.056	0.056	0.057	0.057	0.058
	(0.152)	(0.152)	(0.152)	(0.153)	(0.153)
Corporate	-0.29	-0.29	-0.29	-0.28	-0.28
	(0.23)	(0.23)	(0.23)	(0.24)	(0.24)
REIT	0.13	0.13	0.13	0.13	0.13
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
Unknown Borrower Type	-0.059	-0.060	-0.061	-0.062	-0.063
	(0.163)	(0.163)	(0.164)	(0.164)	(0.164)
$\varepsilon_{i,t}^{DISTRESS}$	0.037	-0.001	-0.047	-0.104	-0.173**
	(0.067)	(0.069)	(0.073)	(0.077)	(0.081)
Year Dummies (2005, 2006, and 2007)	Yes	Yes	Yes	Yes	Yes
MSA Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	1962	1962	1962	1962	1962
Pseudo-R^2	31%	31%	31%	31%	32%

Notes: The table displays estimates of the same model as the one in Table 5, specification 4, but for a range of αs. For convenience, the results for $\alpha = 1$ from Table 5 are also displayed. The estimates are those of a probit where the dependent variable takes a value of 1 if the loan is securitized and 0 otherwise (equation (4) in the text). The independent variables $x_{i,t-1}$ are the same as in Table 3. We identify the distress variable $\varepsilon_{i,t}^{DISTRESS}$ using default rates of the loans (see section 4) under the assumptions that α=0.6, 0.7, 0.8, 0.9 and 1 , i.e. we allow for some difference in the likelihood of distressed CMBS loans entering into default relative to balance sheet loans. The estimates are obtained from a pooled dataset of all loans in our January 2005 to April 2012 sample. In all specifications, the first entry for each variable is the coefficient, the second entry (in parentheses) is the robust standard error, and the third entry is the effect of a 1 unit change in the independent variable (the other characteristics are held fixed at their actual values). Standard errors are estimated using nonparametric bootstrap with 500 replications to take into account the fact that $\varepsilon_{i,t}^{DISTRESS}$ was estimated rather than observed. In all specifications, we include year and MSA fixed effects. *** and ** denote significance at the 1% and 5% levels. Coefficients and standard errors shown on Price per Square Foot are $\times 10^3$.

Table 7: Maximum Likelihood Estimation of Default from Structural Model, Different Values of α

	α=1.0	α=0.9	α=0.8	α=0.7	α=0.6
Constant	-2.45***	-2.42***	-2.38***	-2.35***	-2.33***
	(0.20)	(0.21)	(0.22)	(0.23)	(0.25)
Log Loan Amount	0.17***	0.17***	0.16***	0.16***	0.15***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
LTV	0.18**	0.20**	0.22**	0.26**	0.33*
	(0.08)	(0.09)	(0.10)	(0.13)	(0.17)
Price per Square Foot	-0.07	-0.07	-0.07	-0.06	-0.05
	(0.19)	(0.20)	(0.20)	(0.21)	(0.22)
CBD ($\times 10^{-1}$)	-0.037	0.053	0.162	0.300	0.482
	(1.67)	(1.70)	(1.73)	(1.77)	(1.82)
Multi-building	-0.15	-0.16	-0.17	-0.19	-0.20
	(0.20)	(0.20)	(0.21)	(0.21)	(0.22)
Property built before 1960	-0.31*	-0.31*	-0.31	-0.31	-0.31
	(0.18)	(0.18)	(0.19)	(0.20)	(0.20)
Property built 1960 to 1980	-0.32*	-0.32*	-0.32*	-0.32*	-0.32*
	(0.17)	(0.17)	(0.18)	(0.18)	(0.19)
Property built 1980 to 2000	-0.26*	-0.26	-0.26	-0.27	-0.27
	(0.16)	(0.16)	(0.16)	(0.17)	(0.17)
Equity Fund	-0.080	-0.080	-0.079	-0.078	-0.078
	(0.169)	(0.172)	(0.176)	(0.180)	(0.185)
Corporate	-0.077	-0.076	-0.075	-0.073	-0.070
	(0.210)	(0.213)	(0.218)	(0.223)	(0.230)
REIT	-0.39	-0.40	-0.40	-0.41	-0.42
	(0.39)	(0.40)	(0.40)	(0.40)	(0.41)
Unknown Borrower Type	-0.26	-0.26	-0.25	-0.25	-0.24
	(0.24)	(0.24)	(0.25)	(0.26)	(0.26)
Year Dummies (2005, 2006, and 2007)	Yes	Yes	Yes	Yes	Yes
MSA Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	1962	1962	1962	1962	1962

