

The Big Short: Short Selling Activity and Predictability in House Prices*

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Abstract

We study how investors use financial securities to speculate on the decrease of house prices. Unlike most asset types, houses are subject to high trading frictions and cannot be sold short. Using U.S. data from 2006 to 2013, we find evidence that an increase in the short selling activity of real estate investment trusts (REITs) forecasts a decrease in house prices in the subsequent month. The magnitude and significance of this effect vary with the geographical location of the REITs' underlying properties and with the state of the business cycle.

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1 Introduction

Academics have uncovered numerous examples of how data on financial markets can be used to predict the behavior of variables in the real economy.¹ However, while a substantial part of the literature focuses on forecasting macroeconomic fundamentals and commodity prices, less attention has been paid to the prediction of house prices. This is surprising because housing is one of the largest asset classes in the economy. Moreover, it is difficult to hedge against declining house prices because houses are subject to extremely high transaction costs and short selling constraints. In this paper we study how liquid financial securities can be used to hedge the downside risk of house prices and how investors can speculate on housing market downturns.

The real estate market crash in 2008 provides a unique environment for this analysis. During this period, many investors set up large short positions to speculate on decreasing house prices.² We establish the channel that links financial assets (i.e., Real Estate Investment Trusts or REITs) to real assets (i.e., housing markets) and study how measures of equity lending activity of REITs' stocks forecast house prices. Our hypotheses are based on the fact that investors and managers can hedge risk or speculate on future house price movements through financial assets.³ The lower transaction costs of REITs relative to directly trading in the housing markets allow investors to reflect negative expectations about real estate prices more quickly. If investors are long on the real asset and expect a price decrease, they can short REITs. This position can reduce the downside risk of housing while they attempt to sell the physical asset at the best possible time. Investors with no exposure to house prices that want to speculate on

¹For example, Liew and Vassalou (2000); Ang, Bekaert, and Wei (2007); Kojien, Van Hemert, and Van Nieuwerburgh (2009); and Bailey and Chan (1993) use financial market data to forecast economic growth, inflation, mortgage choices, and commodities, respectively.

²The book by Lewis (2010) describes how many hedge funds profited from the U.S. real estate market crash. They use strategies such as selling futures on the Case-Shiller housing index, buying credit default swaps (CDSs), buying collateralized debt obligations (CDOs), and short selling real estate-related stocks (e.g., stocks of homebuilders and Government-sponsored enterprises). However, these strategies face problems (e.g., illiquid, thin trading or low correlation with housing returns) preventing them from being a feasible way to hedge or speculate on decreasing house prices.

³The online appendix to this paper contains a model that formalizes the economic intuition for these hypotheses.

decreasing prices can short REITs' stocks directly. The delay of real asset prices in adjusting to information is the channel that links current REIT returns to future house price changes. We develop three hypotheses based on this channel and we test them using stock-level data of the equity lending activity on REITs, hand-collected information on the geographical location of underlying properties owned by each REIT, and monthly housing returns between 2006 and 2013.

Our first hypothesis states that the correlation between REITs' stock returns and housing returns varies with the state of the housing market cycle. We classify each month in our sample as being a "boom", an "average", or a "downturn" period.⁴ We find that this correlation is close to zero during "average" periods of the housing market cycle. However, this correlation is significantly positive during housing market downturns. These results suggest that short selling REITs can be a good strategy to speculate on housing market downturns and hedge the downside risk in housing markets. Specifically, the conditional correlation on being in a housing market downturn between aggregate FHFA housing index returns and the REITs' U.S. aggregate index for the period 1991-2010 is 0.299. The equivalent unconditional correlation is 0.075, which includes not only the months of market downturn, but the entire period 1991-2010.

Our second hypothesis relates to short selling activity and house price predictability. If investors expect that house prices will decrease, then they should use correlated securities to act upon this expectation for hedging or speculative reasons. We document that an increase in REIT short selling activity forecasts a decrease in the following month's house prices but only during NBER recessions. We find that a one standard deviation increase in short selling activity of REITs –measured as the fraction of REITs' short interest– leads to a 0.076% decrease in housing returns in the following month during NBER recessions. This is economically significant and

⁴We define "boom" and "downturn" periods as months when housing returns are 1.64 standard deviations above and below their historical sample mean, respectively. "Average" periods contain the months in which housing returns are lower than 1.64 standard deviations above and higher than 1.64 standard deviations below their historical mean. The historical mean is the average of housing returns up to the month in question.

corresponds to a 0.108 standard deviation decrease in house price returns.⁵

Finally, our third hypothesis is related to the geographical cross-section of short selling activity in terms of the location of the properties of the REITs. The large cross-sectional regional differences in house prices during the financial crisis should be also reflected in differences in the short selling of REITs. Consequently, we hypothesize that we can improve the forecasts of house prices by examining REITs' short selling activity and the geographical location of their properties. We find that REITs that invest in properties located in areas that experienced a housing boom during the expansion cycle in 2000s are more sensitive to increases in short-selling activity than REITs invested in properties located in areas that did not experience a housing boom. We find that a one standard deviation increase in the fraction of shares lent out of REITs' with properties in areas that have experienced a housing boom (e.g., the West and Northeast regions of the U.S. Census) forecasts a 0.14% (or 0.16 standard deviations) decrease in house prices in the following month. Furthermore, we do not find any effect for REITs with properties in areas that have not experienced a housing boom (e.g., the Midwest and South regions).

Our findings are related to the intersection of two areas of research. First, our paper contributes to the literature on short selling activity and price predictability. Table 1 shows the gap that our paper fills in the literature. Some authors (e.g., Asquith and Meulbroek (1995), Jones and Lamont (2002), Desai et al. (2002), Boehme, Danielsen, and Sorescu (2006), Cohen, Diether, and Malloy (2007), and Nagel (2005)) have explored the link between short interest and future stock returns. Research that specifically focuses on REITs' short selling activity is very thin. Li and Yung (2004) analyze the determinants of REITs' short interest and find a negative relationship between short interest and returns. Their results are only significant for the highest decile of REITs' short interest. More recently, Blau, Hill, and Wang (2011)

⁵*Short Interest* has a mean equal to 3.25% and a standard deviation of 1.89%. The mean of house price returns is -0.11% and its standard deviation is 0.70%.

documented that short selling activity is high in REITs that perform well and low in underperforming REITs. Chen, Downs, and Patterson (2012) consider heterogeneous beliefs and use the full cross-section of REITs' short interest to test for stock overvaluation. We are not aware of any study that has considered the link between REITs' equity lending data and the underlying housing market. Our results show that REITs' short interest does not provide strong predictability.⁶ However, we find that the use of measures that include information about the supply of REIT shares for short selling purposes (e.g., on loan, utilization, and fees) improves the predictability of house prices.

[INSERT TABLE 1 HERE]

Second, we contribute to the literature on market efficiency by studying how frictions in housing markets can be exploited to speculate on decreasing house prices through financial securities. Frictions in housing markets prevent negative information from being rapidly incorporated into house prices. As a result, house prices are predictable (e.g., see the predictability tests in Campbell et al. (2009) and Corradin, Fillat, and Vergara-Alert (2014), and the literature review in Ghysels et al. (2012).) The empirical studies in Gyourko and Keim (1992), Barkham and Geltner (1995), Naranjo and Ling (1997), Benjamin, Sirmans, and Zietz (2001), Pagliari, Scherer, and Monopoli (2005), and Riddiough, Moriarty, and Yeatman (2005) analyze the connection between REIT returns and house prices (i.e., how returns of financial securities explain housing returns) and show evidence of real estate market inefficiency. In particular, this literature documents that price information does not fully transmit to the unsecuritized markets for a year or more. Row (3) in Table 1 summarizes the main characteristics of the empirical approaches used in these papers. Our paper differs from this literature along two main dimensions. First, all these studies use data from appraisals (i.e., NCREIF indices). Consequently, the infrequent property appraisals that “delays” the incorporation of information in the NCREIF-type

⁶Cohen, Diether, and Malloy (2007) show that short interest is not a sufficient statistic to measure shorting demand. For instance, low short interest could be due to lack of demand or high short selling constraints.

of indices is the channel that drives the predictability in house prices that they observe in the data. Geltner (1998) documents that NCREIF indices have two sources of error: random appraisal error and the lagging of appraised values. Our paper uses unbiased repeated sales indices of houses (i.e., FHFA indices) instead of the indices based on appraisals of income-producing commercial real estate properties (i.e., NCREIF indices).⁷ Second, this literature does not take into account the geographical location of the real estate properties owned by the REITs. As a result, our findings cannot be simply inferred from linking the contributions of the papers in row (2) of Table 1 to the ones in row (3).

Our empirical analyses are robust to the inclusion of financial markets characteristics such as REITs' stock returns and liquidity measures and also to macroeconomic variables such as the term spread and lagged housing returns. Moreover, we estimate a panel VAR that allows for geographical heterogeneity while still being able to estimate a reduced-form system of house price index returns, REITs' stock returns and short selling proxies and allowing for simultaneity among all variables. We find that shocks to short selling have forecasting power to explain changes in house price indices above and beyond the information contained in REITs' stock prices. We also show that short selling measures explain a statistically and economically significant fraction of the variability in house prices.

⁷There is also a literature that examines the effect of housing market frictions on house prices. For example, Aura and Davidoff (2008), Glaeser, Gyourko, and Saiz (2008), Saiz (2010), Davis and Ortalo-Magné (2011) and Han (2013) study how geographic supply constraints affect house prices. Glaeser, Gyourko, and Saks (2005) analyze the effects of local regulation in house prices. Sinai and Souleles (2005) study how the demand for hedging rent risk influences house prices. Nevertheless, this literature does not analyze how economic agents invest in the presence of frictions that prevent information on the housing markets from being efficiently incorporated into the financial markets. Our paper finds that investors can circumvent these restrictions by shorting securities that are correlated with the price of the real asset, such as REITs.

2 Hypotheses Development

Our hypotheses build on the idea that frictions in the real estate markets prevent negative information about housing from being instantaneously incorporated into prices. As a consequence, investors try to sell short financial securities that are correlated with the physical asset's income stream and face lower trading frictions, such as REITs. Variables that indicate an increase in the short selling activity of REITs capture expectations about future prices and, consequentially, about an expected decrease in house prices (e.g., Asquith and Meulbroek (1995); Cohen, Diether, and Malloy (2007)). Therefore, if investors expect house prices to decrease but cannot sell houses outright due to trading frictions, then short selling shares of REITs can be used as a substitute strategy. We conjecture that changes in house prices can be predicted by changes in the intensity of the short selling of REITs' shares.

Figure 1 provides the initial motivation. It displays the equity lending supply (*Supply*) and the equity loans (*On Loan*) as a fraction of the aggregate market capitalization of REITs with more than 50% of their properties located in one of the U.S. census regions (i.e., Northeast, Midwest, South, and West). This figure compares these two measures from the equity lending market to cumulative housing returns. House prices almost doubled in the Northeast and more than doubled in the West region from 2000 to 2007. However, the increase in prices was much lower in the Midwest and the South regions for the same period. We also observe that REITs with properties located in areas that experienced a big run-up in house prices (e.g., REITs with properties in the West and Northeast) presented higher values of the on loan and lending supply measures than REITs with properties located in areas that experienced a small run-up in house prices (e.g., REITs with properties in the Midwest and South). The loan demand of REITs with properties in the Midwest and the South is mostly flat throughout our sample period, while there is a large increase of loan demand for REITs with properties in the West or the Northeast before

Lehman Brothers' bankruptcy in September 2008.⁸

[INSERT FIGURE 1 HERE]

Using REITs to study how the trading activity of financial securities predicts house prices presents many advantages. First, REITs provide a direct link between rents and capital gains in real estate markets through REITs' dividends and stock prices. REITs are corporations that invest in real estate, either through properties or mortgages. They receive favorable tax treatment but are required to distribute 90% of their taxable income to their shareholders. Most REITs opt to pay out 100% during several years. They are designed to provide a structure for investing in real estate similar to the one provided by mutual funds for investing in stocks.⁹ Second, the information about the properties managed by each REIT is publicly available. Therefore, we are able to establish explicit connections between real estate properties and house price indices in different geographical areas. Specifically, we can classify REITs in different geographical areas according to the location of their properties and link stock-level data to the house prices of each area. Third, unlike other strategies (e.g., selling futures on the Case-Shiller index) trading REITs is very liquid in the stock markets markets. Fourth, REITs possess a well-functioning equity lending market for investors that need to borrow shares for delivery following a short sale. Fifth, REITs manage a large amount of assets that are representative of the real estate markets. As of January 2014, publicly-traded REITs comprised 204 companies registered with the U.S. Securities and Exchange Commission with a total market capitalization of \$719 billion.

