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Abstract

We expand on the standard commercial mortgage default model and create a new model by looking beyond the usual factors of option value, insolvency, property type, region, originator type, state foreclosure laws and macroeconomic measures. The new model incorporates measures of local economic conditions, specifically MSA-level commercial property market conditions, county level unemployment, and local home price appreciation. We estimate our new model using a dataset containing the performance histories of over 30,000 CMBS loans that were originated between 1998 and 2012. We find that those local trait variables affect the default rate of CMBS loans significantly and provide improved explanatory power over the standard model. We further explore the impact of local home price measures by comparing the explanatory power of lagged and contemporaneous home price indexes, comparing the power of home price indexes at the state, county, and zip-code level, examining the interaction of home price indexes with commercial property type, looking at the impact of home price indexes over time, and at the impact of introducing local commercial land price indexes. We find that local residential house price-related measures provide a high quality and high frequency signal of local market conditions.

Keywords: default risk, CMBS loan, local trait, hazard model

JEL Code: G21, G12, C41

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Local Traits and Securitized Commercial Mortgage Default

1. Introduction

In 2012, almost 5 years after the onset of the global financial crisis in 2007, the delinquency rate for loans in the Commercial Mortgage Backed Securities (CMBS) market remained close to 10 percent. While many default loans have been resolved, we are now seeing loans mature that were underwritten when property valuations were at their height, often with negative equity. We will continue to see a steady stream of such loans maturing over the next five years. Given the concentration of the financial sector's assets in commercial loans, there is an acute need to improve our understanding of the default behavior of commercial mortgage loans, both to understand how these vulnerable loans may perform over the short-run, and to improve our understanding of the potential credit risks in new CMBS pools. In this paper, we investigate the relationship between securitized commercial mortgage defaults and local traits, in addition to the conventional loan-level and macroeconomic factors.

It is well-established that default is a put option for mortgage borrowers. Having negative equity greatly increases the borrower's chance of default (see, e.g., Titman and Torous, 1989; Vandell, et al, 1993; Quigley and Van Order, 1995). For commercial mortgages, insolvency (negative cash flow) is another critical trigger of default (see, e.g., Goldberg and Capone, 2002; Seslen and Wheaton, 2010). Various other loan-specific and non-loan-specific variables have been shown to explain commercial mortgage default. Loan-specific factors include the underwriting loan-to-value ratio (LTV), loan size, prepayment incentives, property type, prepayment constraints (see, e.g., Goldberg and Capone, 2002; Ciochetti, et al, 2002, 2003; Ambrose and Sanders, 2003). Non-loan-specific factors include macroeconomic variables (yield slope, interest rate volatility, etc.), geography, the legal environment, originator type, and the impact of special servicers (see, e.g., Ambrose and Sanders, 2003; Yildirim, 2008; Archer, et al, 2002; Titman and Tsyplakov, 2007; Black, et al, 2012; Chen and Deng, 2013). However, the importance of local economic traits on CMBS mortgage default risk has not been fully investigated.

There are at least three reasons why local economic traits are important for improving our understanding of commercial mortgage default behavior. First, the accuracy of measurements of default (put) option is usually limited by the availability of a regional property index[1]. Therefore, local economic variables may help capture the variations in property price that are not well-captured by the property price index at a more aggregate level. Second, default is a compounding option for mortgage borrowers, and so expectations about future movements in property price and interest rates affect option values (see, e.g., Kau and Keenan, 1995). In that regard, local economic variables could be proxies of local business cycles that affect borrowers' expectations, and thus affect default. Finally, the recent literature on contagion points to the importance of neighborhood characteristics and economic conditions on default (see, e.g., Harding, Rosenblatt and Yao, 2009).

In this paper, we take advantage of a large national sample of CMBS loans and use it to explore the impact of local traits on commercial mortgage default. Our analysis is based on over 30,000 CMBS loans from the nine US census regions[2]. Our sample period is 1998-2012, which includes the recent recession. Nearly 4,800 CMBS loans suffered default in this period, accounting for about 16 percent of our loan sample.

[1] For example, the widely used NCREIF NPI is only broken down to the four census regions.
[2] Alaska and Hawaii are excluded from our analysis.

We first try to explain the default probabilities of these CMBS loans by estimating an updated hazard model for mortgage default. While the benchmark model includes explanatory variables that are well-established in the existing literature, such as the values of the call and put options, current debt-service coverage ratios (DSCR), information on the property type, region, underwriting terms at origination, and national macro-economic indicators, we expand it to include some less frequently used variables such as the contemporaneous property occupancy rate, originator type, impact of natural disaster (Hurricane Katrina), foreclosure law and loan covenants. While most of the variables included in the benchmark model affect default in a way consistent with the existing literature, the addition of these less frequently used variables in our expanded model significantly adds to our ability to explain CMBS default. For example, in addition to the underwritten and contemporaneous LTV and DSCR, we find contemporaneous occupancy rates at the property level to be an important determinant of CMBS loan default. For state foreclosure law, the availability of deficiency judgments (recourse), affects CMBS loan default significantly, while the expected length of foreclosure does not. We also find that CMBS loans in Katrina-affected areas demonstrated significantly higher default risk.

We then extend the benchmark model by adding local economic traits such as MSA-level commercial real estate market vacancy rates, rent changes, and absorption rates. We find that these additional variables have significant impact on CMBS loan default. For example, markets with higher vacancy rates, or greater declines in rents or net absorption, have a higher default risk. We then test the importance of such local traits at a finer geographic level, for example by examining the relationship between county-level unemployment rates and residential house price appreciation. We find that markets with higher unemployment rates and lower house price appreciation levels have a higher default risk. Overall, local traits at both the MSA and county-level provide additional explanatory power for CMBS loan defaults.

The connection between residential real estate price appreciation and defaults of commercial mortgages particularly attracts our attention, leading us to conduct a detailed exploration of the connection between county-level residential house price indexes and CMBS default. Does the correlation we observe signal some form of spillover from the residential to the commercial market? Or do residential house price indexes simply provide powerful and useful barometers of local market conditions? We explore this question by comparing house price indexes across property types, and find no sign of a stronger relationship for particular property types that would be more exposed to disruption in the residential market. We also find that there is little difference in the explanatory power of residential house prices calculated at the zip code, county, and state levels. This result suggests that the primary benefit of the local residential house price measure is as a high quality and high frequency signal of local market conditions.

Finally, we estimate our model over a subsample of 23 MSAs. We include a recently-developed MSA-level commercial land price index (Nichols, Oliner and Mulhall, 2013) as a proxy for changes in local property values. The land price index is available only bi-annually and, despite having a significant lag, has been found to be a strong predictor of CMBS loan defaults. In this way, it is similar to the 4-quarter lagged zip-code house price appreciation level. However, the land price index does not fully take away the explanatory power of house price appreciation in CMBS loan defaults. In fact, the model that includes both the land price index and the lagged zip-code house price appreciation index yields the highest explanatory power.

In summary, we extend the standard CMBS default model with local market level variables and find that local traits play important roles in explaining CMBS loan defaults. The updated model helps us better understand the risk factors impacting commercial mortgages, and will be a useful tool in risk management and financial regulation.