Notes: The table displays maximum likelihood estimates of the default equation from the structural model (equations 5-7 in the text), which we use to estimate $\varepsilon_{i,t}^{DISTRESS}$. The model is estimated under the assumptions that α=0.6, 0.7, 0.8, 0.9 and 1 , i.e. we allow for some difference in the likelihood of distressed CMBS loans entering into default relative to balance sheet loans. These are the same assumptions used in Table 6. The estimates are obtained from a pooled dataset of all loans in our January 2005 to April 2012 sample. In all specifications, the first entry for each variable is the coefficient, the second entry (in parentheses) is the robust standard error, and the third entry is the effect of a 1 unit change in the independent variable (the other characteristics are held fixed at their actual values). Standard errors are estimated using nonparametric bootstrap with 500 replications. In all specifications, we include year and MSA fixed effects. ***, **, and * denote significance at the 1%, 5% and 10% levels. Coefficients and standard errors shown on Price per Square Foot are $\times 10^3$.

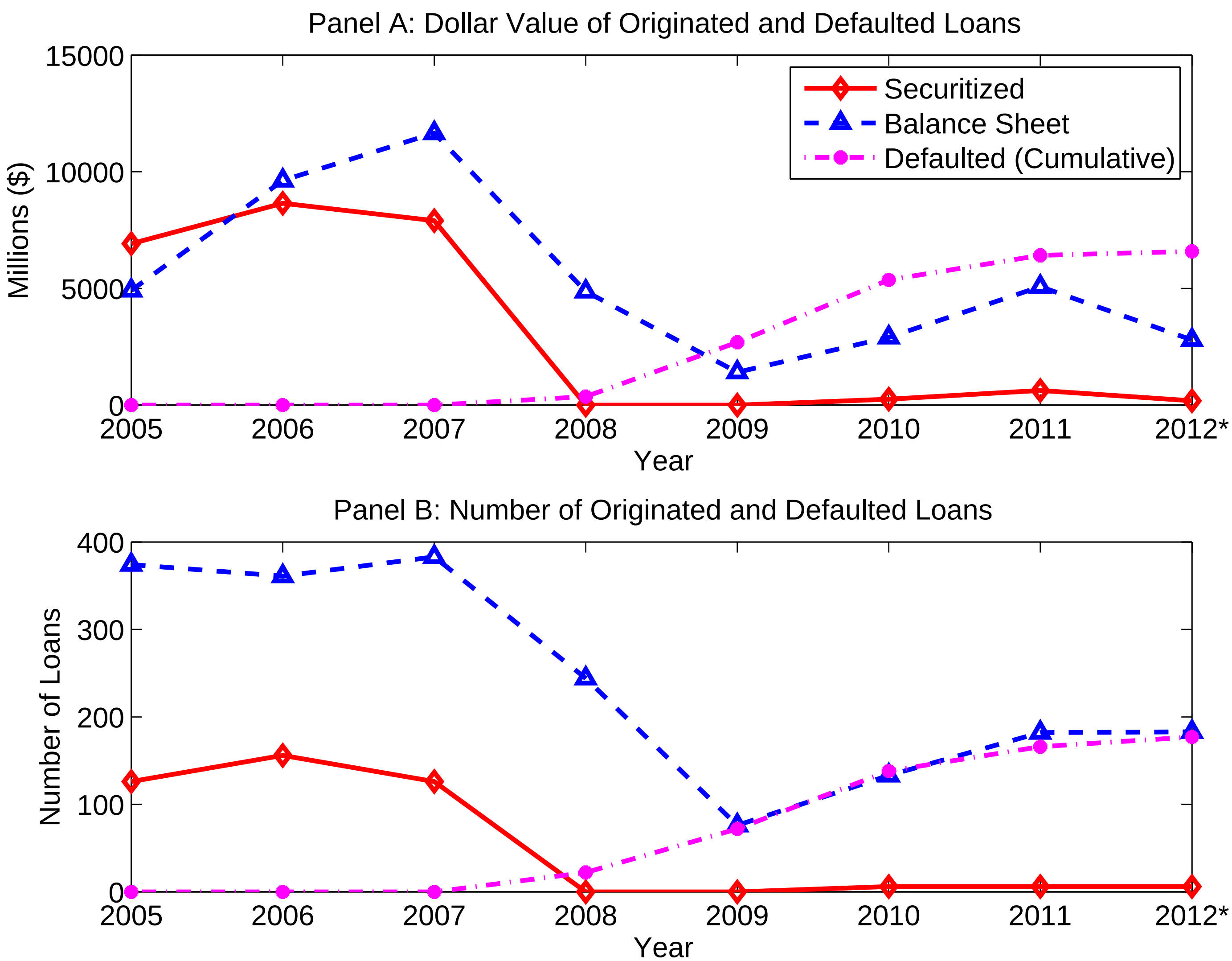

Figure 1: Issuance (Panel A) and defaults (Panel B) of loans on office property in Boston, Las Vegas, Los Angeles, and NYC Metropolitan areas originated between January 2005 and April 2012. * denotes that 2012 issuance numbers are annualized. The data consists of single-property purchase loans only. Default is defined as a completed foreclosure, a foreclosure that has been initiated but not completed, or a borrower bankruptcy.