⁸For instance, the loan demand was very similar for all the REITs in March 2007. It was around 2% of the total sector market capitalization. However, loan demand for REITs with properties in the West and the Northeast almost tripled by September 2007.

⁹REITs invest in different property types such as residential, retail, office, healthcare, hotels, industrial, and self-storage. Residential properties are part of the housing markets. Other property types are closely related, but not part of the housing markets. In this paper, we first implement our empirical analyses using all REITs regarding their property type. Then we replicate these empirical analyses using only REITs that invest in residential properties. Our results are robust to the use of only residential REITs versus using the full sample of REITs.

2.1 Conditional Correlations between REIT and Housing Returns

To formalize our hypotheses, we first define housing return predictability. A variable x_t predicts housing returns r_t if the expected housing return conditional on x_t , that is $E_t[r_{t+1}|x_t]$, is different than the unconditional expected return, $E_t[r_{t+1}]$. If these two terms are equal, then the best predictor of tomorrow's housing returns is the unconditional expected return. In this paper, we use a reduced-form model and show that the equality $E[r_{t+1}|x_t] = E[r_{t+1}]$ does not hold for several predictor variables.¹⁰

Our first hypothesis focuses on the analysis of the time-varying correlation between REIT returns and housing returns. The historical unconditional correlation between these two variables is very low. We conjecture that this correlation increases significantly during housing market downturns. Hypothesis 1 formalizes this conjecture.

Hypothesis 1 *The correlation between REIT returns and housing returns is higher during housing market downturns.*

Let $r_{i,t}$ denote the return on house prices in the geographical area i at time t . Let $r_{i,t}^{REIT}$ denote the return on REIT stock prices in the geographical area i at time t . Let $D_{i,t}^{Bust}$ denote a dummy variable that takes the value of one when the housing market in area i is in a downturn and zero otherwise. We test whether the coefficient β_3 of the following regression model is significantly positive:

$$r_{i,t} = \alpha + \beta_1 \cdot r_{i,t}^{REIT} + \beta_2 \cdot D_{i,t}^{Bust} + \beta_3 \cdot r_{i,t}^{REIT} \cdot D_{i,t}^{Bust} + \epsilon_t \quad (1)$$

¹⁰Previous literature on return predictability focuses on the analysis of statistical inference when the predictor variable is very persistent (e.g., dividend-price ratios) and its innovations are highly correlated with the dependent variable (e.g., stock returns). Campbell and Yogo (2006) and Hjalmarsson (2011) discuss that conventional t-statistics are invalid in these situations and can lead to over-rejection of the null. However, these problems do not apply to our empirical setting because, although the first-order autocorrelation of our explanatory variables is usually large (i.e., higher than 0.9), the correlation of their innovations with house price returns' innovations is very low (i.e., lower than 0.03). Under these conditions, the bias of standard parameters is not an issue for inference.

where ϵ_t is the error term. A positive coefficient of the interaction term, β_3 , indicates that the correlation between the variables $r_{i,t}$ and $r_{i,t}^{REIT}$ is higher when the dummy variable $D_{i,t}^{Bust}$ is one, that is, during housing market downturns.

There is a vast body of empirical literature on real estate that explores the dynamics of REIT returns. For example, Chan, Hendershott, and Sanders (1990) analyze the risk and return of equity REITs using a multi-factor Arbitrage Pricing Model and a set of macroeconomic factors. Howe and Shilling (1988) study the reaction of REIT returns to announcements of new security offerings. Howe and Shilling (1990) find that advisor type and property location partially explains REIT returns. Glascock and Hughes (1995) studies the performance of 245 REITs between 1972 and 1991. More recent papers use multivariate GARCH techniques (e.g., Cotter and Stevenson (2006), Case, Yang, and Yildirim (2012), Chong, Miffre, and Stevenson (2009), Liow et al. (2009), Hiang Liow (2012), Huang and Zhong (2013)), reduced-form models that incorporate copula functions (e.g., Knight, Lizieri, and Satchell (2005), Goorah (2007), Dulguerov (2009), Zhou and Gao (2012), Simon and Ng (2009)), and a mixture of methods (e.g., Michayluk, Wilson, and Zurbruegg (2006), Hoesli and Reka (2013)) to study the dynamics of REIT returns. However, the majority of the papers that examine REIT returns do not link them to real estate returns nor housing returns. Clayton and MacKinnon (2001) analyzes the link between REIT, real estate and financial assets. Using data from 1978 to 1998, they find that REITs only began to exhibit a direct link to real estate returns in the 1990s. They also find that this correlation is cyclical. Oikarinen, Hoesli, and Serrano (2011) and Hoesli and Oikarinen (2012) have recently shown that the dynamics of the long-run REIT market are more closely related to the real estate markets than to the stock markets. Therefore, REITs and direct real estate should be relatively good substitutes in a long-horizon investment portfolio.

2.2 Short Selling Activity and House Price Predictability over the Business Cycle

The link between the real asset (i.e. housing) and the financial security (i.e. REITs) is the basis of our empirical tests on whether proxies for short selling activity can be used to forecast house prices. Housing assets cannot be directly sold short. Consequently, if investors want to speculate on a decline in housing values, then they must look for alternative that is easy to short sell. Thus, an increase in REITs' short selling activity indicates that investors are betting on decreases in REITs' stock prices, which are based on the fundamentals of the real estate markets. This predictability is likely to be stronger during economic downturns when the fundamentals of the real estate markets are more volatile. Hypothesis 2 formalizes this conjecture.

Hypothesis 2 *An increase in REITs' short selling activity forecasts a reduction in next month house prices. This predictability is stronger during economic downturns.*

The following expression provides the regression model that we use to test this hypothesis:

$$r_{i,t} = \alpha + \beta * X_{i,t-1} + \gamma' * z_{i,t-1} + \epsilon_t \quad (2)$$

where ϵ_t is the error term. Let $r_{i,t}$ denote the return on housing in area i , and let $X_{i,t-1}$ be a measure of short selling intensity. We employ four main variables that capture short selling intensity: (i) *On Loan* is the value of shares lent out relative to market capitalization of REITs with property holdings in that area at time $t - 1$, (ii) *Short Interest* is the number of shares sold short reported by the stock exchanges and reported by Compustat, (iii) *Utilization* is defined as the amount on loan divided by the supply of shares available to borrow, and (iv) *Fee*, the borrowing fee measured at the end of the month.¹¹ We test whether these measures are able

¹¹*On Loan* does not take into account the lendable supply and an increase in demand is associated to lower borrowing costs driven by a reduction in short selling constraints rather than to new negative information being

to forecast returns in area i at time t controlling for a vector z of other factors measured at time $t - 1$. Dechow et al. (2001), Chen and Singal (2003), and Arnold et al. (2005) construct equivalent measures for their studies.

2.3 Geographical Cross-Section of Short Selling Activity and House Price Predictability

While average house prices decreased in all U.S. areas and REIT short selling activity increased during the recent housing bust, Figure 1 shows that these effects were different across regions. REITs with a majority of properties located in *Boom* areas present higher short selling activity than REITs with their majority of properties in *No Boom* areas. Our third and last hypothesis tests if areas that experienced higher house price run-ups before the financial crisis in 2008 were more affected by increases in short selling activity. Hypothesis 3 formalizes this conjecture.

Hypothesis 3 *Short sales forecast a higher decrease in house prices in areas with a larger price run-up during the period from January 2000 to December 2007.*

If house prices in some areas were relatively overvalued, then we would expect short sellers being active in correcting the mispricing and obtaining a high potential profit. Hence, we would observe a stronger link between short selling measures and future housing returns.

3 Data

We use United States data due to the availability of both short selling activity of REITs and house price indices by geographical region at monthly frequencies. We match data from the CRSP-Ziman REIT database to a proprietary dataset of lending supply postings and loans incorporated into the financial markets. Hence, *Utilization* can better capture the intensity of short sales constraints.

provided by Markit. Saffi and Sigurdsson (2011) provides further details on this lending supply dataset. The information is collected daily from 125 custodians and 32 prime brokers. Markit estimates that the data cover more than 85% of global equity lending. Out of the 257 REITs that are available in CRSP from July 2006 to July 2013, we can match 245 to our equity lending data. We also collect information on REITs' returns, market capitalization, bid-ask spreads, average daily turnover, and short interest data from CRSP/Compustat.

The equity lending data presents daily information on the quantity of shares available to borrow, the shares effectively lent out, and the loan-weighted average fee. *Supply* is defined as the market value of the shares available to borrow on the last day of the month scaled by market capitalization. *On Loan* is given by the market value of the shares on loan on a given day divided by market capitalization.¹² Finally, *Utilization* is defined as *On Loan* divided by *Supply*, representing the fraction of supply that has been effectively lent out to borrowers. Lastly, *Fee* is based on the value-weighted (VW) fee reported by Markit in the previous seven days in annualized basis points.

We utilize the US Federal Housing Finance Agency (FHFA) House Price Indices as our main measures of house prices. They are weighted, repeat-sales indices. They are available at a monthly frequency for the aggregate US housing market and for U.S. Census Divisions.¹³ We also obtain data on Treasury bond yields from Datastream, defining *Term Spread (10y - 3m)* as the difference between the 10-year and the 3-month Treasury bonds. We also use the Moody's/RCA Commercial Property Price Indices (CPPI) in our empirical analyses. They are are weighted, repeat-sales indices, which are computed using contemporaneous transaction-price-based data on private deals. There are also specific indices CPPI for the different property types (i.e., apartment, retail, industrial, office-central, office-suburban, and hotel). The CPPI data is available at a monthly frequency for the aggregate US housing market and at the quarterly

¹²Note that equity loans are not a perfect measure of short selling, since they might be used as part of tax-arbitrage strategies or hedging strategies (see Christoffersen, Geczy, and Musto (2005).)

¹³At the monthly frequency this is largest level of granularity available.

frequency for the main US metropolitan areas.

Table 2 presents the summary statistics for the main variables based on the pooled sample that we use in our empirical analyses. There is an average of 114.13 REITs with an average market capitalization of \$5,128 million. The average equal-weighted monthly REIT return in the period is positive (0.99%) but has high standard deviation (7.86%), reflecting the large price fluctuations observed during our sample period. Examining the short selling measures, we find that an average of 29% of REITs market capitalization is available to borrow, with 6.41% actually being lent out. The mean annualized loan fee is 23.87 basis points per annum (bps p.a.) The large slack supply available to borrow is captured by the 18.62% average value for utilization, meaning that only an average of one fifth of the lendable shares is effectively lent out.

[INSERT TABLE 2 HERE]

Moreover, we match the returns on the FHFA House Price Indices calculated for each region with data on the REITs in the CRSP-Ziman database. For each REIT, we also hand-collect data on the composition of their property portfolio and classify them into ten groups based on the location of their underlying properties using U.S. Census regions. First, U.S. states are divided into four main regions: West (*Hawaii, Alaska, Washington, Oregon, California, Montana, Idaho, Wyoming, Nevada, Utah, Colorado, Arizona, New Mexico*); Northeast (*Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut, New York, New Jersey, Pennsylvania*); Midwest (*North Dakota, South Dakota, Minnesota, Nebraska, Iowa, Kansas, Missouri, Michigan, Wisconsin, Illinois, Indiana, Ohio*); and South (*Kentucky, Tennessee, Mississippi, Alabama, Delaware, Maryland, District of Columbia, Virginia, West Virginia, North Carolina, South Carolina, Georgia, Florida, Oklahoma, Arkansas, Texas, Louisiana*). We perform our analyses at the U.S. Census region level because the number of REITs with most of the properties in a single U.S. state is low. Therefore, most of the REITs are diversified across

several states and it is not possible to classify REITs at the U.S. state level according to the location of their properties.