The rest of the paper is organized as follows. In section 2, we explain how our data is sourced in section 3, we introduce the Cox proportional hazard model and explain the specifications of our model; in section 4, we explore the correlation between residential home prices and CMBS default rates in more detail; and in section 5, we conclude the paper.

2. Data

Morningstar provided the CMBS loan data adopted in this study. Their database covers substantially all CMBS deals in US, gathered from monthly master servicers' reports. The format of this report is laid out in the CRE Finance Council's Investor Reporter Package (IRP) [3] which provides an internally consistent set of data across all CMBS loans. Although Morningstar includes data from when the modern CMBS market era began in 1995[4], information on CMBS from 1995 to 1998 has not bee found to be reliable, leading us to exclude loans originated before 1998. Thus our full data sample includes 106,010 CMBS loans originated between 1998 and 2011. The current study has a simple advantage over earlier studies as they tended to use much smaller and less diverse data sets. For example, Vandell et al (1993), Ciochetti and Vandell

[3] The CRE Finance Council, as the main trade association for the CMBS market, has developed the IRP as a consistent set of data reports to be completed by loan servicers and made available to the trustees on CMBS deals.

[4] Before that date, a substantial portion of the CMBS loans were from non-performing Savings and Loan Companies who originated those loans with the intention of holding them in their portfolios, but later liquidate them through the Resolution Trust Company (RTC). Since1995, there has been a substantial increase in lending by banks and mortgage companies for the sole purpose of securitization.

(1999) and Ciochetti et al (2002) employed much smaller samples from life insurance companies. Other authors such as Archer et al (2001), and Goldberg and Capone (2002) studied only multifamily mortgage loans securitized by RTC and the GSEs, respectively. More recently, Ambrose and Sanders (2003) assembled a sample of 4,257 CMBS loans that were originated between 1995 and 2000. Seslen and Wheaton (2005) studied about 20,000 CMBS loans that were originated during 1992 and 2003, while Yildirim (2008) employed a database consisting of over 50,000 CMBS loans originated between 1998 and 2005. Black et al (2012) used the same Morningstar data employed in the current study to examine differences in loan performance across differing loan originator types.

Morningstar provides data on the underlying loans and properties for each CMBS deal. This data is updated monthly with the latest performance information. As a result, the database includes over 8 million loan performance records and we are able to construct an event history for each CMBS loan with the loan's status in each period being reflected as being prepaid[5], delinquent, foreclosed or current. The database also includes loan specific information such as LTV, NOI, original balance, current balance, actual rate (mortgage coupon rate adjusted by points), maturity term, amortization period, property type, location, prepayment provisions, originator details, and servicers (both master and special servicers). Most of the information provided was collected when the loan was originated or secured, but the IRP also requires borrowers to provide regular updates of the current LTV, NOI, occupancy rate, and DSCR for each property. Although a failure to provide such an update results in a technical default on the loan, servicers have been unwilling to enforce this rule, resulting in many properties missing updates on their contemporaneous LTV, NOI, occupancy rates and DSCR. For the purposes of our current study,

[5] We defined defeased loans as prepaid for the purpose of our analysis.

we focus on fixed-rate mortgage loans of six major property types: multifamily, retail, office, industrial, hotel, and other. The 'other' category includes properties such as assisted living facilities, medical offices, and other atypical forms of commercial real estate. We exclude non-MSA loans and loans from Hawaii and Alaska. We also exclude loans with 'interest-only' periods. To ensure accuracy, we verified the loan information provided pertaining to rate, LTV, and original balance at origination, and excluded a number of loans with invalid information on these variables. This left us with a final sample of 30,053 loans from 9 census regions and 48 American states.

Table 1 provides a performance summary of our loan sample. Default is defined in the current study as being delinquent for over 60-days. The default rates reported on the table are the cumulative numbers of loans that underwent default between June 1998 and December 2012 as a percentage of the sample. Of a total of 30,053 loans, 4,803 underwent default, representing a sample default rate of 15.98%[6]. Recall that loans in our sample were originated between 1998 and 2011, and differed in age at the time of data collection. The default rates in Table 1 are not adjusted by vintage.

Table 2 provides a distribution of our sample by year of loan origination. It reflects the development of the CMBS market, demonstrating general growth between 1998 and 2006, and a notable decline in 2007 and 2008. The table clearly shows the substantial slowdown in the CMBS market in 2007 as the residential mortgage market crisis unfolded. Out of the total of 30,053 CMBS loans, only 100 were originated in 2008 and 3 in 2009. The CMBS market slowly recovered in 2010 and 2011; in our sample, 351 and 160 loans were originated in those years.

[6] In our sample, 8.31% of loans are prepaid (including defeasance).

Table 3 provides a distribution of loan data by property type (without adjusting for the dollar value of the loan). Of our sample, 28% are multifamily loans, 31% are retail loans, 20% are office loans, 6% are industrial loans, 7% are hotel loans and the remaining 9% are classified as other. Table 4 reports the loan sample by region. Loans are not evenly distributed across regions. The Pacific and South Atlantic census regions account for roughly 42% of the sample, with New England accounting for only 4%.

Table 5 reports the means of key loan underwriting variables. The average original loan balance across the sample is $9.9 million, the average LTV is 69% and the average DSCR is 1.47. The data does not indicate whether the underwritten DSCR reflects any pro-forma assumptions regarding growth in property NOI. The average maturity time of the loan is 118 months, and the average amortization is nearly 30 years, reflecting the wide use of balloon mortgages. We can also identify the type of originator for the loan using the same definitions[7] that Black, et al (2011) found to be significant in explaining loan defaults. Table 6 reports the distribution of loans by originator type. Commercial banks represent 45% of the sample, while investment banks represent 18%. Insurance companies were third largest group, representing 16% of the sample.

3. A Hazard Model of CMBS Loan Default

3.1 The Cox proportional hazard model

[7] We identified the original lender as either a commercial bank, investment bank, conduit lender, foreign bank, or insurance company.

The Cox proportional hazard model has become the standard tool for mortgage default risk analysis[8]. It is convenient mainly because it allows us to work with our full sample even though some observations were censored when we collected our data. We assume that the hazard rate of a CMBS loan at a certain age follows the following form:

$$h_i\left(\tau; Z_i\left(t\right)\right) = h_0\left(\tau\right)\exp\left(Z_i\left(t\right)'\beta\right), i = 1, \cdots n\ . \qquad (1)$$

Here $h_0\left(\tau\right)$ is the baseline hazard function, which depends only on the age (duration) of the loan, τ [9]; $Z_i\left(t\right)$ is a vector of proportional covariates for individual loan i that represent time-varying or time-invariant risk factors. In this proportional hazard model, changes in the covariates shift the hazard rate proportionally without otherwise affecting the duration pattern of default risk.