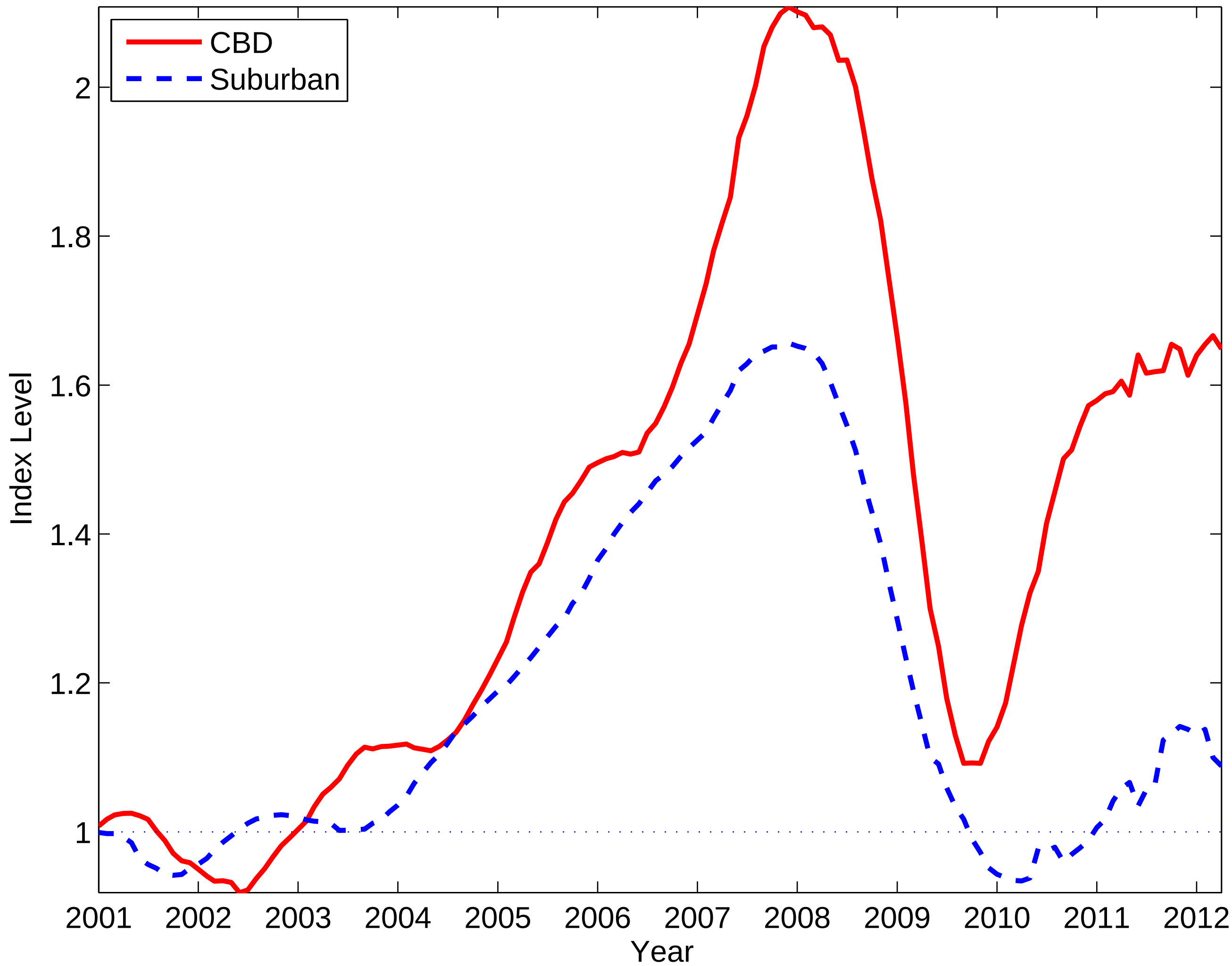

Figure 2: Office property price indices for central business district (CBD) and suburban regions from January 2001 to April 2012. The indices are Real Capital Analytics' (RCA) repeat transaction national office price series, normalized to equal 1 in January 2001.