We allocate each REIT to a particular state and region according to the location of their properties. If more than 50% of the investments of a REIT are located in one of the four U.S. Census regions, then it is classified as part of that specific regional group, that is, *Northeast*, *Midwest*, *South*, and *West*. If there is no single region having more than 50% of the REIT's properties but the REIT has more than 50% of its properties in a combination of two regions, we create a group for the specific combination two regions. The pairs *Northeast+South*, *Northeast+West*, *Midwest+South*, and *South+West* have at least one REIT. By mixing the single region with the mixed regions we have eight regional groups. If the REIT has properties over different regions but there is no combination of two regions accounting for more than 50% of the REIT's properties, then the REIT is classified as *Diversified*. REITs that invest in mortgages instead of properties are assigned to the category *Mortgage REITs*. Other REITs that do not fall into any of the categories above are excluded from our multivariate analysis and grouped as *Unclassified*. Note that we use all REITs included in the CRSP-Ziman database, regardless of whether they focus on residential or commercial real estate. We find even stronger results if we only include residential REITs (i.e. the property type variable *PTYPE* = 8 in the CRSP-Ziman database).

Finally, because our main goal is to examine differences between REITs exposed to areas that have experienced a boom in house prices from those that did not, we group the REITs within the eight regional groups that we have just described into two categories: *Boom* and *No Boom* areas. *Boom* is defined as areas in which house prices had a cumulative run-up higher than 75% during the period January 2000 - December 2007, while *No Boom* accounts for those areas where prices increased by less than 75%. These criteria aim to separate regions that experienced a large price run-up during the expansion cycle of the housing markets in the 2000s (mostly in the Northeast and the West) from those that did not (mostly in the Midwest and the South). Our results are robust to alternative choices of the starting month to compute the price run-up (i.e.,

January 2000), the ending month that represents a month at the peak of the housing cycle (i.e., December 2007), and to alternative levels of cumulative price increases (i.e., 75%).

Table 3 displays descriptive statistics for the number of REITs in each group per month. From Panel A, the majority of REITs (i.e., an average of 62.30 observations per month) have geographically diversified investments. Our dataset contains an average of 4.04, 1.00, 13.24, and 4.93 REITs each month within the categories *Northeast*, *Midwest*, *South*, and *West*, respectively. *South+West* is the most populated category within those that contain REITs with most of their properties in two regions. An average of 9.23 REITs in our sample invest only in *mortgages* and 12.38 REITs remain as *Unclassified*. In Panel B, we find that the average number of REITs with properties located in *No Boom* areas is 25.39 REITs, approximately twice as many as those in *Boom* areas. In Panel C we recompute the geographical breakdown using only residential REITs. Given the small number of REITs that invest only on residential properties, there is a marked reduction in data availability, with an average of only 3 to 4 REITs for each region.

[INSERT TABLE 3 HERE]

Table 4 shows the link between REITs' short selling activity and the geographical location of their properties. It shows that REITs with a majority of properties located in the Northeast and the West present higher *Supply* (35.29% and 35.38%) and *On Loan* (8.08% and 10.29%) than those with a majority of properties located in the Midwest and South (18.17% and 29.31% of supply, and 2.81% and 7.42%, respectively). At the aggregate level, REITs with majority of properties located in *Boom Areas* present higher supply (35.22%), on loan (10.30%) and short interest (8.75%) than the REITs with majority of properties located in *No Boom Areas* (28.36%, 7.44%, and 6.85%, respectively).

[INSERT TABLE 4 HERE]

Figure 2 displays the time series of REITs' short selling activity and cumulative housing returns (left axis) for *Boom*, *No Boom*, *Diversified*, and *Mortgage* groups for the period January 2000 - July 2013. The dynamics of REITs' lending markets is shown in terms of lending supply and on loan amount as a fraction of the aggregate REITs' total market capitalization (right axis). The aggregate lending supply of REITs with most of their properties in *Housing Boom Areas* was around 33% in July 2007, similar to the 30% observed for REITs properties in areas with no housing boom. The amount of REITs lent out to investors more than doubles from January 2007 to September 2008, going from 5% to above 13% of market capitalization. This figure also shows the decrease in lending supply and on loan amount that followed the Lehman Brother's bankruptcy in September 2008. Overall, this figure exhibits that short selling activity is higher for REITs with most of their properties located in *Housing Boom Areas* than REITs with most of their properties located in *No Housing Boom Areas*, as well as diversified REITs, and mortgage REITs.

[INSERT FIGURE 2 HERE]

Finally, Table 5 presents the correlations among the variables of this study. The returns of the FHFA House Price Index exhibit very low correlation with their matched REITs' returns (0.04) . They also present negative correlation with measures of short selling activity, the REITs' stock turnover, the 10-year Treasury yield, and the term spread. As expected, lending supply is negatively correlated to lending fees (-0.02), but positively correlated to shares on loan (0.62), short interest (0.28), and utilization (0.18).

[INSERT TABLE 5 HERE]

4 Empirical Results

In this Section, we test the hypotheses that we developed in Section 2 using the data that we described in Section 3. First, we test the hypothesis on the conditional correlation between REIT and housing returns that we presented in Subsection 2.1. Second, we test the hypothesis on short selling activity and house price predictability over the business cycle that we developed in Subsection 2.2. Third, we test the hypothesis on the geographical cross-section of short selling activity and house price predictability that we stated in Subsection 2.3. Fourth, we run the tests that involve short selling activity as the predictor with commercial real estate price data instead of house price data. Finally, we address some issues related to time dynamics and simultaneity.

4.1 Conditional Correlations between REIT and Housing Returns: Empirical Results

A necessary condition for using REITs to hedge or speculate on house price fluctuations is that the returns of these two assets are correlated, such that investors can use the financial security (i.e. REITs) to capture movements in the real asset (i.e., house prices). We begin our empirical analysis by testing if the correlation between REIT and housing returns is higher during market downturns (i.e., Hypothesis 1 that we developed in Subsection 2.1). Panel A of Table 6 displays the initial results for the tests of Hypothesis 1. Column 1 shows the correlation between the FHFA housing returns ($Ret(FHFA)$) and CRSP-Ziman REIT market index returns ($Ret(REIT)$) for the four geographical U.S. Census regions and for the aggregate U.S. market. In columns (2) and (3), we calculate the conditional correlations in periods of housing market downturn (*Bust Periods*) and no housing market downturn (*No Bust Periods*, that is, “boom” and “average” periods of the housing market cycle). Periods of housing market downturn in a given region are defined as those the months in which returns on the FHFA index are 1.64

standard deviations below the historical mean up to that particular month. Two main results arise from this table. First, we find a positive and significant correlation between $Ret(FHFA)$ and $Ret(REIT)$ in the full sample (0.075 with a p-value of 2.1%). Second, this correlation varies significantly according to the state of the housing market. During periods of housing market downturn, we find a positive correlation for the all regions except for the Northeast. This correlation is equal to 0.299 for the U.S. aggregate series. During no-downturn periods, the correlation is in fact negative and significant for all regions. This means that REITs returns tend to be lower when the FHFA housing index returns are above-average. In all cases, the difference between downturn (*Bust Periods*) and no-downturn (*No Bust Periods*) is statistically significant.

[INSERT TABLE 6 HERE]

Rather than displaying correlations, Panel B of Table 6 shows estimates for the regression specified in (1) for each of the U.S. Census regions and the aggregate U.S. series. We regress housing returns ($Ret(FHFA)$) on REITs' returns ($Ret(REIT)$), a dummy for the periods of housing downturn (*Bust Dummy*), and the interaction term $Ret(REIT) \times Bust Dummy$. First, we find that the coefficient for $Ret(REIT)$ is negative and statistically significant in all cases. Second, the coefficient for $Ret(REIT) \times RE Bust Dummy$ is positive and significant in all cases, as Hypothesis 1 states. We find a larger and positive correlation between the housing returns ($r_{i,t}$) and REITs' stock returns ($r_{i,t}^{REIT}$) during housing downturns (i.e. $RE Bust Dummy=1$). The null hypothesis that the sum of $Ret(REIT) \times RE Bust Dummy$ and $Ret(REIT)$ coefficients is equal to zero is rejected in all cases. These results are equivalent to the ones that we provide in Panel A and support Hypothesis 1: correlations between REIT and housing returns are higher during economic downturns.

4.2 Short Selling Activity and House Price Predictability over the Business Cycle: Empirical Results

We examine if equity short selling activity can forecast next month's house prices and if this predictability varies over the business cycle (i.e., Hypothesis 2). We expect not only that higher levels of short selling activity predict lower house prices in the future, but that this effect is stronger during recessions. Table 7 displays the results of the multivariate regressions that we run in order to test Hypothesis 2. We define $D(NBER\ Recession)$ as a dummy variable equal to 1 for months classified as a recession by the NBER and zero otherwise. We estimate regressions with four alternative measures of lagged short selling activity: (i) $On\ Loan_{i,t-1}$; (ii) $Short\ Interest_{i,t-1}$, (iii) $Utilization_{i,t-1}$ and $Fee_{i,t-1}$. We also interact each of these measures with the NBER recession dummy to allow for asymmetric effects of short selling predictability conditional on the state of the overall economy (as captured by the NBER dummy). As further control variables, we use the lagged returns on the equal-weighted CRSP-Ziman aggregate index ($Lag\ Ret(REIT)$) to account for the expectations about future prices embedded in REITs' stock returns, the average bid-ask spreads ($Bid-Ask\ Spread\ (\%)$) and log turnover ($Ln(Turnover)$) to control for liquidity, and the term spread between short and long maturity Treasury bonds ($Term\ Spread\ (10y - 3m)$).¹⁴ Finally, we include house price returns in the previous month to capture for the potential persistence in house price returns.

[INSERT TABLE 7 HERE]

Columns (1)-(4) of Table 7 exhibit the results using data for all REITs from the CRSP Ziman dataset. We find statistically significant and positive coefficients for $On\ Loan$ in column (1) and $Short\ Interest$ in column (2), but the asymmetry with respect to the business cycle is

¹⁴The online appendix contains additional regressions showing that including the returns of the aggregate CRSP U.S. index as an additional control variable do not affect our findings. Our results are also robust to replacing $Lag\ Ret(REIT)$ with the CRSP U.S. index returns.

only significant for *On Loan*. For example, a one standard deviation increase in short interest, leads to a 0.076% ($=-0.04*1.89\%$) decrease in the FHFA House Price Index in the following month (raw *Short Interest* has mean equal to 3.25%). This is economically significant and corresponds to a 10.8% standard deviation decrease in house price returns (the mean return of the FHFA index is -0.11% with standard deviation 0.70%). Moreover, columns (1) and (2) show that higher turnover in REITs stocks predict higher housing returns. A lower term spread of interest rates also forecasts higher housing returns. Overall, we find a much stronger link between short-selling and housing returns during recessions, exactly when we would expect investors to increase short sales of REITs to hedge for lower house prices.