Let j denote the individual loan failing at t_j and $R(t)$ denote the set of loans at risk of default at the beginning of time t. The vector of coefficients β is estimated from a partial likelihood function:

$$L(\beta) = \prod_{j=1}^{k} \frac{\exp\left[Z_j\left(t_j\right)'\beta\right]}{\sum_{l \in R(t_j)} \exp\left[Z_l\left(t_j\right)'\beta\right]}\ . \qquad (2)$$

The baseline function $h_0\left(\tau\right)$ is then estimated non-parametrically. The estimation of the aforementioned hazard model requires the construction of an event history for each loan which tracks the default (current) event and corresponding risk factors in each month (quarter) starting from the time of loan origination to loan maturity, loan default or loan censoring - whichever is earliest. We estimate our models based on these quarterly loan-event histories, that reflect the

[8] Quigley and Van Order (1991), Vandell, et al (1993) and Deng, Quigley and Van Order (1996) are among the early researchers who modeled mortgage default risk using the Cox proportional hazard modeling framework.
[9] Notice that the loan duration time τ is different from the calendar time t, which allows for the identification of the model.

frequency of many of the macro-economic and local market variables we have merged with the CMBS data in the manner described below.

3.2 Covariates

We merge a large number of variables, including the term structure of the interest rate, inflation, corporate credit spread, and local CRE market conditions by property type obtained from CBRE, the Nichols-Oliner-Mulhall commercial land price index, and the CoreLogic zip-code level house price indexes. We then construct a number of time-varying covariates that we include in our model in addition to the loan specific time invariant covariates. We first report the set of standard covariates that have been used in the previous literature, before discussing the new measures developed for the current paper.

Standard Covariates

Current LTV: Having negative equity is a well-documented reason for mortgage default, making current (contemporaneous) LTV a natural risk factor to include in our model (see, e.g. Vandell, 1993; Seslen and Wheaton 2010). Since many properties in our sample do not regularly report updated values, much of the data for servicer-reported current LTV levels is missing. Therefore, a national property type index is traditionally used to estimate the updated LTV, and often, property specific indexes, such as those produced by NCREIF, are used as well. We improve on this convention by developing three different definitions of the current LTV using the NCREIF national property-type specific indexes, a set of NCREIF regional property-type specific indexes, and MSA level property-type specific indexes from the CBRE. The final set of indexes are based on the transaction capitalization rates collected by Real Capital Analytics. While national index-derived LTV estimates have been used widely in the previous literature, the use of local property-type price indexes to reflect current LTV is a distinct innovation of the paper. Current LTV is expected to have a positive impact on CMBS loan defaults.

Current DSCR: In addition to negative equity, negative cash flow (insolvency) is another significant trigger of commercial mortgage default (see, e.g. Goldberg and Capone 2002, Seslen and Wheaton 2010). Therefore, we include the DSCR reported to the master servicer on the CRE Finance Council's IRP. If the DSCR was not reported, but the NOI was, we construct the DSCR from the reported NOI and the scheduled mortgage payments. In a few cases where both current DSCR and NOI are not reported, we use the last reported DSCR. In theory, DSCR has a negative correlation with default risk.

Interest rate volatility: Since the 1990s, researchers have considered mortgage default as the borrower's exercise of a put option. A rational borrower would make the decision to default when the put option is "in the money" (see, e.g. Quigley and Van Order 1995, Deng, Quigley and Van Order 2000). The use of the current LTV as a covariate captures a portion of this effect[10]. Since the value of the put option increases with volatility in state variables such as the interest rate, we include interest rate volatility as a covariate. We use the volatility of the 10-year Treasury rate computed from the daily data in our model.

Commercial property value volatility: Commercial property value is another state variable that determines the value of the put option. We therefore include a measure of commercial property value volatility in addition to interest rate volatility. Our measure is based on the NCREIF property value index (NPI). We calculate the volatility measure separately for each property type/census division combination.

[10] The true option value should be captured by the value of the "expected" LTV, which depends greatly on the volatilities of state variables.

Origination loan balance: The size of the loan is thought to be related to the transaction cost of mortgage default. This is found to be a particularly significant factor for residential mortgage default (e.g. Clapp et al 2001, Deng and Gabriel 2006). To test the impact of loan size on commercial mortgage default, we include it as a covariate and use the log form in our models.

Origination LTV: Some researchers believe that the loan to value ratio at origination (or at the time of down payment) not only affects the equity position of the borrower during the life of the loan, it also reveals the borrower's default propensity, or the borrower's ability to save. Further, it generally reflects the borrower's overall financial health and affects his default decision by reflecting sunk costs (see, Yezer, Phillips and Trost 1994, Kelly 2009). Additionally, lenders are thought to sometimes invest different levels of due diligence on high LTV and low LTV loans. We include origination LTV in our models for these reasons.

Refinance incentive: Prepayment and default are two competing risks in mortgage loans (Deng, Quigley and Van Order, 2000). Hence, higher refinance incentives should dampen default risk. However, when prepayment is restricted, as it is with many of our sample loans, these risks no longer compete in the same way, and default incentives are enhanced in a low interest rate environment (see, e.g., Childs, Ott and Riddiough, 1997). In our model, we calculate the difference in the market value of the loan and the book value of the loan as refinance incentives and include it as a covariate.

Property type: The literature in this area (see, e.g., Vandell, et al, 1993; Ciochetti, et al, 2002; Ambrose and Sanders, 2003; and An, 2007) has shown that commercial mortgage default varies systematically with collateral property type. Typically, multifamily loans are the least risky, followed by retail and office property loans. Industrial and hotel loans are viewed as the most risky of all commercial property collateral. Accordingly, we control for collateral property type in our models.

Region: Many of the existing studies include census region or census division fixed-effects (see, e.g., Ambrose and Sanders, 2003; Ciochetti, et al, 2002, 2003; Yildirim, 2008). Although we use the NCREIF property index by-region in constructing current LTV in our benchmark models, we still also include dummy variables for census divisions to capture possible regional fixed-effects. The Mid Atlantic region is used as the reference group for the nine US census divisions.

Loan covenants: Unlike residential mortgage loans, commercial mortgage loans usually have loan covenants such as prepayment restrictions. We suspect that prepayment lockout and yield maintenance clauses limit the borrowers' ability to refinance into more affordable loans, and thus increase the chances of default. Therefore, we include a time varying variable that indicates whether the loan is currently within lock out, or if it is in the yield maintenance period.

Macroeconomic variables: We use the growth of the coincident index as a sufficient proxy for macroeconomic conditions. Stronger growth in this index indicates strong economic conditions that reduce the default risk[11].

Foreclosure law: Ciochetti (1997) and Archer et al (2001) argue that the incidence of foreclosure can be correlated with the type of foreclosure process – whether judicial or power of sale. One hypothesis is that we can extend this reasoning to the rate of 60-day delinquencies and expect a positive relationship between the strictness of state foreclosure laws and the default rate. Knowing that it is both difficult and costly for lenders to pursue a foreclosure, borrowers will be more likely to default when their mortgages are under water, expecting that their lender will

[11] We also tested the yield slope and corporate credit spread in our model but found that they are highly correlated with the coincident index and add no additional explanatory power.

negotiate a deal in order to avoid the foreclosure. On the other hand, Riddiough and Wyatt (1994) argue that lenders are more likely to be tough to distressed borrowers if they know that the borrowers are likely to take advantage of their fear of entering into a costly judicial foreclosure process. This approach can reverse the relationship between the strictness of the state foreclosure law, and the default rate. To take into account this possibility, in addition to the number of months for a lender to complete the initial action of foreclosure, we include in our model an indicator of whether a deficiency judgment is allowed in a particular state. We expect that allowing deficiency judgment would increase the borrower’s cost of default and thus reduce the default probability, similar to what Ghent and Kudlyak (2011) found for residential mortgages.