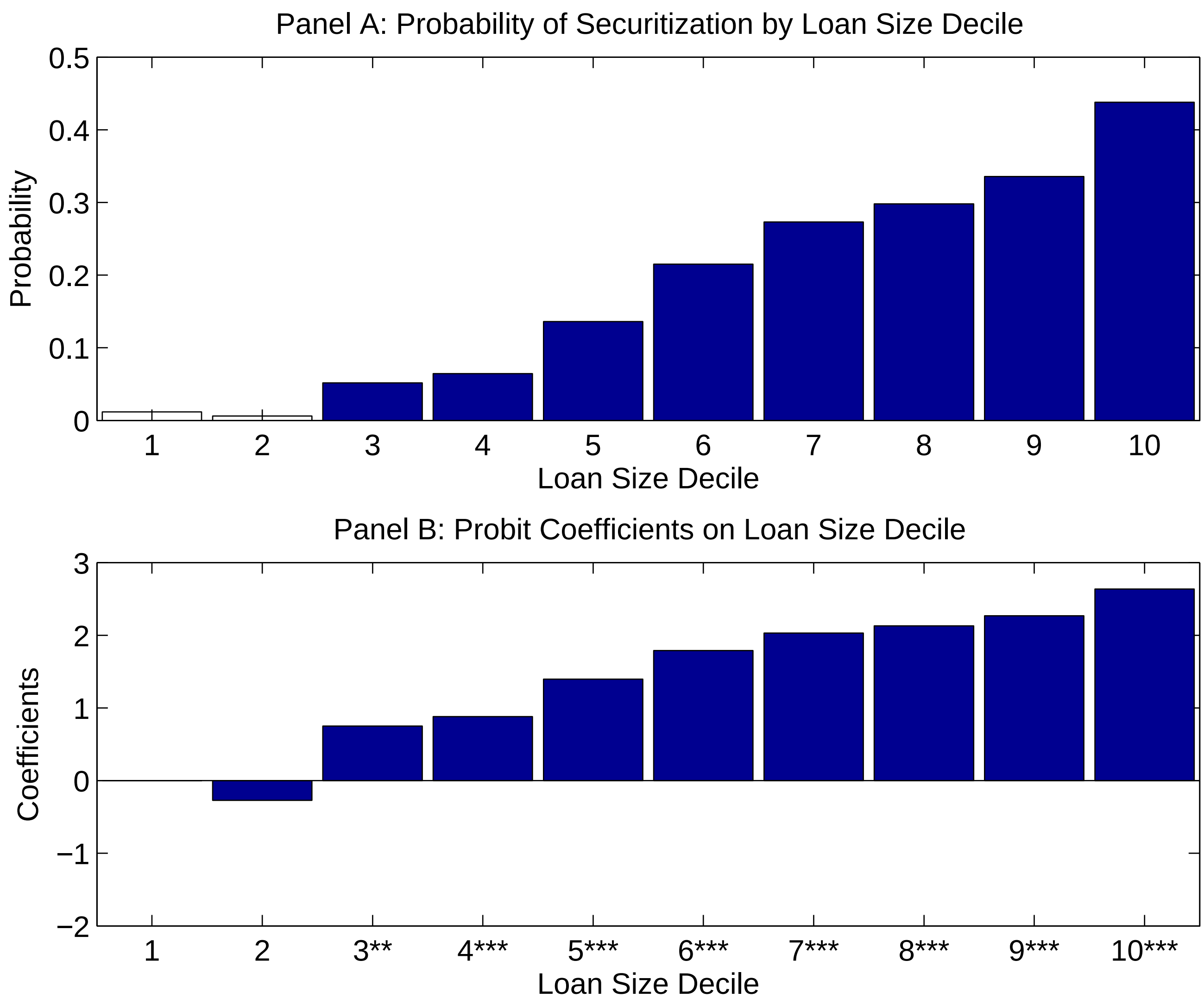

Figure 3: Probit estimates from the CMBS selection equation (equation (2)) shown in Table 3, specification 5. In Panel A, each bar shows the probability that a loan of a given size decile is securitized. The displayed probabilities are averaged over all loans. In Panel B, the probit coefficients on each loan size deciles are displayed, with the exception of decile 1. The data comprises size and securitization of office property loans in Boston, Las Vegas, Los Angeles, and NYC Metropolitan areas originated between January 2005 and April 2012. $***$ and $**$ denote significance at the 1% and 5% levels.

Appendix: Estimation Details and Supplementary Results

We have the index model:

$$\begin{aligned}
\Pr\left(D_{i,t+1}=1\right) &= \left(CMBS_{i,t}+\alpha\left(1-CMBS_{i,t}\right)\right)\Pr\left(\tilde{x}_{i,t-1}\eta+\varepsilon_{i,t+1}^{DISTRESS}>0\right) \\
&= \left(CMBS_{i,t-1}+\alpha\left(1-CMBS_{i,t-1}\right)\right)F\left(\tilde{x}_{i,t-1}\eta\right).
\end{aligned}$$

assuming that $\varepsilon_{i,t+1}^{DISTRESS}$ has a symmetric cumulative distribution function $F(\cdot)$.

The density of $D_{i,t+1}$ given $\tilde{x}_{i,t-1}$, η, α, and $CMBS_{i,t}$ is thus

$$f\left(D_{i,t+1}|\tilde{x}_{i,t-1},\eta,\alpha\right)=\left\{\begin{array}{c}