A potential issue with these results is that they use data from all REITs to forecast house prices rather than just the short selling measures for residential REITs. Columns (1)-(4) use data from all REITs available in the CRSP-Ziman dataset, regardless of the property types that they invest in (e.g., residential, retail, office, healthcare, hotels, industrial, and self-storage). Thus, our results could be affected by REITs that are unrelated to housing assets but that are still included in the calculation of short sales measures, reducing their forecasting power. Only 5% of REITs in our sample are classified as being residential (i.e., *PTYPE* = 8 in the CRSP-Ziman dataset), meaning that the number of REITs with available short sales data in each region is small (i.e., it ranges from 3 to 4 per region). If investors want to hedge the risk of decreasing house prices by shorting REITs, then the average variation in the short selling intensity of residential REITs would be a stronger predictor than the average variation computed by using all types of REITs with investments in a particular region. Thus, our estimates could be affected by a measurement problem deriving from including all types of REITs (commercial, mortgages, etc.) to forecast housing returns. In columns (5)-(8) we re-estimate our regressions by computing short sales intensity measures with only residential REITs. Given our focus on using REITs data to predict house prices, the more related our financial securities are to the underlying asset, the more significant our results should be. During NBER recessions, we get a negative and

significant relationship for all measures of short selling apart from *Short Interest*. For example, using results in column (5), we find a -0.040 coefficient for *On Loan*, which becomes even more negative during NBER recessions (i.e., the *SS Variable * D(NBER Recession)* coefficient is also negative). Similar results also hold for *Utilization*. Overall, these results show that some, but not all, measures of short selling can forecast house prices. Short interest, which is commonly used in many previous papers, does not have much power to explain house prices. This highlights the advantages of using our proxies for short selling intensity computed from equity lending data. Overall, we find evidence that the returns of real assets (i.e., housing) can be predicted by the behavior of lagged characteristics of financial securities (i.e., short selling intensity of REITs), in line with Hypothesis 2.

4.3 Geographical Cross-Section of Short Selling Activity and House Price Predictability

Hypothesis 3 tests if the predictability of the short sales activity varies according to the geographical location of REITs' properties. We expect to find a stronger link between REIT short selling and housing returns in areas with larger house price run-ups, as investors attempt to hedge or speculate on lower house prices by establishing short positions on REITs' stocks. Using hand-collected data on REITs' property holdings, we classify each REIT as belonging to one of the following categories (D_i^{LOC}): *Boom*, *No Boom*, and *Diversified*.¹⁵ Then, for each category, we compute short selling activity for REITs with the majority of their properties in each of these three regions.¹⁶ We use returns of the *No Boom* regions as our benchmark and estimate a panel regression of next-period housing returns in a particular area as a function of measures of short selling (x) for that particular area plus control variables (z), including other

¹⁵REITs that invest in mortgages are not included in our calculations.

¹⁶For *Diversified* REITs we use returns of the aggregate US house price index as the dependent variable.

control variables time fixed-effects:

$$r_{i,t} = \alpha + \theta_t + \beta_1 \cdot x_{i,t-1} + \gamma_r' \cdot z_{t-1} + \beta_2 \cdot x_{i,t-1} \cdot D_i^{LOC} + \epsilon_t. \quad (3)$$

Table 8 displays the tests of Hypothesis 3 using this panel regression. In columns (1)-(4) we show results using data for all types of REITs (e.g., residential, hotels, offices, etc.) to construct short sales measures for each area. In columns (5)-(8) we only use those REITs investing in residential properties (i.e. with variable *PTYPE* in the CRSP-Ziman database being equal to 8), in a similar approach to the one used in Table 7). In all cases, we find that the impact of short selling activity on housing returns varies within our groups. While there is no explanatory power for the benchmark *No Boom* area (i.e., the *SS Variable* coefficient is not significant), we find negative and significant coefficients for the *SS Variable * D(Boom)* and *SS Variable * D(Diversified)*. For example, from column (7), a one standard deviation increase in *Utilization* leads to a 0.23% (= -0.028*8.05%) decrease in the FHFA House Price Index in the following month. This is economically significant and corresponds to a 0.32% standard deviation decrease in house price returns.¹⁷ This result is one of the key contributions of our paper. It shows that an increase in *Utilization* of REITs forecasts declines in house prices in areas that experienced a housing boom, but not for those areas that did not present a housing boom. The predictive power of *Utilization* in column (7) and *Fee* in column (8) for REITs with properties in *Boom* areas is significantly stronger than the predictability for REITs with properties in *No Boom* areas. Finally, a lower term spread of interest rates also forecasts higher housing returns in all specifications.

[INSERT TABLE 8 HERE]

Altogether, these results support our hypothesis that measures of short selling derived from residential REITs, in particular *Utilization* and *Fee*, can forecast future house prices. Further-

¹⁷Note that the mean return of the FHFA index is -0.11% with a standard deviation of 0.70%.

more, there is an important asymmetric component in this relationship, with house prices reacting differently depending on the areas in which the underlying properties of the REITs are located. As a result, we find consistent house price predictability in line with our hypothesis for REITs with properties located in areas that experienced a housing boom prior to our sample period.

4.4 Predictability Using Commercial REITs Data

As a robustness test, we also estimate the effects of the short selling activity of REITs on commercial real estate prices. A majority of REITs make their investments in commercial rather than residential real estate. While the main results are all based on using house price indices, an obvious extension is testing our hypothesis using real estate returns for alternative property types. Unlike our prior for asymmetries across different geographical areas, we are agnostic about the differences in the forecasting power across property types.

We compute short selling intensity measures of REITs that focus on several property types and match them to the Moody's/RCA Commercial Property Price Indices (CPPI) for apartments, commercial, industrial, office and the aggregate U.S. series. The CPPI data are weighted, repeat-sales indices, which are computed using contemporaneous transaction-price-based data on private deals. There are also specific indices CPPI for the different property types, which are available at a monthly frequency. The property types for each REIT come from the CRSP-Ziman dataset, use the "property" (variable PTYPE) and "sub-property" types (variable PSUB): *Commercial* (PSUB=9 and PSUB=16), *Apartments* (PTYPE=8 and PSUB=2), *Industrial* (PSUB=8), *Office* (PSUB=13) and *Diversified* (PSUB = 4 and PSUB=11). The average number of REITs in each property type is 15, with *Office* being the most common REITs' property type (average of 28 REITs per month). We assign the U.S. aggregate CPPI index to track returns of diversified REITs.

Table 9 shows the results of testing the impact of short selling measures on the property-type index returns rather than house price returns. Columns (1)-(4) display the tests of Hypothesis 2 by also including the NBER recession dummy and the same set of control variables used in Table 7. In all cases, property returns are negative and significant during the months classified as recession by the NBER, unlike the equivalent results that we obtained for house price returns in Table 7. The coefficients for *On Loan* (column 1), *Utilization* (column 3) and *Fee* (column 4) are not statistically significant. In Panel B, columns (5)-(8) test for possible asymmetries between *Apartments* (i.e., residential REITs), which are likely to be more affected by the housing market bubble than other commercial properties. We add a dummy variable equal to 1 for the *Apartments* CPPI index and 0 otherwise and also an interaction of this dummy variable with our short selling measures. We find that this interaction term is statistically significant for all the short selling measures that we use in this empirical analysis. However, we also find significant evidence of differences in forecasting power across the property types.

[INSERT TABLE 9 HERE]

4.5 Aggregate Short Selling Activity and House Price Predictability

In Table 10 we use measures of short selling activity for the whole U.S. stock market rather than just REITs. Note that by using aggregate short selling data we no longer estimate regressions using the cross-section of REITs along different geographical areas. Instead, we have estimated regressions using aggregate U.S. stock market measures of short selling measures to forecast the aggregate U.S. housing returns series. As further robustness, we also include the lagged return of the stock market to control for any possible biases between stock market returns and aggregate short selling. We also include We find much weaker evidence of predictability. While the coefficients for *On Loan* and *Utilization* are statistically significant using the full sample of REITs in Panel A, using only residential REITs does not show any evidence

of predictability. This is what we would expect given that information using all stocks is bound to be less correlated to housing prices than if we use REITs-based only, because of the higher cash-flow correlation of the latter.

[INSERT TABLE 10 HERE]

4.6 Time Dynamics and Simultaneity

The estimated regressions above do not account for the possible reverse causality of the explanatory variables. For instance, housing returns and REITs returns might be endogenously determined because they both depend on future expectations of house prices. As a robustness test, we construct panel vector autoregression (PVAR) models to estimate the joint dynamics of house price returns, REITs returns, and short selling variables as in Holtz-Eakin, Newey, and Rosen (1988) and Pesaran and Smith (1995).¹⁸ Although PVAR regressions are commonly used in the macroeconomic literature, they are not widely used in finance. The use of a PVAR model has two important advantages in our setup. First, it captures the dynamic relationships among all the time series in the analysis. Second, it allows for heterogeneity at the area-level and the reduced-form specification assumes that all variables in the system are endogenous. Before estimating the PVAR model, we use the panel unit root test developed by Choi (2001) on each of the short selling variables to rule out non-stationarity. Results in Panel A of Table 11 reject the null hypothesis that the short sales measures contain a unit root.¹⁹

[INSERT TABLE 11 HERE]

To setup the PVAR models, we start by selecting the optimum number of lags to use in the autoregression. Panel B of Table 11 exhibits the lag-selection analysis using *On Loan* as the

¹⁸We thank Inessa Love for making the panel VAR routines used in Love and Zicchino (2006) available to researchers.

¹⁹In unreported results we have also explored the existence of a cointegrating vector among house prices, REITs index levels and equity lending variables but have not been able to find any evidence to support this hypothesis.

measure of short selling. Results indicate that one lag is the optimal choice for the empirical analysis regardless of whether we use the Bayesian information criterion (BIC), Akaike's information criterion (AIC), and the Hannan-Quinn information criterion (QIC).²⁰ Thus, for a given set of variables, the first-order panel auto-regression specification is given by:

$$z_{i,t} = \Gamma_0 + \Gamma_1 z_{i,t-1} + f_i + \theta_t + \epsilon_{i,t} \quad (4)$$

where z denotes our endogenously determined variables: short selling activity, $Ret(REIT)$, and $Ret(FHFA)$. Let i denote each of the groups according to the geographical location of the REITs properties. Group fixed-effects (f_i) control for any heterogeneity due to unobservable characteristics in each geographical-based group and monthly time-effects are captured by θ_t . Unlike the previous tables, the PVAR specification assumes that each cross-sectional unit follows the same underlying structure, with fixed coefficients (Γ_1) for all different geographically-based groups. The main benefit of this approach is that we can exploit the cross-sectional variation in house prices to improve the quality of our estimates.

The outcomes of the PVAR analysis are shown in Table 12. Each panel in this table reports results for a particular measure of short selling activity. For example, Panel A shows that the loan demand for REITs' stocks has a negative and significant impact on next month's house price index returns. All panels present evidence consistent with a negative relationship between short selling measures and future stock returns in line with Hypothesis 2. As expected, we also find that increases in $Ret(REIT)$ returns forecast an increase in $Ret(FHFA)$ in the following month in all panels. This can be explained by the fact that REITs stocks incorporate information much faster than house price indices. These results are in contrast with the multivariate regressions reported in Table 8 and show the importance of addressing the endogeneity issues among house prices, REITs returns and short selling measures.

²⁰Results are the same for other short selling measures.

[INSERT TABLE 12 HERE]

Another useful output of VAR models is the ability to estimate the reaction of a particular endogenous variable to a shock in another endogenous variable. Because of the likely correlation among shocks to endogenous variables, we must make an identifying assumption to be able to orthogonalize the residuals. We use variables that appear earlier in the vector z because, in the short-run, they are deemed “more exogenous” than latter ones.²¹

Figure 3 displays impulse-response graphs with the response of house price returns over twelve months given a one standard deviation shock to alternative short sales proxies. We also report 95% bootstrapped confidence intervals based on 500 simulations. Results are similar to what we find in our univariate regressions: a shock to short selling measures leads to a decrease in house price returns in the next month. For example, a one standard deviation shock to short interest is associated with a -0.076% decrease in house prices next month, which is equivalent to a 0.11 standard deviation change in house prices. These shocks are also very persistent, with low returns being observed even six months after the initial shock. The same standard deviation shock to short selling *On Loan* yields a similar change in house prices. In Panels A and C, we observe that the impact of shocks are no longer statistically significant after six months. Panel B (*Short Interest*) shows that the effect is statistically significant only in the first month after the shock.

[INSERT FIGURE 3 HERE]

These results are corroborated by the variance decomposition analysis that we show in Figure 4. Each Panel exhibits the fraction of forecasting residuals’ variance over twelve months that can be explained by each particular variable of short selling activity and by REITs returns. For example, Panel A shows that 11.9% of the 12-month residual variability in $Ret(FHFA)$ can be explained by shocks to *On Loan* and 4.8% are due to shocks to $Ret(REITs)$. The ex-

²¹Our results are unaffected by the ordering in which variables enter the system.

plained fraction of forecasting residuals' variance for *On Loan*, *Short Interest*, and *Utilization* is similar to the one found for $Ret(REIT)$. This analysis highlights the usefulness of proxies for measures of REITs' short selling to forecast changes in house prices above and beyond the information contained in the dynamics of REITs return.