Originator type: An, Deng and Gabriel (2011) argue that different types of commercial mortgage originators have different incentives to collect and use information related to default risk. Titman and Tsyplakov (2010) and Black, et al (2012) find significant differences in CMBS delinquency rates across different originator types. We generally classify originators as commercial bank, investment bank, insurance company, domestic conduit lender, and foreign-owned entity, and include dummy variables in our models to represent them.

Additional Covariates

Current occupancy rate: The property occupancy rate reflects the health of the property and its cash flow over the long term as commercial real estate tends to include many long term leases. Therefore, we suspect that the current occupancy rate of a mortgaged property provides more information than the current NOI that is included in standard models to provide information on the current DSCR and LTV. As we did for current LTV and current DSCR, we use the most recently reported occupancy rate provided by the borrower to the master servicer.

Natural disasters: Natural disasters affected many commercial properties in Louisiana, Mississippi, Alabama, and Florida, particularly Hurricane Katrina. After Katrina, many industry publications reported the degree to which CMBS pools were exposed to properties in the affected areas. Because of how significant a factor this was, we include a dummy variable for Katrina-affected states.

MSA Level CRE Market Measures: There is significant variation across markets in terms of their CRE fundamentals. Some markets, such as Las Vegas, are highly sensitive to swings in the general macro-economy. Others, such as Albany, are far more insulated. The ability of a CRE borrower to continue to service his debt reflects trends in the local CRE market. To measure this, we include measures of the change in real rents[12], the current absorption rate[13], and the current vacancy rate by property type, from the 53 MSAs reported by CBRE.

County Level Unemployment Rate: In addition to the CRE market measures, we wanted to include a measure of the immediate health of the local market for each property. We include the county level unemployment rate as a measure of the health of the local economy.

State, County, and Zip-Code Level Residential Home Price Appreciations: The final and most significant addition to our models is the Core Logic home price index generated according to differing geographic detail (state, county and zip-code level). In order to maintain

[12] We measure the change in the real rent index provided by CBRE as the ratio from loan origination to the current period.
[13] The absorption rate is defined as the ratio of spaces newly leased in a particular period over the sum of the amount of vacant space in the previous period and the amount of new space provided by buildings completed in that later period.

comparability with the unemployment measure, our standard models include the growth[14] in the county level house price index. We explore the relative explanatory power of the state and zip-code level indexes.

It is important to note that some of the local economic variables used in our analysis are not available for CMBS loans from all areas of our sample. As a result, we often limit our model estimation to the sub-sample of observations for which all the local economic variables are available.

3.3 The impacts of option value, insolvency triggers, occupancy, property type, loan covenants, the macro economy, foreclosure laws and natural disasters

Table 7 presents sample descriptive statistics from our event-history data. Here, each observation represents a loan record in a specific quarter. While the loan data is provided on a monthly basis, we converted them to quarterly frequency in order to reflect the frequency of many of the time-varying factors we merged with the data. Our use of CRE value indexes from different levels of geographical detail does introduce some additional error in our measure of current LTV. In response we bound the lower level of this variable at 10%. A current DSCR of zero means the property is not generating a positive NOI. Approximately 92% of the loan quarters are within their lock out period which is reflected in the mean of our variable, “lock out”. Another 38% of the loan quarters are within their yield maintenance periods.

Table 8 reports the results of the Partial Likelihood estimate of our baseline hazard model. This specification includes all of the standard variables included in the literature, with a few new additions. All continuous variables are standardized such that they have a mean of zero and a

[14] We define growth in the home price indexes as the log of the ratio of the index from the current period to origination.

standard deviation of one so that we can interpret the hazard ratio as indicating how one standard deviation of shock (in that variable) affects the default risk. The three models reported on this table differ only by the level of geographical detail used to update the measure of current LTV.

The first column reports results using the standard definition of current LTV, estimated using national property specific CRE price indexes. The coefficients of the standard variables are mostly consistent with that of previous research, with a few surprises. Primarily, defaults are found to be higher in the Mountain, West South Central and East North Central census divisions. The volatility of the treasury rate is negative and significant, which is counter to what would be expected from the theory. Interestingly, the impact on loan default of the LTV at the origination of the loans is significant, in only at the 10 percent level of significance and negative. This may reflect the impact of the endogenity of the underwriting process in which underwriters demand greater equity for loans with higher default risk. This pattern was also observed by Archer et al. (2002). Alternative specifications presented later in the paper show this coefficient switching signs and becoming positive, suggesting that including more detailed measures of local economic conditions may control for some of the endogenity in the underwriting process.

We see that the current DSCR (a measure of insolvency) is highly significant. The lower the current DSCR, the higher the risk of default. Likewise, using the national indexes, the measure of the current LTV is also highly significant, although positive. Consistent with our assumptions, the refinance incentive is significant and negative. The growth in the coincident index is also significant and negative, thus successfully acting as a proxy for the general macroeconomic conditions.

Loans collateralized by different types of properties demonstrate significantly different default risk. Here the reference group is property types other than multifamily, retail, office, hotel and industrial properties ("other types"). Interestingly, office and multifamily loans are shown to be more risky than all other types, all else being equal.

The inclusion of the current occupancy rate as an improvement over the standard model appears to be a successful one. Properties with higher current occupancy rates demonstrate a lower risk of default. We also find evidence that supports the theory that default is in effect a mechanism to prepay as suggested by Childs, Ott and Riddiough (1997). The yield maintenance variable in our sample is positive and significant for CMBS loan default We also see that Katrina had a significant impact on the default rate and that the risk of default was significantly higher in states where Katrina had an impact.

For originator type, the reference group is life insurance companies which are usually most conservative in their commercial mortgage lending. They tend to originate safer loans, and this is reflected in the positive and significant coefficients of other originator types. This result is consistent with the findings of Black et al (2012).

Model 1 represents a state of the art CMBS default model incorporating both the full range of covariates explored in the existing literature, as well as several important new measures. Models 2 and 3 change only the level of geographic detail used to calculate the current LTV, with the regional indexes used in model 2 and the MSA indexes used in model 3. While the impact of the current LTV remains significant and positive, the coefficient actually declines as we move to finer levels of geographical detail. We limit the sample only to the observations in which we have data at every level of geographical detail, so that we can compare the AIC and SBC measures to evaluate the relative fit of the three models. Interestingly the one using the current LTV estimated with the national CRE price indexes has the best fit. This result, while counter-intuitive, may reflect the increasing imprecision in CRE prices indexes estimated over smaller sample sizes by census region and MSA. Given our desire to control for local market conditions before adding additional local market variables, we will use the specification with the current LTV estimated using the MSA level CRE price indexes for the rest of the paper.