\left[F\left(\tilde{x}_{i,t-1}\eta\right)\right]^{D_{i,t+1}}\left[1-F\left(\tilde{x}_{i,t-1}\eta\right)\right]^{1-D_{i,t+1}}CMBS_{i,t} \\
\left[\alpha F\left(\tilde{x}_{i,t-1}\eta\right)\right]^{D_{i,t+1}}\left[1-\alpha F\left(\tilde{x}_{i,t-1}\eta\right)\right]^{1-D_{i,t+1}}\left(1-CMBS_{i,t}\right)
\end{array}\right\}$$

so the log likelihood of observation i is

$$\begin{aligned}
\ell_i\left(\eta\right) &= D_{i,t+1}\ln\left\{\left[CMBS_{i,t}+\alpha\left(1-CMBS_{i,t}\right)\right]F\left(\tilde{x}_{i,t-1}\eta\right)\right\} \\
&\quad+\left(1-D_{i,t+1}\right)\ln\left\{1-\left[CMBS_{i,t}+\alpha\left(1-CMBS_{i,t}\right)\right]F\left(\tilde{x}_{i,t-1}\eta\right)\right\}
\end{aligned}$$

and grouping observations by their securitization status we can write the log likelihood for the sample as

$$\begin{aligned}
\mathcal{L}\left(\eta\right) &= \sum_{i=1}^{N_{CMBS}}\left\{D_{i,t+1}\ln F\left(\tilde{x}_{i,t-1}\eta\right)+\left(1-D_{i,t+1}\right)\ln\left(1-F\left(\tilde{x}_{i,t-1}\eta\right)\right)\right\} \\
&\quad+\sum_{i=1}^{N_{BAL.SHEET}}\left\{D_{i,t+1}\ln\left[\alpha F\left(\tilde{x}_{i,t-1}\eta\right)\right]+\left(1-D_{i,t+1}\right)\ln\left(1-\alpha F\left(\tilde{x}_{i,t-1}\eta\right)\right)\right\}
\end{aligned}$$

which can be estimated using maximum likelihood.