[INSERT FIGURE 4 HERE]

5 Conclusion

This paper investigates how investors can use financial securities to bet on price decreases of physical assets that face high transaction costs and short sales constraints. More specifically, we study how Real Estate Investment Trusts (REITs) can be used to hedge the downside risk of housing markets or speculate on the decrease of house prices.

We construct a dataset of monthly data of REIT's equity lending activity and FHFA index returns between July 2006 and July 2013. We use the link between U.S. house prices and REITs to test if short selling activity has forecasting ability about next month's future house prices across geographical areas and over economic downturns. Our main findings are as follows. First, the correlation between REIT returns and FHFA housing returns is significantly positive only during housing downturns. Second, an increase in short selling activity forecasts decreases in house prices in the following month. Third, this relationship becomes more negative in areas that have just experienced a *housing boom* than in those without a boom. We find that a one standard deviation increase in the fraction of shares on loan of REITs with properties in *housing boom* areas (e.g., West region in the U.S.) forecasts a 0.135% (0.16 standard deviations) decrease in house prices in the following month. We do not find any effect in REITs with properties in *no housing boom* areas (e.g., Midwest region in the U.S.) We also employ panel vector autoregressions (PVAR) to account for simultaneous determination and area-level heterogeneity between short selling, REITs stock returns and house prices. In this case, a one

standard deviation shock to REITs' loan demand forecasts a 0.11% (0.15 standard deviations) decrease in house prices next month.

These results show the usefulness of financial data in forecasting changes in real assets' prices and how specific geographical areas were affected differently by short selling activity during the financial crisis in 2008-2009. In particular, the demand for shorting REITs captured by the fraction of market capitalization on loan can help to forecast future house prices, with an important asymmetric component depending on the location of the underlying properties of the REITs. Short selling can be a useful tool for market participants to hedge against future price decreases and regulators can track measures from the equity lending market to improve forecasts of house prices and implement policies to prevent real estate bubbles. Furthermore, imposing short selling constraints on stocks like REITs –that invest in assets subject to high transaction costs– matters for price efficiency. For example, our results suggest that banning the short selling of REITs eliminates a hedging mechanism that is accessible to investors.

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Table 1. Contribution to the Literature

This table summarizes the empirical strategies used in the literature that studies how the short selling activity of stocks and REITs predicts returns –rows (1) and (2), respectively– and the literature that analyzes how aggregate REITs returns forecasts real estate prices –row (3)–. It also compares these empirical strategies to the one in our paper in row (4).

Main Independent variable	Dependent variable	Level of analysis	Geographical level	Geographical cross-section	Papers
(1) Short selling activity of stocks (Usually short interest)	Stock returns	Individual stocks	US aggregate	—	Asquith and Meulbroek (1995), Jones and Lamont (2002), Desai et al. (2002), Boehme, Danielsen, and Sorescu (2006), Cohen, Diether, and Malloy (2007), and Nagel (2005)
(2) Short selling activity of REITs (Only short interest)	Stock returns	Individual stocks	US aggregate	No	Li and Yung (2004), Blau, Hill, and Wang (2011), and Chen, Downs, and Patterson (2002).
(3) Aggregate REITs returns	Real estate prices (Appraisals: NCREIF)	Portfolio	US aggregate	No	Gyourko and Keim (1992), Barkham and Geltner (1995), Ling and Naranjo (1997), Benjamin, Sirmans, and Zietz (2001), Pagliari, Scherer, and Monopoli (2005), and Riddiough, Moriarty and Yeatman (2005)
(4) Short selling activity of REITs (Both short interest and equity lending)	House prices (Real transactions: FHFA)	Individual REITs	US aggregate US regional US property types	Yes	Our paper

Table 2. Descriptive Statistics

This table shows descriptive statistics of monthly data from July 2006 to July 2013. *Market Cap* is the average REIT size in the sample in million of US dollars. *Ret(Individual REIT)* is the average monthly return of the individual REITs. *Average Bid-Ask* spread is the average bid-ask spread at the close of the market. *Average Daily Turnover* is the average daily turnover as a fraction of market capitalization. *Supply* is the amount of stocks available to borrow scaled by market capitalization. *On Loan* is the fraction effectively lent out. *Short Interest* is the number of shares that are sold short as a fraction of market capitalization. *Utilization* is *On Loan* divided by *Supply*. *Fee* is the average seven-day transaction weighted fee expressed in annualized basis points. *Ret(FHFA)* is the monthly change in the FHFA Index. *Ret(REIT)* is the mean return of the CRSP-Ziman REIT Index. Finally, *10y T-bond Yield* is the constant maturity yield of Treasury bonds and *Term Spread* is the difference between the 10-year and the 3-month T-Bond yields.

Variable	Obs.	Mean	Median	Std.Dev.	Min.	Max.	Skewness	Kurtosis
Number of REITs	420	114.13	113.00	7.65	103.00	138.00	1.48	5.26
Market Cap (US mil.)	420	5,128	3,560	4,034	778	19,489	1.40	4.47
Ret(Individual REIT)	420	0.99%	1.50%	7.86%	-30.21%	39.93%	0.03	7.77
Avg. Bid-Ask Spread (%)	420	0.14%	0.09%	0.14%	0.03%	1.14%	2.84	14.19
Avg. Daily Turnover	420	0.28%	0.23%	0.15%	0.09%	1.04%	1.84	7.10
Supply (%)	420	29.00%	30.28%	6.58%	13.35%	40.44%	-0.73	2.79
On Loan (%)	420	6.41%	6.07%	3.10%	1.23%	15.21%	0.58	2.60
Short Interest (%)	420	3.25%	2.85%	1.89%	0.15%	10.64%	1.15	4.15
Utilization (%)	420	18.62%	17.57%	8.05%	5.23%	44.17%	0.41	2.41
Fee (bps p.a.)	420	23.87	12.32	36.56	-0.04	318.80	4.65	28.85
Ret(FHFA)	420	-0.11%	-0.03%	0.70%	-2.02%	1.75%	-0.02	2.56
Ret(REIT)	420	0.64%	1.10%	7.82%	-30.21%	27.88%	-0.71	6.82
10y T-bond Yield	420	3.22%	3.32%	1.01%	1.51%	5.03%	-0.02	1.92
Term Spread (10y - 3m)	420	1.98%	2.15%	1.22%	-0.60%	3.79%	-0.67	2.45

Table 3. Number of REITs per Geographical Location of the REITs Properties

Panel A shows the summary statistics on the number of REITs that we classify in eleven groups according to the geographical location of their properties as follows using data from July 2006 to July 2013. If more than 50% of the properties of a REIT are located in one of the four U.S. Census regions, then it is classified as part of that specific regional group, respectively, *Northeast*, *Midwest*, *South*, and *West*. If there is no region containing more than 50% of the REIT's properties but the REIT has more than 50% of its properties in a combination of two regions, then we create a group for the specific combination of two regions. Only the pairs *Northeast+South*, *Northeast+West*, *Midwest+South*, and *South+West* have at least one REIT. In total we have eight regional groups. If the REIT has properties over different regions but there is no combination of any two regions accounting for more than 50% of the REIT's properties, then the REIT is classified as *Diversified*. *Mortgage REITs* is assigned to REITs that invest in mortgages instead of properties. *Unclassified* includes all REITs that do not belong to any of the previous groups. Panel B shows the summary statistics grouped by areas that have experienced a *boom* in their housing markets (*Housing Boom Areas*), defined as areas in which house prices had a cumulative run-up of more than 75% during the January 2000 - December 2007 period, and areas that have not (*No Housing Boom Areas*). Panel C displays the same statistics for the subgroup of residential REITs.

Geographical Location of the REITs Properties	Mean	St.Dev.	Min.	Max.
<i>Panel A: By U.S. Census Regions</i>				
Northeast (N)	4.04	0.19	4	5
Midwest (M)	1.00	0.00	1	1
South (S)	13.24	1.46	11	17
West (W)	4.93	0.40	4	6
N+S	1.00	0.00	1	1
N+W	2.06	0.24	2	3
M+S	6.62	0.79	6	8
S+W	11.27	0.76	10	14
Diversified	62.30	5.63	56	77
Mortgage REITs	9.23	1.75	6	13
Unclassified	12.38	0.86	11	14
<i>Panel B: By Boom vs. No Boom. All REITs</i>				
No Housing Boom Areas	25.39	2.30	23	30
Housing Boom Areas	12.21	0.87	11	15
Diversified	62.30	5.63	56	77
Mortgage REITs	9.23	1.75	6	13
Unclassified	12.38	0.86	11	14
<i>Panel C: By Boom vs. No Boom. Only residential REITs</i>				
No Housing Boom Areas	4.00	0.79	3	5
Housing Boom Areas	2.94	0.24	2	3
Diversified	3.53	0.87	3	5
Unclassified	4.11	0.46	3	6

Table 4. Short Selling Measures per Geographical Location of the REITs Properties

This table shows the average and the standard deviation of short selling measures according to the geographical location of the majority of the REITs properties using data from July 2006 to July 2013. *Supply* is the amount available to borrow scaled by market capitalization, *On Loan* is the fraction effectively lent out. *Short Interest* is the number of shares sold short as a fraction of market capitalization. *Utilization* is the fraction of supply used for short selling purposes. *Fee* is the average seven-day transaction weighted fee expressed in annualized basis points.

Geographical Location of the REITs Properties		Supply (%)	On Loan (%)	Short Interest (%)	Utilization (%)	Fee (bps p.a.)
<i>Panel A: By U.S. Census Regions:</i>						
Northeast (N)	Mean	35.29	8.08	2.27	18.74	23.86
	St.Dev.	3.59	2.88	1.07	7.01	33.62
Midwest (M)	Mean	18.17	2.81	0.03	13.31	66.90
	St.Dev.	3.58	1.28	0.27	6.91	110.62
South (S)	Mean	29.31	7.42	3.49	22.59	40.75
	St.Dev.	2.57	2.28	1.22	7.86	55.76
West (W)	Mean	35.38	10.29	5.00	23.84	10.45
	St.Dev.	3.52	4.28	3.21	9.48	9.90
N+S	Mean	33.93	10.12	9.20	23.70	23.02
	St.Dev.	4.96	6.81	4.96	14.89	45.74
N+W	Mean	31.32	4.31	0.92	11.71	11.63
	St.Dev.	4.51	1.99	1.63	6.66	12.87
M+S	Mean	29.48	5.98	0.71	17.74	17.40
	St.Dev.	2.98	2.02	0.36	5.79	19.39
S+W	Mean	29.47	5.23	3.70	15.62	12.03
	St.Dev.	3.25	2.55	1.75	7.45	7.66
Diversified	Mean	31.18	7.71	6.83	19.35	28.11
	St.Dev.	3.80	2.56	2.32	5.15	26.01
Mortgage REITs	Mean	19.86	5.27	5.96	22.38	45.24
	St.Dev.	2.48	2.50	2.13	10.66	70.97
Unclassified	Mean	30.12	7.14	6.76	20.73	15.78
	St.Dev.	3.95	2.66	2.04	6.41	12.83
<i>Panel B: By Boom vs. No Boom:</i>						
No Housing Boom Areas	Mean	28.36	7.44	6.85	23.63	46.92
	St.Dev.	3.16	1.98	1.83	5.68	46.23
Housing Boom Areas	Mean	35.22	10.30	8.75	24.68	22.30
	St.Dev.	3.60	2.93	3.08	6.53	21.30
Diversified	Mean	31.18	7.71	6.83	19.35	28.11
	St.Dev.	3.80	2.56	2.32	5.15	26.01
Mortgage REITs	Mean	19.86	5.27	5.96	22.38	45.24
	St.Dev.	2.48	2.50	2.13	10.66	70.97
Unclassified	Mean	30.12	7.14	6.76	20.73	15.78
	St.Dev.	3.95	2.66	2.04	6.41	12.83