3.4 Local market conditions, house price appreciation and CMBS loan default

Next we extend our analysis to consider local market variables, such as MSA economic and space market conditions. These variables may capture unobservable effects at the MSA level, and may also help alleviate problems in our data such as the inaccurate measure of LTV. Unfortunately, because there is limited data of good quality on the commercial real estate market at the MSA level, we turned to the CBRE commercial real estate database for indicators of the local market. We were able to collect information on the vacancy rates, rental growth rate and the net absorption[15] for only 53 MSAs. As a result, the size of the loan sample is reduced.

In Table 9, we extend model 3 by adding our first set of local market variables – the CBRE measures for the growth in real rent, the absorption rate, and the vacancy rate. Again, all three of these measures are at the MSA level and are property-type specific. The results are shown in model 4 presented in Table 9, although the hazard model is estimated based on a smaller sample for the reason discussed earlier. The local market variables all are significant and have the expected sign. Markets that have stronger demand for CRE space as reflected in higher absorption rates, lower vacancy rates, or stronger rent growth all demonstrate lower CMBS

[15] Net absorption is defined as the number of units newly leased in that period minus the sum of newly constructed units delivered to the market and the newly available units that were not re-let upon the expiration of the previous lease.

default rates. This may reflect stronger cash flow at the property level, which directly impacts default risk. Alternatively, it may reflect the impact of expectations about future movements in local property prices on a borrower's decision to exercise the "default" option on their loans.

Finally, we include two additional measures of the local economic condition that are specific to an even smaller geographical area,, namely the county level unemployment rate and the county level residential house price index. The county unemployment rate provides a direct measure of the strength of the local job market and the corresponding demand for commercial space. The residential real estate price change proxies for the impact of residential prices on the local commercial real estate market. Theoretically, the commercial real estate market and the residential real estate market are linked in a number of ways. For example, from the supply side, land prices can simultaneously drive both commercial and residential real estate values (Gyourko, 2009). From the demand perspective, sentiments in the residential real estate market affect the commercial real estate market such that the values of residential and commercial real estate are correlated. The use of the CoreLogic county level house price index (HPI) allows us to link each commercial property with the immediate local residential market.

Model 5 in table 9 reflects the results of the hazard model that includes the county unemployment rate and the lagged county house price appreciation as additional explanatory variables. It shows that house price appreciation is negatively correlated with CMBS loan default, while the county unemployment rate is positively correlated. An analysis of the goodness of fit statistic shows a dramatic jump in explanatory power as a result of the introduction of these county level measures.[16]

4. Impact of Local Home Price Appreciation on CMBS Default

The covariate that resulted in the greatest increase in explanatory power when it was introduced into the model was the county-level residential house price index. The significance of this measure raises an interesting question. Does the correlation between the residential house price index and CMBS default represent a direct contagion effect from the residential to the commercial market? Or do the residential house price indexes provide a particularly valuable measure of local market conditions because they are available much more frequently and with significantly less noise than CRE price indexes?

While we do not formally test for the contagion effect in this paper, we do provide some preliminary analysis in this section of the relationship between CMBS default and residential house price indexes. If there is a contagion effect, we should see stronger correlations between CMBS defaults and lagged residential home prices at finer levels of geographical detail. We should also see residential home prices having a significantly greater impact on CRE markets that are more directly linked to the housing sector, such as apartment and retail. We also explore whether the impact of residential house prices has been consistent across time periods, and if the explanatory power of residential home prices can be replaced by a competing CRE land price index.

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[16] In response to comments from an anonymous referee, we confirmed that the results from our base specification (model 1) and our final specification (model 5) are consistent when we include MSA-level fixed effects, or when we cluster the standard errors by MSA,

Tables 10 and 11 report the results of the analysis conducted using lagged and contemporaneous residential home prices at three different levels of geographical detail – state, county, and zip-code. The tables only report the coefficients of the relevant variables. If the primary driver behind the significance of the residential house price index in the CMBS default models is contagion, the lagged series should have the greater explanatory power, as should data from the smallest geographical level. Surprisingly, there is very little difference in explanatory power across the 6 different models. In particular, the contemporaneous house price indexes produce results very similar to the lagged house price indexes. For this reason, we use the zip-code level residential price indexes for the remainder of the paper.

Table 12 reports the results from interacting the zip-code level residential house price index with property type. If contagion is driving the correlation between the residential prices and CMBS default, we should see a stronger connection in CRE markets more closely tied to the residential market. The apartment market is apparently closely tied to the residential market. The retail market also tends to be very closely tied to the residential market as a demand for new homes triggers an increase in demand for durables and other goods. We find limited evidence of this effect, with the interaction between the retail indicator and the lagged zip-code level residential house price index being just outside the 10 percent confidence level. The interaction of the retail indicator with the contemporaneous zip-code level index is significant and negative.

The significance of the residential house price index in the CMBS default model raises an important question. If rating agencies, investors, and regulators included such measures in their CRE default models prior to the crisis, would they have been able to better anticipate the sharp decline in CRE loan performance? Table 13 interacts the zip-code level residential home price index with a series of time dummies to determine if the relationship is constant over time. We find that prior to 2005, the relationship between residential house price indexes and the CMBS default was much weaker. The relationship strengthened significantly during the boom years of 2005, 2006 and 2007, then declined during the crash of 2008 and 2009. It has since demonstrated weaker levels of correlation similar to what was seen pre-2005. While we still see a significant and negative correlation between residential home price indexes and CMBS default across all time periods, these results suggest that this relationship may have a cyclical component. Of interest is the fact that this correlation peaked in strength just prior to the onset of the sharp correction in property values, and the dramatic surge in CMBS defaults.

Finally we introduce a competitor for the residential house price index. In Table 14, we compare the results derived from the lagged zip-code level residential house price index to that obtained from a commercial land price index constructed by Nichols, Oliner and Mulhall (2012). The land price index is based on commercial real estate transactions of raw land or land for re-development and it includes a separate index for each of the 23 major MSAs. Again, the introduction of this index further reduces the sample size of our analysis. All the analysis run for this table is limited to the smaller sample size, so that we can compare goodness of fit across the specifications. For each loan record, we calculate the cumulative commercial land price appreciation since the loan's origination and use this value as an additional explanatory variable.

Comparing the goodness of fit measures of models using the residential house price index (model 5q) and the commercial land price index (model 5f), we see a near tie. When both variables are included in model 5g, the fit improves and both variables are significant and negative. When combined with those in the rest of this section, this result suggests that the residential house price index reflects information on local market conditions. The commercial land price index also provides valuable information.

5. Conclusions

As securitization has intensified in the past two decades, commercial mortgage lending has become increasingly national: money flows from the capital market to every corner of the country. Increasingly, standardized mortgage loans are being made across properties located in different areas and those loans are then sold and securitized in a national market. As a result, mortgage bankers, investment bankers and regulators seek to model and price the commercial mortgage credit risk by focusing more on the common trends of the “fundamentals”. These fundamentals include option values, insolvency rates and property types along with broader measures of the macro economy and some local exogenous control variables, such as region and state foreclosure laws.