We can thus take $\hat{\varepsilon}_{i,t+1}^{DISTRESS}$ as an estimate of $\varepsilon_{i,t}^{DISTRESS}$ to estimate (4). We follow Chesher and Irish (1987) in computing the generalized residuals as the derivative of the log-likelihood of each observation with respect to the constant term, i.e.,

$$
\begin{aligned}
\hat{\varepsilon}_{i,t+1} &= E\left(\varepsilon_{i,t+1}^{DISTRESS} | D_{i,t+1}, \tilde{x}_{i,t-1}, \eta, \alpha, CMBS_{i,t}\right) \\
&= \frac{\partial \ell_i(\eta)}{\partial \eta} \\
&= \left\{ \begin{array}{c} \frac{D_{i,t+1} f(\tilde{x}_{i,t-1}\eta)}{F(\tilde{x}_{i,t-1}\eta)} + \frac{-(1-D_{i,t+1}) f(\tilde{x}_{i,t-1}\eta)}{1-F(\tilde{x}_{i,t-1}\eta)} CMBS_{i,t} \\ \frac{D_{i,t+1} f(\tilde{x}_{i,t-1}\eta)}{F(\tilde{x}_{i,t-1}\eta)} + \frac{-(1-D_{i,t+1})\alpha f(\tilde{x}_{i,t-1}\eta)}{1-\alpha F(\tilde{x}_{i,t-1}\eta)} (1 - CMBS_{i,t}) \end{array} \right\} \\
&= \left\{ \begin{array}{c} \frac{(D_{i,t+1} - F(\tilde{x}_{i,t-1}\eta)) f(\tilde{x}_{i,t-1}\eta)}{F(\tilde{x}_{i,t-1}\eta)[1-F(\tilde{x}_{i,t-1}\eta)]} CMBS_{i,t} \\ \frac{(D_{i,t+1} - \alpha F(\tilde{x}_{i,t-1}\eta)) f(\tilde{x}_{i,t-1}\eta)}{F(\tilde{x}_{i,t-1}\eta)[1-\alpha F(\tilde{x}_{i,t-1}\eta)]} (1 - CMBS_{i,t}) \end{array} \right\} \qquad (8)
\end{aligned}
$$

See also Cox and Snell (1968), Pagan and Vella (1989), and Greene (2000, pp. 916-917) for discussions of generalized residuals. Intuitively, the effect of α in (8) is to increase the residual for balance sheet loans that do not default. If $\alpha < 1$, the balance sheet loans had on average higher risk than what we observe purely from the default and the factor α corrects accordingly.

Table A1: Probit Estimation of Loan Securitization, Different Values of α (Loan Amount in Deciles)

	α=1.0	α=0.9	α=0.8	α=0.7	α=0.6
Constant	-2.87***	-2.88***	-2.88***	-2.89***	-2.90***
	(0.62)	(0.62)	(0.62)	(0.62)	(0.62)
LTV	-1.21***	-1.21***	-1.20***	-1.20***	-1.20***
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
Price per Square Foot ($\times 10^{-3}$)	-0.23	-0.24	-0.24	-0.24	-0.24
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
CBD	-0.58***	-0.58***	-0.59***	-0.59***	-0.59***
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Multi-building	0.24	0.25	0.25	0.25	0.25
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
Property built before 1960	-0.100	-0.10	-0.10	-0.09	-0.09
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
Property built 1960 to 1980	-0.042	-0.041	-0.040	-0.038	-0.036
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Property built 1980 to 2000	0.18	0.18	0.18	0.18	0.19
	(0.14)	(0.14)	(0.15)	(0.15)	(0.15)
Equity Fund	0.11	0.11	0.11	0.11	0.11
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Corporate	-0.23	-0.23	-0.23	-0.23	-0.23
	(0.25)	(0.25)	(0.25)	(0.25)	(0.25)
REIT	0.19	0.19	0.19	0.19	0.19
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Unknown Borrower Type	0.22	0.22	0.21	0.21	0.21
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
γ	0.018	-0.021	-0.067	-0.124	-0.192**
	(0.068)	(0.070)	(0.073)	(0.077)	(0.080)
Year Dummies (2005, 2006, and 2007)	Yes	Yes	Yes	Yes	Yes
MSA Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	1962	1962	1962	1962	1962
Pseudo-R^2	33%	33%	33%	33%	34%