Table 5. Correlations

This table shows the correlations of the main variables used in the empirical analysis from July 2006 to July 2013. *Ret(FHFA)* is the monthly average return of the FHFA House Price Index. *Ret(REIT)* is the monthly average return of the CRSP-Ziman REIT Index. *Market Cap (US mil.)* is the average REIT size in the sample. *Ret(Individual REIT)* is the average monthly return of the individual REITs. *Bid-Ask spread* is the average bid-ask spread at the close of the market. *Daily Turnover* is the average daily turnover as a fraction of the market capitalization. *Supply* is the amount available to borrow scaled by market capitalization. *On Loan* is the fraction effectively lent out. *Utilization* is the number of shares on loan divided by the number of shares available to borrow. *VW Fee* is the average seven-day transaction weighted fee expressed in annualized basis points. *10y T-Bond Yield* is the constant maturity yield of Treasury Bonds. *Term Spread* is the difference between the 10-year and the 3-month T-Bond yields.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Ret(FHFA)	1												
(2) Ret(REIT)	0.04	1											
(3) Market Cap (US mil.)	0.20	0.04	1										
(4) Ret(Individual REIT)	-0.01	0.88	0.03	1									
(5) Avg. Bid-Ask Spread (%)	-0.40	-0.25	-0.23	-0.14	1								
(6) Avg. Daily Turnover	-0.31	-0.02	-0.13	-0.01	0.34	1							
(7) Supply (%)	-0.20	-0.08	-0.18	-0.03	0.15	-0.07	1						
(8) On Loan (%)	-0.51	-0.13	-0.43	-0.08	0.48	0.30	0.62	1					
(9) Short Interest (%)	-0.43	-0.08	-0.37	-0.03	0.40	0.38	0.28	0.69	1				
(10) Utilization (%)	-0.47	-0.13	-0.44	-0.09	0.53	0.35	0.18	0.85	0.70	1			
(11) VW Fee (bps p.a.)	-0.18	-0.06	-0.14	-0.01	0.28	0.18	-0.04	0.31	0.29	0.48	1		
(12) 10y T-Bond Yield	-0.40	-0.07	-0.26	-0.06	0.36	-0.01	0.03	0.43	0.34	0.58	0.27	1	
(13) Term Spread (10y - 3m)	-0.19	0.03	-0.01	0.07	-0.06	0.37	0.14	-0.01	0.05	-0.19	-0.11	-0.37	1

Table 6. Test of Hypothesis 1. Conditional Correlations between REIT and Housing Returns

Panel A displays the correlation between the returns of the FHFA House Price Index, $Ret(FHFA)$, and the returns of the aggregate portfolio of REITs, $Ret(REIT)$, according to the geographical location of the majority of the REITs properties (i.e., the U.S. Census regions Northeast, Midwest, South, and West, and the U.S. Aggregate) and split by housing market cycles. Column (1) uses the full sample. Column (2) and column (3) use only the periods of downturn in the housing markets (i.e., *Bust Periods*) and the periods of no housing downturn (i.e., *No Bust Periods*, that is, “boom” and “average” periods of the housing market cycle), respectively. *Bust periods* only includes months in which the FHFA House Price Index is 1.64 standard deviations below its historical mean from 1990 to the period in question. p-values are reported below each coefficient in brackets. Panel B shows the formal test of Hypothesis 1. It displays the results of regressing $Ret(FHFA)$ on $Ret(REIT)$, a dummy for the periods of housing bust (*Bust Dummy*), and the interaction term $Ret(REIT) \times Bust Dummy$. Standard deviations are reported in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. This test uses data from January 1991 to December 2010.

Panel A. Conditional correlations between $Ret(FHFA)$ and $Ret(REIT)$

	All Periods (Full Sample) (1)	Bust Periods (2)	No Bust Periods (3)
Northeast (N)	0.003 [0.961]	0.168 [0.136]	-0.150* [0.059]
Midwest (M)	0.050 [0.442]	0.290*** [0.009]	-0.267*** [0.001]
South (S)	0.065 [0.316]	0.374*** [0.001]	-0.244*** [0.002]
West (W)	0.151** [0.020]	0.376*** [0.001]	-0.160** [0.044]
U.S. Aggregate	0.075** [0.021]	0.299*** [0.000]	-0.187*** [0.000]

Panel B: Conditional Regressions of $Ret(FHFA)$ on $Ret(REIT)$ by Geographical Regions

Region	$Ret(REIT)$ (%)	Bust Dummy	$Ret(REIT) \times$ Bust Dummy	Intercept	Adj. R^2	Obs.
Northeast (N)	-0.025** [0.011]	-0.062 [0.103]	0.044** [0.022]	0.402*** [0.062]	0.013	239
Midwest (M)	-0.029*** [0.008]	-0.069 [0.073]	0.059*** [0.018]	0.360*** [0.034]	0.072	239
South (S)	-0.030*** [0.007]	-0.020 [0.073]	0.070*** [0.019]	0.390*** [0.035]	0.084	239
West (W)	-0.034*** [0.011]	-0.066 [0.139]	0.107*** [0.021]	0.461*** [0.073]	0.081	239
U.S. Aggregate	-0.030*** [0.005]	-0.054 [0.051]	0.070*** [0.011]	0.403*** [0.027]	0.060	956

Table 7. Test of Hypothesis 2. Short Selling Activity and House Price Predictability over the Business Cycle

The table displays results of panel OLS regressions of next month returns of the population-weighted FHFA House Price Index for three categories using data from July 2006 to July 2013. *Boom*; *No Boom*; and *Diversified*. *Boom (No Boom)* is defined as U.S. Census' regions where house prices had a cumulative run-up of more than (less than) 75% during the period January 2000 - December 2007. *Diversified* are those with properties over different regions but there is no combination of any two regions accounting for more than 50% of the REIT's total investments. *SS* denotes the short selling measure of REITs assigned to each particular group: *On Loan* is the value of share lent out scaled by market capitalization. *Short Interest* is the number of shorted shares scaled by market capitalization. *Utilization* is the number of shares on loan divided by the number of shares available to borrow. *Fee* is the average value-weighted lending fee. *D(NBER Recession)* is a dummy variable equal to 1 during periods classified as a recession by NBER, zero otherwise. *Lag Ret(REIT)* is the return of the CRSP-Ziman REIT index. *Bid-Ask spread* is the average bid-ask spread at the close of the market. *Ln(Turnover)* is the log of daily turnover scaled by market capitalization. *Lag Ret(FHFA)* is the previous month's price change based on FHFA House Prices Indices. *Diversified* and *Mortgage* are assigned the U.S. aggregate FHFA index returns. All regressions have year-month fixed-effects. Standard deviations are clustered at the category level and are reported in parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

SS Variable:	Panel A: All REITs				Panel B: Residential REITs Only			
	On Loan (1)	Short Interest (2)	Utilization (3)	Fee (4)	On Loan (5)	Short Interest (6)	Utilization (7)	Fee (8)
Lag Ret(REIT)	0.009 [0.010]	0.010 [0.010]	0.010 [0.010]	0.008 [0.010]	0.011 [0.010]	0.012 [0.011]	0.011 [0.011]	0.012 [0.010]
Bid-Ask Spread (%)	-0.693 [0.242]	-0.663 [0.367]	-0.592 [0.397]	-0.820 [0.337]	-0.262 [0.109]	-0.264 [0.144]	-0.261 [0.107]	-0.186 [0.142]
Ln(Turnover)	0.383* [0.117]	0.319* [0.109]	0.233 [0.150]	0.240 [0.109]	0.278** [0.053]	0.311** [0.049]	0.288** [0.046]	0.139 [0.076]
Term Spread (10y - 3m)	-0.158** [0.029]	-0.129** [0.024]	-0.126** [0.028]	-0.124* [0.039]	-0.121** [0.028]	-0.103** [0.017]	-0.129** [0.026]	-0.062** [0.009]
Lag Ret(FHFA)	-0.035 [0.072]	-0.010 [0.074]	0.008 [0.068]	-0.010 [0.093]	0.012 [0.051]	0.079 [0.037]	0.027 [0.051]	0.135 [0.052]
D(NBER Recession)	0.880*** [0.054]	-0.055 [0.152]	0.111 [0.260]	-0.512 [0.221]	0.210 [0.116]	0.097 [0.258]	0.261 [0.185]	-0.183 [0.124]
SS Variable	-0.037* [0.010]	-0.040* [0.010]	-0.004 [0.003]	-0.270 [0.641]	-0.040** [0.006]	-0.042 [0.024]	-0.017** [0.002]	1.133 [0.517]
SS Variable * D(NBER Recession)	-0.112** [0.009]	-0.035 [0.025]	-0.013 [0.012]	0.607 [0.557]	-0.048*** [0.002]	-0.046 [0.028]	-0.023** [0.004]	-1.697* [0.461]
Observations	252	252	252	252	252	252	252	252
Adjusted R ²	0.516	0.489	0.485	0.496	0.542	0.507	0.535	0.487

Table 8. Test of Hypothesis 3. Geographical Cross-Section of Short Selling Activity and House Price Predictability

The table displays results of panel OLS regressions of next month return of the population-weighted FHFA House Price Index for three categories using data from July 2006 to July 2013. *Boom*; *No Boom*; and *Diversified*. *Boom (No Boom)* is defined as U.S. Census' regions where house prices had a cumulative run-up of more than (less than) 75% during the period January 2000 - December 2007. *Diversified* are those with properties over different regions but there is no combination of any two regions accounting for more than 50% of the REIT's total investments. *SS* denotes the short selling measure of REITs assigned to each particular group: *On Loan* is the value of share lent out scaled by market capitalization. *Short Interest* is the number of shorted shares scaled by market capitalization. *Utilization* is the number of shares on loan divided by the number of shares available to borrow. *Fee* is the average value-weighted lending fee. *D(·)* are the dummy variables for each category and *No Boom* is used as the benchmark group. *NBER Recession* is a dummy variable equal to 1 during periods classified as a recession by NBER, zero otherwise. *Lag Ret(REIT)* is the return of the CRSP-Ziman REIT index. *Bid-Ask spread* is the average bid-ask spread at the close of the market. *Ln(Turnover)* is the log of daily turnover scaled by market capitalization. *Lag Ret(FHFA)* is the previous month's price change based on FHFA House Prices Indices. *Diversified* and *Mortgage* are assigned the U.S. aggregate FHFA index returns. All regressions have year-month fixed-effects. Standard deviations are clustered at the category level and are reported in parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

SS Variable:	Panel A: All REITs				Panel B: Residential REITs Only			
	On Loan (1)	Short Interest (2)	Utilization (3)	Fee (4)	On Loan (5)	Short Interest (6)	Utilization (7)	Fee (8)
Lag Ret(REIT)	0.010 [0.010]	0.010 [0.010]	0.010 [0.010]	0.011 [0.009]	0.011 [0.010]	0.012 [0.010]	0.011 [0.010]	0.012 [0.009]
Bid-Ask Spread (%)	-0.853 [0.347]	-0.955 [0.395]	-0.945 [0.413]	-1.097* [0.287]	-0.276 [0.119]	-0.276 [0.143]	-0.268 [0.113]	-0.306 [0.169]
Ln(Turnover)	0.348 [0.157]	0.303 [0.105]	0.340 [0.144]	0.285 [0.104]	0.214* [0.064]	0.227** [0.027]	0.226** [0.046]	0.136 [0.074]
Term Spread (10y - 3m)	-0.085** [0.017]	-0.090* [0.023]	-0.090** [0.016]	-0.064 [0.026]	-0.066** [0.015]	-0.072** [0.013]	-0.075* [0.018]	-0.055* [0.014]
Lag Ret(FHFA)	-0.023 [0.070]	-0.017 [0.072]	-0.025 [0.077]	-0.014 [0.079]	-0.007 [0.054]	0.069 [0.049]	0.002 [0.054]	0.112 [0.057]
D(Boom)	0.223 [0.130]	0.118 [0.058]	0.412* [0.132]	0.022 [0.022]	0.550*** [0.055]	0.150* [0.042]	0.638*** [0.048]	-0.007 [0.077]
D(Diversified)	0.018 [0.103]	0.089 [0.053]	0.247* [0.073]	0.110** [0.024]	-0.020 [0.032]	0.044 [0.088]	0.008 [0.014]	0.003 [0.020]
SS Variable	-0.034 [0.058]	0.054 [0.039]	0.006 [0.021]	0.384 [0.142]	-0.043 [0.031]	-0.003 [0.013]	-0.014 [0.012]	0.531 [0.712]
SS Variable * D(Boom)	-0.041 [0.025]	-0.104* [0.025]	-0.030** [0.006]	-0.897** [0.135]	-0.048 [0.017]	-0.063** [0.012]	-0.028** [0.006]	-1.498* [0.410]
SS Variable * D(Diversified)	-0.018 [0.014]	-0.065** [0.007]	-0.019*** [0.001]	-0.667** [0.105]	-0.005 [0.005]	-0.023 [0.023]	-0.005*** [0.000]	-0.293** [0.044]
Observations	252	252	252	252	252	252	252	252
Adjusted R ²	0.504	0.494	0.504	0.511	0.548	0.505	0.545	0.493