However, lessons from the recent financial crisis reveal that the existing default credit risk models fail miserably and that the default experiences of CMBS loans vary substantially across different geographic locations. It is natural then to ask whether those variations can be explained fully by the conventional risk factors suggested by existing research, or whether local traits also contribute to variations in CMBS loan defaults. In this study, we find many of the common fundamental factors to be significant driver of CMBS loan default. At the same time, however, we find local traits to also be important in explaining the variations in CMBS loan default rates. Most notably, an appreciation of the local residential real estate market, and of the MSA-level commercial land value is negatively correlated with CMBS loan default.

These findings are important to commercial mortgage and CMBS investors, as well as to rating agencies, loan servicers and financial regulators. The findings confirm that investors should pay greater attention to local traits when pricing CMBS deals, and that rating agencies, loan servicers and financial regulators need to update their default credit risk models by controlling for these local trait effects in addition to the more common default risk “fundamentals”.

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Table 1: Loan Performance Outcomes

Termination type	Number	Percent
Default	4,803	15.98
Prepay	2,736	9.10
Mature	4,245	14.13
Censor	18,269	60.79
Sum	30,053	100

Note: Default is defined as over 60 days of delinquency; defeasance is treated as prepayment; and censor means that the loan is current (not defaulted, not prepaid, or mature) at the data collection date.

Table 2: Origination Year Distributions of our Sample

Origination year	Number	Percent
1998	260	0.87
1999	437	1.45
2000	1,578	5.25
2001	2,386	7.94
2002	1,986	6.61
2003	1,236	4.11
2004	3,261	10.85
2005	6,199	20.63
2006	6,901	22.96
2007	5,195	17.29
2008	100	0.33
2009	3	0.01
2010	351	1.17
2011	160	0.53
Sum	30,053	100

Table 3: Loan Sample Break Down by Property Type

Property type	Number	Percent
Multifamily	8,291	27.59
Retail	9,154	30.46
Office	5,902	19.64
Industrial	1,921	6.39
Hotel	2,178	7.25
Other	2,607	8.67
Sum	30,053	100

Table 4: Loan Sample Break Down by Census Region

Census Region	Number	Percent
Pacific	6,127	20.39
Mountain	2,871	9.55
West North Central	1,105	3.68
West South Central	3,879	12.91
East North Central	3,384	11.26
East South Central	1,252	4.17
Mid Atlantic	3,721	12.38
South Atlantic	6,636	22.08
New England	1,078	3.59
Sum	30,053	100

Tables 5: Descriptive Statistics of the Underwriting Variables

	Mean	Std.Dev.	Min	Max
Original balance ($000)	9, 944	20,705	78	780,000
LTV (%)	68.88	11.62	10.00	129.10
DSCR	1.47	0.53	0.11	9.88
Amortization (month)	352	59	6	730
Maturity (moth)	118	40	4	478
Note rate (%)	6.20	0.95	1.96	12.50

Tables 6: Distribution of Loans by Originator Type

	Number	Percent
Domestic conduit	1,641	5.46
Foreign entities	4,819	16.03
Investment banks	5,285	17.59
Commercial banks	13,647	45.41
Insurance Companies	4,661	15.51
Sum	30,053	100

Table 7: Descriptive Statistics of the Event History Sample

Variable	Mean	Std Dev	Min.	Max.
Log loan balance	15.46	1.01	11.27	20.48
Original LTV	68.64	12.04	10	129.1
Original DSCR	1.49	0.56	0.11	9.88
Current LTV – national index	57.81	21.53	10.00	148.11

Current LTV – regional index	57.86	21.44	10.00	150.00
Current LTV – MSA index	54.68	20.42	10.00	150.00
Current DSCR	1.51	0.62	0.11	9.99
Current occupancy rate	91.64	11.28	10.3	100
Prepayment incentive	0.032	0.037	-0.17	0.33
Leading Index	0.38	1.25	-2.93	2.1
Growth in Coincident Index	0.15	0.67	-1.55	1.07
Volatility of the 10 year treasury rate (based on daily rates)	0.092	0.04	0.024	0.33
Volatility of the NCREIF Price Index	33.01	26.19	0.18	192.92
Lock out	0.85	0.36	0	1
Yield maintenance	0.64	0.48	0	1
Months to complete initial action of foreclosure	4.41	2.46	1	9
In state where deficiency judgment is allowed	0.67	0.47	0	1
In states where Katrina had an impact	0.13	0.34	0	1
Domestic conduit	0.059	0.23	0	1
Foreign entities	0.16	0.37	0	1
Investment banks	0.17	0.38	0	1
Commercial banks	0.46	0.50	0	1
MSA commercial RE vacancy rate by property type	15.80	8.53	0.10	39.25
MSA commercial RE real rent growth rate by property type	1.05	0.14	0.41	2.17
MSA commercial RE net absorption by property type	0.0079	0.031	-0.52	0.38
County unemployment rate	6.80	2.84	1.30	32.10
State house price appreciation	0.041	0.29	-0.86	1.09
4-quarter lagged state house price appreciation	0.062	0.26	-0.76	1.09
County house price appreciation	0.047	0.30	-0.98	1.24
4-quarter lagged county house price appreciation	0.067	0.26	-0.96	1.24
Zip-code house price appreciation	0.040	0.31	-1.12	1.36
4-quarter lagged Zip-code house price appreciation	0.063	0.27	-1.06	1.36
Number of observations (loan-quarter)		685,030		

Note: MSA vacancy rates, real rent growth, and net absorption are all by property type. House price appreciation is the log of the ratio from the current period to origination.

Table 8: Maximum Likelihood Estimates of the Hazard Models with Current LTV Based on Different Levels of Geographical Detail

	Model 1		Model 2		Model 3	
Covariates	Coeff. (S.E.)	Hazard Ratio	Coeff. (S.E.)	Hazard Ratio	Coeff. (S.E.)	Hazard Ratio
Current LTV – national index	0.874*** (0.033)	2.40				
Current LTV – regional index			0.646*** (0.028)	1.91		
Current LTV - MSA index					0.550***	1.73

					(0.028)	
Current DSCR	-1.195*** (0.039)	0.30	-1.188*** (0.039)	0.31	-1.215*** (0.039)	0.30
Current occupancy rate	-0.274*** (0.016)	0.76	-0.292*** (0.016)	0.75	-0.287*** (0.020)	0.75
Vol. of 10-year Treasury rate	-0.044* (0.025)	0.96	-0.091*** (0.025)	0.91	-0.073*** (0.024)	0.93
Vol. of NCREIF Price Index	-0.016 (0.032)	0.98	-0.012 (0.031)	0.99	-0.019 (0.032)	0.98
Log balance	0.149*** (0.023)	1.16	0.160*** (0.023)	1.17	0.159*** (0.023)	1.17
Original LTV	-0.075* (0.042)	0.93	0.032 (0.051)	1.03	0.057 (0.041)	1.06
Original DSCR	0.062 (0.049)	1.06	0.039 (0.051)	1.04	0.009 (0.052)	1.01
Refinance incentive	-3.666*** (0.762)	0.03	-1.879*** (0.695)	0.15	-1.006 (0.680)	0.37
Growth in Coincident Index	-0.083*** (0.020)	0.92	-0.143*** (0.020)	0.87	-0.173*** (0.020)	0.84
Multifamily	0.405*** (0.095)	1.50	-0.392*** (0.096)	0.68	0.147 (0.095)	1.16
Retail property	0.171 (0.092)	1.19	-0.393*** (0.094)	0.68	0.115 (0.092)	1.12
Office	0.380*** (0.097)	1.46	-0.526*** (0.101)	0.59	0.108 (0.097)	1.11
Hotel	-0.009 (0.111)	0.99	0.566*** (0.115)	1.72	-0.013 (0.111)	0.99
Industrial	0.125 (0.118)	1.13	-0.515*** (0.121)	0.60	0.120 (0.118)	1.13
Pacific	-0.056 (0.117)	0.95	0.063 (0.117)	1.07	0.112 (0.116)	1.12
Mountain	0.636*** (0.109)	1.89	0.686*** (0.110)	1.99	0.682*** (0.108)	1.98
West North Central	0.276* (0.150)	1.32	0.234 (0.150)	1.26	0.338** (0.149)	1.40
West South Central	0.439*** (0.121)	1.55	0.535*** (0.122)	1.71	0.446*** (0.121)	1.56
East North Central	0.699*** (0.102)	2.01	0.638*** (0.102)	1.89	0.503*** (0.103)	1.65
East South Central	0.151 (0.167)	1.16	0.153 (0.167)	1.17	0.217 (0.165)	1.24
South Atlantic	0.065	1.07	0.070	1.07	0.209	1.23