Notes: 1) The dependent variable in each model takes a value of 1 if the loan is securitized and 0 otherwise. 2) The first entry for each variable is the coefficient and the second entry (in parentheses) is the standard error. 3) REIT borrowers include publicly traded and non-traded REITs. 4) *** and ** denote significance at the 1% and 5% levels. 5) Coefficients and standard errors estimated using nonparametric bootstrap with 500 replications.

Table A2: Maximum Likelihood Estimation of Default, Different Values of α (Loan Amount in Deciles)

	α=1.0	α=0.9	α=0.8	α=0.7	α=0.6
Constant	-2.50***	-2.47***	-2.43***	-2.39***	-2.35***
	(0.27)	(0.28)	(0.29)	(0.30)	(0.31)
LTV	0.16*	0.18**	0.20**	0.24**	0.30*
	(0.08)	(0.09)	(0.10)	(0.12)	(0.15)
Price per Square Foot ($\times 10^{-3}$)	0.007	0.005	0.004	0.004	0.008
	(0.17)	(0.18)	(0.19)	(0.20)	(0.20)
CBD	0.042	0.051	0.062	0.074	0.090
	(0.167)	(0.170)	(0.173)	(0.177)	(0.181)
Multi-building	-0.16	-0.17	-0.18	-0.19	-0.21
	(0.20)	(0.20)	(0.21)	(0.21)	(0.22)
Property built before 1960	-0.34*	-0.35*	-0.35*	-0.35*	-0.34*
	(0.18)	(0.19)	(0.19)	(0.20)	(0.20)
Property built 1960 to 1980	-0.30*	-0.31*	-0.31*	-0.31	-0.30
	(0.17)	(0.18)	(0.18)	(0.19)	(0.19)
Property built 1980 to 2000	-0.26	-0.26	-0.27	-0.27	-0.27
	(0.16)	(0.16)	(0.17)	(0.17)	(0.18)
Equity Fund	-0.098	-0.098	-0.099	-0.100	-0.101
	(0.167)	(0.171)	(0.175)	(0.179)	(0.184)
Corporate	-0.038	-0.037	-0.036	-0.034	-0.032
	(0.218)	(0.222)	(0.227)	(0.233)	(0.240)
REIT	-0.40	-0.41	-0.42	-0.44	-0.45
	(0.39)	(0.39)	(0.40)	(0.40)	(0.41)
Unknown Borrower Type	-0.21	-0.21	-0.21	-0.21	-0.21
	(0.25)	(0.25)	(0.26)	(0.26)	(0.27)
Year Dummies (2005, 2006, and 2007)	Yes	Yes	Yes	Yes	Yes
MSA Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	1962	1962	1962	1962	1962

Notes: 1) The dependent variable in each model takes a value of 1 if the loan defaults before May 1, 2012 and 0 otherwise. 2) The first entry for each variable is the coefficient and the second entry (in parentheses) is the standard error. 3) REIT borrowers include publicly traded and non-traded REITs. 4) ***, **, and * denote significance at the 1%, 5%, and 10% levels. 5) In the specification presented, the loan amount is included in deciles rather than as a continuous variable. 6) Coefficients and standard errors estimated using nonparametric bootstrap with 500 replications.

Table A3: Probit Estimation of Loan Securitization, Different Values of α, p=0.75