Table 9. Short Selling Activity and Commercial Real Estate Predictability

The table displays results of OLS regressions of next month changes of the population-weighted RCA Commercial Property Price Index (CPPI) returns for each property type (i.e. Apartments, Commercial, Industrial, and Office) using data from July 2006 to July 2013. In Panel A we use all commercial REITs, while in Panel B we also include a dummy variable (*D(Residential)*) equal to 1 for the commercial REITs that solely invest in apartment properties, zero otherwise. *SS* denotes the short selling measure of REITs assigned to each particular group: *On Loan* is the value of share lent out scaled by market capitalization. *Short Interest* is the number of shorted shares scaled by market capitalization. *Utilization* is the number of shares on loan divided by the number of shares available to borrow. *Fee* is the average value-weighted lending fee. *D(·)* are the dummy variables for each category and *No Residential* is used as the benchmark group. *NBER Recession* is a dummy variable equal to 1 during periods classified as a recession by NBER, zero otherwise. *Lag Ret(REIT)* is the return of the CRSP-Ziman REIT index. *Bid-Ask spread* is the average bid-ask spread at the close of the market. *Ln(Turnover)* is the log of daily turnover scaled by market capitalization. *Lag Ret(CPPI)* is the previous month's price change based on CPPI Indices. All regressions have year-month fixed-effects. Standard deviations are clustered at the category level and are reported in parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

SS Variable:	Panel A: All REITs				Panel B: Control for Residential REITs			
	On Loan (1)	Short Interest (2)	Utilization (3)	Fee (4)	On Loan (5)	Short Interest (6)	Utilization (7)	Fee (8)
Lag Ret(REIT)	0.008 [0.004]	0.007 [0.004]	0.008 [0.004]	0.008 [0.004]	0.007 [0.004]	0.007 [0.004]	0.008 [0.004]	0.007 [0.004]
Bid-Ask Spread (%)	-0.110 [0.271]	-0.119 [0.283]	-0.108 [0.273]	-0.121 [0.273]	-0.116 [0.275]	-0.131 [0.284]	-0.114 [0.277]	-0.111 [0.276]
Turnover (%)	-0.326*** [0.079]	-0.352*** [0.059]	-0.321*** [0.078]	-0.341*** [0.082]	-0.370*** [0.063]	-0.370*** [0.052]	-0.368*** [0.062]	-0.390*** [0.069]
Term Spread (10y - 3m)	0.039 [0.040]	0.036 [0.042]	0.038 [0.040]	0.038 [0.040]	0.039 [0.040]	0.039 [0.041]	0.038 [0.040]	0.036 [0.041]
Lag Ret(CPPI)	0.482*** [0.049]	0.483*** [0.049]	0.481*** [0.048]	0.483*** [0.049]	0.470*** [0.041]	0.471*** [0.042]	0.468*** [0.041]	0.471*** [0.043]
D(NBER Recession)	-0.904** [0.258]	-0.902** [0.258]	-0.904** [0.257]	-0.903** [0.257]	-0.897** [0.262]	-0.894** [0.265]	-0.900** [0.261]	-0.902** [0.263]
D(Residential)					0.312*** [0.080]	0.286* [0.120]	0.355*** [0.089]	0.259*** [0.025]
SS Variable	-0.005 [0.004]	0.004 [0.014]	-0.003 [0.002]	-0.018 [0.047]	-0.002 [0.002]	-0.004 [0.013]	-0.001 [0.002]	0.032 [0.036]
SS Variable * D(Residential)					-0.022* [0.009]	-0.027 [0.025]	-0.012** [0.004]	-0.809*** [0.085]
Observations	504	504	504	504	504	504	504	504
Adjusted R ²	0.782	0.782	0.782	0.782	0.783	0.783	0.783	0.783

Table 10. Test of Hypothesis 2. Aggregate Short Selling Activity and Aggregate U.S. Housing Prices

The table displays results of OLS regressions of next month returns of the aggregate U.S. FHFA House Price Index using data from July 2006 to July 2013. *SS* denotes the aggregate short selling measure of using all U.S. stocks; *On Loan* is the value of share lent out scaled by market capitalization, *Utilization* is the number of shares on loan divided by the number of shares available to borrow, and *Fee* is the average value-weighted lending fee. *D(NBER Recession)* is a dummy variable equal to 1 during periods classified as a recession by NBER, zero otherwise. *Lag Ret(Ziman REIT)* is the return of the CRSP-Ziman REIT index. *Bid-Ask spread* is the average bid-ask spread at the close of the market. *Ln(Turnover)* is the log of daily turnover scaled by market capitalization. *Lag Ret(FHFA)* is the previous month's price change based on FHFA House Prices Indices and *Lag Ret(MKT)* is the previous month's return of the CRSP U.S. market return. *Diversified* and *Mortgage* are assigned the U.S. aggregate FHFA index returns. All regressions have year-month fixed-effects. Standard deviations are clustered at the category level and are reported in parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

SS Variable:	Panel A: All REITs			Panel B: Residential REITs Only		
	On Loan (1)	Utilization (2)	Fee (3)	On Loan (4)	Utilization (5)	Fee (6)
Lag Ret(Ziman REIT)	0.001 [0.011]	-0.000 [0.011]	-0.000 [0.011]	0.002 [0.011]	0.000 [0.011]	-0.000 [0.012]
Bid-Ask Spread (%)	-0.923 [0.715]	-0.928 [0.721]	-0.805 [0.752]	-1.124 [0.749]	-1.358* [0.743]	-0.804 [0.758]
Ln(Turnover)	0.518** [0.243]	0.582** [0.238]	0.724*** [0.238]	0.400 [0.275]	0.324 [0.270]	0.712*** [0.244]
Term Spread (10y - 3m)	-0.146 [0.115]	-0.139 [0.116]	-0.096 [0.118]	-0.172 [0.118]	-0.171 [0.115]	-0.087 [0.125]
Lag Ret(FHFA)	0.165 [0.123]	0.177 [0.123]	0.224* [0.126]	0.156 [0.123]	0.147 [0.122]	0.224* [0.127]
Lag Ret(MKT)	0.025 [0.019]	0.024 [0.019]	0.029 [0.020]	0.023 [0.019]	0.022 [0.019]	0.029 [0.021]
D(NBER Recession)	-0.326 [0.308]	-0.321 [0.314]	-0.544* [0.310]	0.710 [1.167]	2.575 [1.556]	-0.439 [0.557]
Aggregate SS Variable	-0.286** [0.114]	-0.080** [0.035]	-0.001 [0.002]	-0.140 [0.195]	-0.015 [0.049]	-0.000 [0.003]
SS Variable *D(NBER Recession)				-0.265 [0.288]	-0.162* [0.086]	-0.001 [0.004]
Observations	83	83	83	83	83	83
Adjusted R ²	0.586	0.580	0.550	0.586	0.596	0.543

Table 11. Panel Vector Autoregressions's Unit Root Tests and Lag Selection

Panel A presents panel data unit root tests of short selling measures activity using the Fischer-type test as in Choi (2001). We use data from July 2006 to July 2013 and compute market capitalization-weighted short selling for all REITs belonging to each one of three panel units: *Boom*; *No Boom*; and *Diversified*. *Boom* (*No Boom*) is defined as U.S. Census' regions where house prices had a cumulative run-up of more than (less than) 75% during the period January 2000 - December 2007. *Diversified* are those with properties over different regions but there is no combination of any two regions accounting for more than 50% of the REIT's total investments. We use the following measures of short selling activity: *On Loan*, *Short Interest*, *Utilization*, and *Fee*. All tests are based on Augmented Dickey-Fuller using two lags, include a drift term, and subtract cross-section averages for each panel. We report test statistics and associated p-values for the null hypothesis that all panels contain a unit root for a particular variable. Panel B reports values for the Bayesian information criterion (BIC), Akaike's information criterion (AIC), and the Hannan-Quinn information criterion (QIC) for up to four lags for the system comprised by *On Loan*, *Ret(REITs)*, and *Ret(FHFA)*.

Panel A: Panel Data Unit Root Test

H ₀ : All panels contain unit root		
Variable	Z-stat	p-value
On Loan	-2.64	0.004
Short Interest	-3.36	0.000
Utilization	-3.70	0.000
Fee	-4.45	0.000
Number of Panels (N)	3	
Number of Periods (T)	85	

Panel B: Information Criteria for Alternative Lags

Lag	BIC	AIC	QIC
1	-156.53	-33.55	-83.19
2	-123.38	-31.14	-68.37
3	-82.85	-21.36	-46.17
4	-42.32	-11.57	-23.98

Table 12. Panel Vector Autoregressions

This table shows first-order panel vector autoregressions of monthly house price returns, REIT returns and short selling variables split across the location of properties in REIT's portfolios. We use data from July 2006 to July 2013. Each panel unit corresponds to one of three categories: *Boom*; *No Boom*; and *Diversified*. *Boom (No Boom)* is defined as U.S. Census' regions where house prices had a cumulative run-up of more than (less than) 75% during the period January 2000 - December 2007. *Diversified* are those with properties over different regions but there is no combination of any two regions accounting for more than 50% of the REIT's total investments. $Ret(REIT)_t$ is the return of the CRSP-Ziman REIT index. $Ret(FHFA)_t$ are housing returns for each category, based on the population-weighted FHFA House Price Indices. Stock-level characteristics are aggregated using market capitalization as weights for all REITs belonging to a particular area. We use the following measures of short selling activity: *On Loan*, *Short Interest*, *Utilization*, and *Fee*. Following Love and Zicchino (2006), each variable is time-demeaned to control for time-specific effects. We report standard deviations clustered at the geographical category-level in parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: On Loan				Panel B: Short Interest			
	$On\ Loan_t$	$Ret(REIT)_t$	$Ret(FHFA)_t$		$Short\ Interest_t$	$Ret(REIT)_t$	$Ret(FHFA)_t$
	$On\ Loan_{t-1}$	0.884*** [0.043]	-0.329 [0.234]		$Short\ Interest_{t-1}$	0.886*** [0.027]	-0.070*** [0.007]
	$Ret(REIT)_{t-1}$	-0.036*** [0.010]	0.117*** [0.008]		$Ret(REIT)_{t-1}$	-0.024*** [0.005]	0.016*** [0.006]
	$Ret(FHFA)_{t-1}$	-0.147 [0.150]	0.295 [1.067]		$Ret(FHFA)_{t-1}$	0.004 [0.067]	0.256*** [0.050]
Panel C: Utilization				Panel D: Fee			
	$Utilization_t$	$Ret(REIT)_t$	$Ret(FHFA)_t$		Fee_t	$Ret(REIT)_t$	$Ret(FHFA)_t$
	$Utilization_{t-1}$	0.870*** [0.047]	-0.096 [0.092]		Fee_{t-1}	0.524*** [0.150]	-0.114 [0.198]
	$Ret(REIT)_{t-1}$	-0.092*** [0.019]	0.121*** [0.007]		$Ret(REIT)_{t-1}$	-0.005 [0.003]	0.016*** [0.006]
	$Ret(FHFA)_{t-1}$	-0.522 [0.421]	0.486 [1.057]		$Ret(FHFA)_{t-1}$	-0.062*** [0.004]	0.289*** [0.036]

Figure 1. REITs' Short Selling Activity: US Census Regions.