	(0.134)		(0.134)		(0.132)	
New England	0.214	1.24	0.022	1.02	0.016	1.02
	(0.144)		(0.148)		(0.143)	
Lock out	-0.016	0.98	-0.005	1.00	0.015	1.02
	(0.073)		(0.072)		(0.073)	
Yield maintenance	0.420***	1.52	0.329***	1.39	0.346***	1.41
	(0.046)		(0.046)		(0.046)	
Months to complete initial action of foreclosure	-0.054*	0.95	-0.040	0.96	0.007	1.01
	(0.028)		(0.028)		(0.028)	
In state where deficiency judgment is allowed	-0.222***	0.80	-0.205***	0.82	-0.120**	0.89
	(0.056)		(0.056)		(0.056)	
In states where Katrina had an impact	0.744***	2.10	0.739***	2.09	0.535***	1.71
	(0.096)		(0.096)		(0.097)	
Domestic conduit	0.524***	1.69	0.534***	1.71	0.519***	1.68
	(0.095)		(0.096)		(0.095)	
Foreign entities	0.473***	1.61	0.529***	1.70	0.503***	1.65
	(0.075)		(0.096)		(0.075)	
Investment banks	0.368***	1.45	0.457***	1.58	0.419***	1.52
	(0.076)		(0.076)		(0.076)	
Commercial banks	0.207***	1.23	0.315***	1.37	0.249***	1.28
	(0.069)		(0.069)		(0.069)	
Number of Loan Events	444,913		444,913		444,913	
-2 LogL	41,914		42,163		42,296	
AIC	41,978		42,227		42,360	
SBC	42,164		42,413		42,547	
Degrees of Freedom	32		32		32	
Likelihood Ratio	4,854		4,605		4,471	
Score	5,009		4,836		4,692	
Wald	4,698		4,604		4,551	

Note: *** for p<1%, ** for p<5%, * for p<5%, and b for p<10%. The mid-Atlantic is the reference group for regions; for property types, other types are the reference group; insurance companies are the reference group for loan originators.

Table 9: Maximum Likelihood Estimates of the Hazard Models with MSA and County Level Economic Indicators

	Model 4		Model 5	
Covariates	Coeff. (S.E.)	Hazard Ratio	Coeff. (S.E.)	Hazard Ratio

Current LTV – MSA index	0.471*** (0.029)	1.60	0.193*** (0.032)	1.21
Current DSCR	-1.173*** (0.039)	0.31	-1.163*** (0.040)	0.31
Current occupancy rate	-0.292*** (0.016)	0.75	-0.279*** (0.016)	0.76
Vol. of 10-year Treasury rate	-0.078*** (0.025)	0.93	-0.027 (0.025)	0.97
Vol. of NCREIF Price Index	0.002 (0.033)	1.00	0.035 (0.034)	1.04
Log balance	0.141*** (0.023)	1.15	0.129*** (0.023)	1.14
Original LTV	0.136*** (0.042)	1.15	0.313*** (0.043)	1.37
Original DSCR	0.030 (0.053)	1.03	0.032 (0.053)	1.03
Refinance incentive	-1.579** (0.693)	0.21	-2.143*** (0.738)	0.12
Growth in Coincident Indicator	-0.182*** (0.021)	0.83	-0.139*** (0.023)	0.87
Multifamily	0.862*** (0.120)	2.37	0.623*** (0.122)	1.86
Retail property	0.181* (0.092)	1.20	0.200** (0.092)	1.22
Office	0.309*** (0.010)	1.36	0.397*** (0.100)	1.49
Hotel	0.080 (0.112)	1.08	0.084 (0.112)	1.09
Industrial	0.364*** (0.126)	1.44	0.365*** (0.127)	1.44
Pacific	0.051 (0.117)	1.05	-0.344*** (0.119)	0.71
Mountain	0.589*** (0.110)	1.80	0.141 (0.113)	1.15
West North Central	0.431*** (0.149)	1.54	0.383** (0.151)	1.47
West South Central	0.552*** (0.123)	1.74	0.514*** (0.126)	1.67
East North Central	0.423** (0.166)	1.53	0.120 (0.107)	1.13
East South Central	0.434*** (0.166)	1.54	0.403** (0.164)	1.50

South Atlantic	0.412*** (0.134)	1.51	0.283** (0.136)	1.33
New England	-0.007 (0.134)	0.99	0.093 (0.145)	1.10
Lock out	0.039 (0.073)	1.04	0.016 (0.074)	1.02
Yield maintenance	0.343*** (0.046)	1.41	0.475*** (0.047)	1.61
Months to complete initial action of foreclosure	0.064** (0.028)	1.07	0.024 (0.030)	1.02
In state where deficiency judgment is allowed	-0.009 (0.057)	0.99	0.097* (0.058)	1.10
In states where Katrina had an impact	0.361*** (0.097)	1.44	0.122 (0.101)	1.13
Domestic conduit	0.532*** (0.095)	1.70	0.504*** (0.095)	1.66
Foreign entities	0.497*** (0.075)	1.64	0.466*** (0.075)	1.59
Investment banks	0.403*** (0.076)	1.50	0.333*** (0.076)	1.40
Commercial banks	0.243*** (0.069)	1.28	0.173*** (0.069)	1.19
MSA vacancy rate by property type	0.377*** (0.043)	1.46	0.192*** (0.045)	1.21
MSA real rent growth rate by property type	-0.266*** (0.027)	0.77	-0.160*** (0.028)	0.85
MSA net absorption by property type	-0.067*** (0.023)	0.94	-0.025 (0.024)	0.98
County unemployment rate			0.294*** (0.032)	1.34
4-quarter lagged county house price appreciation			-0.344*** (0.038)	0.71
Number of obs	444,913		444,913	
-2 LogL	42,2118		41,713	
AIC	42,118		41,787	
SBC	42,392		42,002	
Degrees of Freedom	35		37	
Likelihood Ratio	4,649		5,055	
Score	4,834		5,134	
Wald	4,611		4,847	

Note: *** for p<1%, ** for p<5%, * for p<5%, and b for p<10%. The mid-Atlantic is the reference group for regions; for property types, the “other type” are the reference group;

insurance companies are the reference group for loan originators. MSA vacancy rates, real rent growth, and net absorption are all by property type. Rent growth is the ratio from the time of loan origination to the current period. House price appreciation is the log of the ratio from the current period to origination.