	α=1.0	α=0.9	α=0.8	α=0.7	α=0.6
Constant	-2.37***	-2.37***	-2.37***	-2.38***	-2.38***
	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
Log Loan Amount	0.50***	0.50***	0.50***	0.50***	0.50***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
LTV	-0.99***	-0.99***	-0.98***	-0.98***	-0.98***
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Price per Square Foot ($\times 10^{-3}$)	-0.50***	-0.50***	-0.50***	-0.50***	-0.51***
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
CBD	-0.68***	-0.68***	-0.68***	-0.68***	-0.68***
	(0.15)	(0.14716)	(0.15)	(0.15)	(0.15)
Multi-building	0.22	0.22	0.22	0.22	0.22
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Property built before 1960	-0.015	-0.014	-0.012	-0.011	-0.009
	(0.168)	(0.168)	(0.168)	(0.168)	(0.169)
Property built 1960 to 1980	-0.029	-0.028	-0.028	-0.028	-0.027
	(0.161)	(0.161)	(0.161)	(0.162)	(0.162)
Property built 1980 to 2000	0.22	0.22	0.22	0.22	0.23
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Equity Fund	0.056	0.056	0.057	0.057	0.058
	(0.152)	(0.152)	(0.152)	(0.153)	(0.153)
Corporate	-0.29	-0.29	-0.29	-0.28	-0.28
	(0.23)	(0.23)	(0.23)	(0.24)	(0.24)
REIT	0.13	0.13	0.13	0.13	0.13
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
Unknown Borrower Type	-0.059	-0.060	-0.061	-0.062	-0.063
	(0.163)	(0.163)	(0.164)	(0.164)	(0.164)
γ	0.046	0.005	-0.045	-0.107	-0.184**
	(0.073)	(0.077)	(0.081)	(0.086)	(0.091)
Year Dummies (2005, 2006, and 2007)	Yes	Yes	Yes	Yes	Yes
MSA Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	1962	1962	1962	1962	1962
Pseudo-R^2	31%	31%	31%	31%	32%

Notes: 1) The dependent variable in each model takes a value of 1 if the loan is securitized and 0 otherwise. 2) The first entry for each variable is the coefficient and the second entry (in parentheses) is the standard error. 3) REIT borrowers include publicly traded and non-traded REITs. 4) *** and ** denote significance at the 1% and 5% levels. 5) Coefficients and standard errors estimated using nonparametric bootstrap with 500 replications.

Table A4: Probit Estimation of Loan Securitization, Different Values of α, p=0.5

	α=1.0	α=0.9	α=0.8	α=0.7	α=0.6
Constant	-2.37***	-2.37***	-2.37***	-2.38***	-2.38***
	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
Log Loan Amount	0.50***	0.50***	0.50***	0.50***	0.50***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
LTV	-0.99***	-0.99***	-0.99***	-0.98***	-0.98***
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Price per Square Foot ($\times 10^{-3}$)	-0.50***	-0.50***	-0.50***	-0.50***	-0.51***
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
CBD	-0.68***	-0.68***	-0.68***	-0.68***	-0.68***
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Multi-building	0.22	0.22	0.22	0.22	0.22
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Property built before 1960	-0.015	-0.014	-0.013	-0.012	-0.012
	(0.168)	(0.168)	(0.168)	(0.168)	(0.169)
Property built 1960 to 1980	-0.028	-0.028	-0.028	-0.029	-0.029
	(0.161)	(0.161)	(0.161)	(0.161)	(0.162)
Property built 1980 to 2000	0.22	0.22	0.22	0.22	0.22
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Equity Fund	0.055	0.056	0.057	0.057	0.058
	(0.152)	(0.152)	(0.152)	(0.152)	(0.153)
Corporate	-0.29	-0.29	-0.29	-0.28	-0.28
	(0.23)	(0.23)	(0.23)	(0.23)	(0.24)
REIT	0.13	0.13	0.13	0.13	0.13
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
Unknown Borrower Type	-0.058	-0.060	-0.061	-0.062	-0.064
	(0.163)	(0.163)	(0.164)	(0.164)	(0.164)
γ	0.067	0.021	-0.036	-0.108	-0.200*
	(0.086)	(0.091)	(0.097)	(0.104)	(0.112)
Year Dummies (2005, 2006, and 2007)	Yes	Yes	Yes	Yes	Yes
MSA Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	1962	1962	1962	1962	1962
Pseudo-R^2	31%	31%	31%	31%	31%

Notes: 1) The dependent variable in each model takes a value of 1 if the loan is securitized and 0 otherwise. 2) The first entry for each variable is the coefficient and the second entry (in parentheses) is the standard error. 3) REIT borrowers include publicly traded and non-traded REITs. 4) ***, **, and * denote significance at the 1%, 5%, and 10% levels. 5) Coefficients and standard errors estimated using nonparametric bootstrap with 500 replications.

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