This figure plots measures of the average equity lending activity (*Supply* and *On Loan*) of REITs with more than 50% of their properties located in one of the U.S. census regions (i.e., Northeast, Midwest, South, West). We compare these measures to the FHFA House Price Index (HPI). *Supply* is the amount available to borrow scaled by market capitalization. *On Loan* is the fraction effectively lent out. The left side of the vertical axis shows the scale for the house price index (1.0 = January 2000). The right side of the vertical axis shows the scale for *Supply* and *On Loan*. Short selling measures are only available from July 2006 to July 2013.

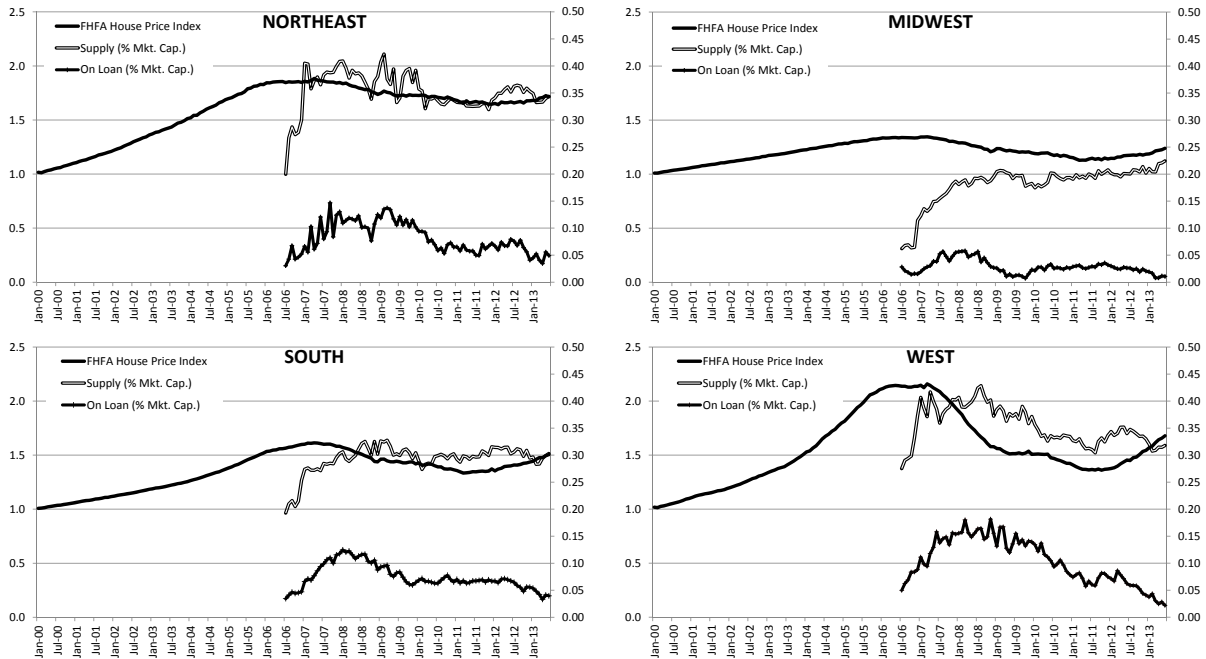


Figure 2. REITs' Short Selling Activity: Boom vs. No Boom.

This figure plots measures of the average equity lending activity (*Supply* and *On Loan*) of REITs with more than 50% of their properties located in U.S. census regions that presented a boom in house prices in the period 2000-2007 (*Housing Boom Areas*) versus REITs with more than 50% of their properties in regions with no housing boom (*No Housing Boom Areas*). We compare these measures to the FHFA House Price Index (HPI). *Supply* is the amount available to borrow scaled by market capitalization. *On Loan* is the fraction effectively lent out. The left side of the vertical axis shows the scale for the house price index (1.0 = January 2000). The right side of the vertical axis shows the scale for *Supply* and *On Loan*. Short selling measures are only available from July 2006 to July 2013.

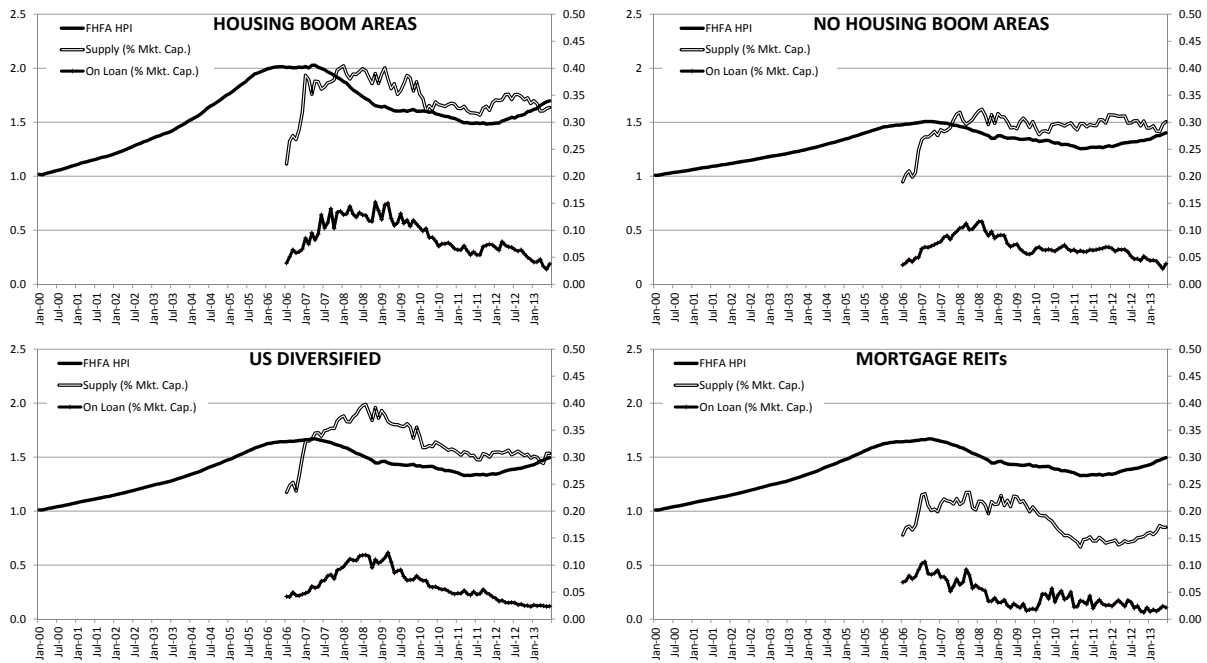


Figure 3. Impulse Response Functions of Housing Returns

The figure plots the values (in percentage points) of the impulse-response (IR) function for the Panel VAR estimated in Table 12 given a one standard deviation (SD) shock to alternative short selling measures. We consider the following 4 measures of short selling activity: *On Loan* is the fraction effectively lent out (Panel A), *Short Interest* is the number of shorted shares scaled by market capitalization (Panel B), *Utilization* is the number of shares on loan divided by the number of shares available to borrow (Panel C), and *Fee* is the average value-weighted lending fee in annualized basis points (Panel D). We use the FHFA House Price Index (HPI) as a measure of house prices. In the sample period, the growth in the FHFA HPI has a monthly mean of -0.112% and a standard deviation equal to 0.696%. Dotted red lines correspond to 5% and 95% confidence intervals calculated over 500 bootstrapped simulations.

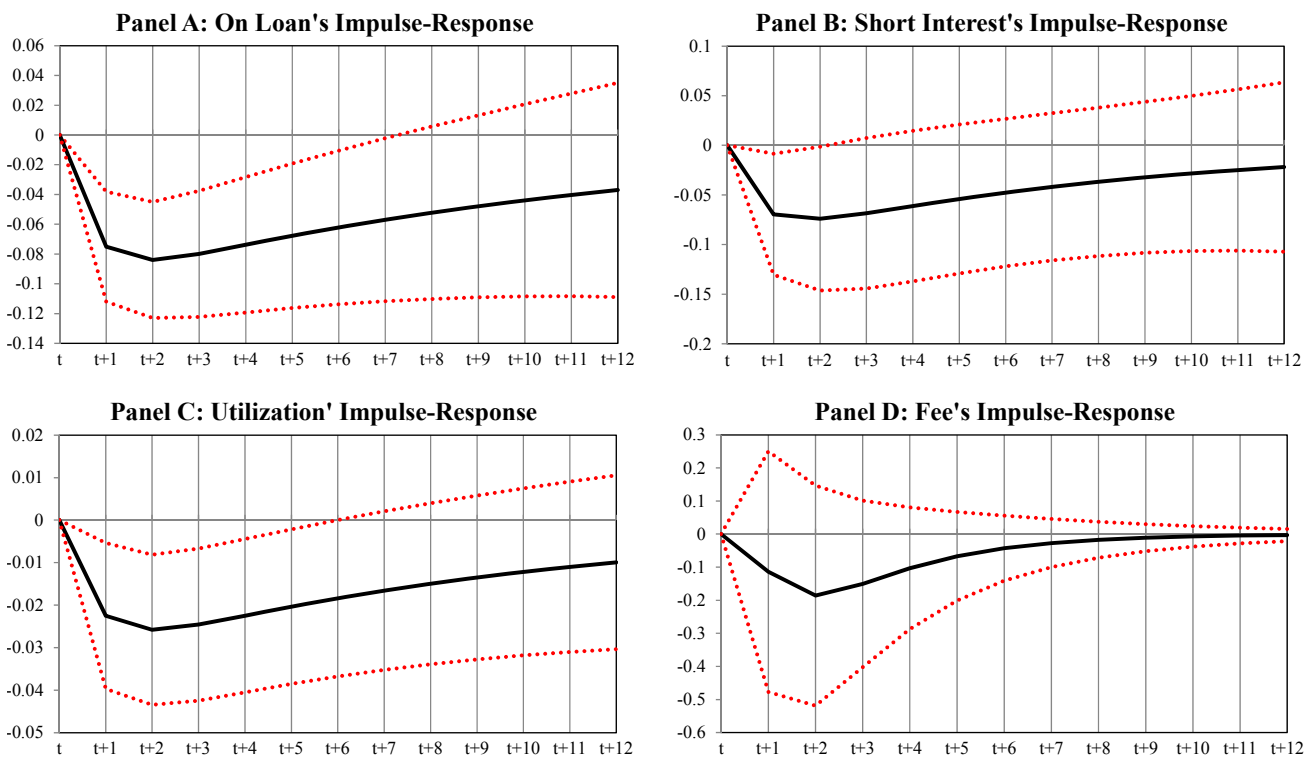


Figure 4. Variance Decomposition

This figure shows variance decompositions from first-order panel vector autoregressions of monthly house price returns, REIT returns and short selling variables split by the location of properties in REIT's portfolios. We use data from July 2006 to July 2013. Each panel unit corresponds to one of three categories: *Boom*; *No Boom*; and *Diversified*. *Boom* (*No Boom*) is defined as U.S. Census' regions where house prices had a cumulative run-up of more than (less than) 75% during the period January 2000 - December 2007. *Diversified* are those with properties over different regions but there is no combination of any two regions accounting for more than 50% of the REIT's total investments. $Ret(REIT)$ is the return of the CRSP-Ziman REIT index. $Ret(FHFA)$ are house price returns for each category based on the population-weighted FHFA House Price Indices. Stock-level characteristics are aggregated based using market capitalization as weights for all REITs belonging to a particular area. We use the following measures of short selling activity: *On Loan*, *Short Interest*, *Utilization*, and *Fee* and plot the fraction variance explained by each short selling measure and $Ret(FHFA)$.