Table 10: Hazard Model with Alternate Lagged House Price Series

	Model 5		Model 5a		Model 5b	
Covariates	Coeff. (S.E.)	Hazard Ratio	Coeff. (S.E.)	Hazard Ratio	Coeff. (S.E.)	Hazard Ratio
4-quarter lagged county house price appreciation	-0.344*** (0.038)	0.71				
4-quarter lagged state house price appreciation			-0.370*** (0.038)	0.69		
4-quarter lagged zip-code house price appreciation					-0.243*** (0.029)	0.78
Number of obs	444,913		444,913		444,913	
-2 LogL	41,713		41,701		41,726	
AIC	41,787		41,775		41,800	
SBC	42,002		41,991		42,015	
Degrees of Freedom	37		37		37	
Likelihood Ratio	5,055		5,067		5,042	
Score	5,134		5,131		5,151	
Wald	4,847		4,864		4,874	

Note: *** for p<1%, ** for p<5%, * for p<5%, and b for p<10%. House price appreciation is the log of the ratio from the current period to origination. Coefficients for other variables are not reported. They are available upon request.

Table 11: Hazard Model with Alternate Contemporaneous House Price Series

	Model 5c		Model 5d		Model 5e	
Covariates	Coeff. (S.E.)	Hazard Ratio	Coeff. (S.E.)	Hazard Ratio	Coeff. (S.E.)	Hazard Ratio
4-quarter contemporaneous county house price appreciation	-0.306*** (0.038)	0.74				
4-quarter contemporaneous state house price appreciation			-0.311*** (0.038)	0.73		
4-quarter contemporaneous zip-code house price appreciation					-0.232*** (0.029)	0.79
Number of obs	444,913		444,913		444,913	

-2 LogL	41,731	41,728	41,732
AIC	41,805	41,802	41,806
SBC	42,021	42,018	42,0212
Degrees of Freedom	37	37	37
Likelihood Ratio	5,037	5,039	5,035
Score	5,127	5,126	5,145
Wald	4,840	4,848	4,874

Note: *** for p<1%, ** for p<5%, * for p<5%, and b for p<10%. House price appreciation is the log of the ratio from the current period to origination. Coefficients for other variables are not reported.

Table 12: Hazard Models with House Price Interacted with Property Type

	Model 6		Model 7	
Covariates	Coeff. (S.E.)	Hazard Ratio	Coeff. (S.E.)	Hazard Ratio
4-quarter lagged zip-code house price appreciation	-0.271*** (0.088)	0.76		
4-quarter lagged zip-code house price appreciation * Multifamily	0.024 (0.050)	1.03		
4-quarter lagged zip-code house price appreciation * Retail	-0.077 (0.050)	0.93		
4-quarter lagged zip-code house price appreciation * Office	0.018 (0.42)	1.02		
4-quarter lagged zip-code house price appreciation * Hotel	0.008 (0.020)	1.01		
4-quarter lagged zip-code house price appreciation * Industrial	-0.0007 (0.428)	0.99		
4-quarter contemporaneous zip-code house price appreciation			-0.137*** (0.082)	0.87
4-quarter contemporaneous zip-code house price appreciation * Multifamily			-0.019 (0.046)	0.98
4-quarter contemporaneous zip-code house price appreciation * Retail			-0.125*** (0.047)	0.88
4-quarter contemporaneous zip-code house price appreciation * Office			-0.021 (0.040)	0.98
4-quarter contemporaneous zip-code house price appreciation * Hotel			-0.018 (0.020)	0.98
4-quarter contemporaneous zip-code house price appreciation * Industrial			-0.035 (0.033)	0.97
Number of obs	374,262		444,913	
-2 LogL	34,969		47,714	

AIC	35,053	41,798
SBC	35,291	42,042
Degrees of Freedom	42	42
Likelihood Ratio	4,498	5,054
Score	4,671	5,241
Wald	4,281	4,869

Note: *** for p<1%, ** for p<5%, * for p<5%, and b for p<10%. House price appreciation is the log of the ratio from the current period to origination. Coefficients for other variables are not reported.

Table 13: Hazard Models with House Price Interacted with Time

	Model 8		Model 9	
Covariates	Coeff. (S.E.)	Hazard Ratio	Coeff. (S.E.)	Hazard Ratio
4-quarter lagged zip-code house price appreciation * Pre 2005	-0.069* (0.040)	0.93		
4-quarter lagged zip-code house price appreciation * 2005-2007	-0.456*** (0.079)	0.64		
4-quarter lagged zip-code house price appreciation * 2008-2009	-0.195*** (0.026)	0.82		
4-quarter lagged zip-code house price appreciation * Post 2009	-0.086*** (0.018)	0.92		
4-quarter contemporaneous zip-code house price appreciation * Pre 2005			-0.092** (0.042)	0.91
4-quarter contemporaneous zip-code house price appreciation * 2005-2007			-0.380*** (0.068)	0.68
4-quarter contemporaneous zip-code house price appreciation * 2008-2009			-0.121*** (0.022)	0.89
4-quarter contemporaneous zip-code house price appreciation * Post 2009			-0.042** (0.017)	0.96
Number of obs	444,913		444,913	
-2 LogL	41,695		41,726	
AIC	41,775		41,806	
SBC	42,008		42,039	
Degrees of Freedom	40		40	
Likelihood Ratio	5,072		5,041	
Score	5,238		5,227	
Wald	4,779		4,781	

Note: *** for p<1%, ** for p<5%, * for p<5%, and b for p<10%. House price appreciation is the log of the ratio from the current period to origination. Coefficients for other variables are not reported.

Table 14: Hazard Model with Lagged House Price and Land Price Series

	Model 5		Model 5f		Model 5g	
Covariates	Coeff. (S.E.)	Hazard Ratio	Coeff. (S.E.)	Hazard Ratio	Coeff. (S.E.)	Hazard Ratio
4-quarter lagged zip-code house price appreciation	-0.245*** (0.036)	0.78			-0.189*** (0.039)	0.83
MSA Commercial Land Price Index			-0.258*** (0.042)	0.77	-0.170*** (0.046)	0.84
Number of obs	296,590		296,590		296,590	
-2 LogL	26,917		26,928		26,904	
AIC	26,987		26,998		26,976	
SBC	27,178		27,189		27,172	
Degrees of Freedom	35		35		36	
Likelihood Ratio	3,589		3,579		3,603	
Score	3,677		3,668		3,685	
Wald	3,387		3,367		3,385	

Note: *** for p<1%, ** for p<5%, * for p<5%, and b for p<10%. House price appreciation is the log of the ratio from current period to origination. Coefficients for other variables are not reported.