CMBS and Conflicts of Interest: Evidence from a Natural Experiment on Servicer Ownership*

Maisy Wong†

University of Pennsylvania

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Abstract

I study a natural experiment in commercial mortgage-backed securities (CMBS) where some special servicers changed owners (treatment group) from 2009-2010 but not others (placebo group). The ownership change linked *sellers* (special servicers who liquidate CMBS assets on behalf of bondholders) and *buyers* (new owners), presenting a classic self-dealing conflict. Loss rates for liquidated loans increase 8 percentage points (implying aggregate losses of $2 billion for bondholders) after treated special servicers changed owners, relative to placebo servicers. I provide the first direct measure of self-dealing that links buyers and sellers in securities markets in the United States.

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†Wharton Real Estate. 3620 Locust Walk, 1464 SHDH, Philadelphia, PA 19104-6302. Email: maisy@wharton.upenn.edu.

1 Introduction

Self-dealing has been alleged to harm investors but it is hard to measure (Shleifer and Vishny, 1997). The recent wave of foreclosures of securitized assets has put a spotlight on intermediaries that manage distressed securitized assets on behalf of bondholders. Reported incidents of self-dealing have raised concerns that some intermediaries may direct private benefits to their affiliates at the expense of distant bondholders. However, it is hard to quantify the extent of this problem for securitized assets because it is hard to track them after securitization. Moreover, self-dealing incentives are endogenous and often correlated with omitted variables.

The commercial mortgage-backed securities (CMBS) market provides a useful context to address the empirical challenges in the self-dealing literature. It is the second most important source of credit in the commercial real estate sector with total assets of $572 billion (FRB, 2014). Each CMBS trust comprises a pool of mortgages that are in turn collateralized by non-residential properties. Crucially, compared to other securitized assets, it is relatively easier to track the chain of ownership of CMBS assets because real estate transactions are recorded publicly.

I study self-dealing conflicts involving special servicers. These are debt firms managing distressed mortgages on behalf of bondholders. When a mortgage in a CMBS portfolio is non-performing, the special servicer decides whether to liquidate it and at what price, with the goal of maximizing the net present value of assets for bondholders. Liquidations of mortgages typically involve selling the underlying collateral (non-residential properties).

Between December 2009 and September 2010, ownership changes for four of the five major special servicers linked sellers and buyers, presenting a classic self-dealing conflict. As *sellers*, special servicers are incentivized to liquidate distressed mortgages at *higher* prices to maximize the net present value for bondholders. At the same time, their new owners who are *buyers* prefer *lower* prices. Moreover, the new owners also have affiliated service providers that provide lending, brokerage and titling services. This raised concerns that special servicers may be incentivized to maximize fee streams to these affiliates, at the expense of bondholders.

My research design centers around using ownership changes of special servicers as "shocks to links" to affiliates that change the likelihood of self-dealing. I first show that special servicers did not liquidate much before 2009 so there was little concern over self-dealing conflicts since there were so few sales by special servicers. As special servicers began selling more distressed mortgages after 2009, the changes in ownership linked major sellers to potential buyers in the commercial real estate market, sharply increasing the likelihood of self-dealing around the event dates. There is no sharp change for the placebo group because they did not change owners and the major special servicer in the placebo group is not an active buyer of commercial real estate assets.

These ownership changes are highly controversial. According to the Wall Street Journal, special servicers are "burdened by conflicts of interest caused in part by new ownership..." and allegedly "cutting bad deals and often failing to disclose conflicts of interest" (Yoon, 2012). Several media and analyst reports of transactions that linked these special servicers with their new owners fueled concerns amongst investors. For example, Yoon (2012) described an analyst report that presented twelve large mortgages as the "poster children of questionable behavior". Motivated by these concerns raised by market participants, I begin by developing a research design to identify the causal impact of ownership changes on losses.

I compare changes in loan loss rates for treated special servicers before and after they changed owners versus placebo servicers. I use a panel data estimation strategy that includes 9408 loans liquidated between 2003 and 2012 and controls for special servicer fixed effects, month of liquidation fixed effects, and pre-determined loan controls. The key regressor is the interaction between an indicator for post-event liquidations and an indicator for loans liquidated by treated special servicers. For placebo servicers, I use the ownership changes for treated servicers as placebo dates. The identification assumption is that unobserved determinants of loan loss rates are uncorrelated with the interaction term, conditional on the fixed effects and loan controls.

I find that loans liquidated after treated special servicers changed owners have loss rates that are 8 percentage points higher than loans liquidated before ownership changes, relative to placebo servicers. This effect on loss rates (losses divided by balance before losses) implies loans liquidated by treated servicers in the post period (2010 to 2012) experienced additional aggregate losses of $2 billion due to the ownership change. This is a sizable magnitude considering special servicers liquidated approximately $65 billion in loans with total losses of $28 billion between 2008 and 2013 (O'Callahan, 2013).

My empirical strategy addresses three threats to identification. First, even though the ownership changes happened during the crisis, I show that sharp changes in unobserved economic conditions would bias *against* finding higher loss rates after 2010 because commercial property prices rose beginning 2010, consistent with the lower loss rates exhibited by placebo servicers. Second, I demonstrate that the higher loss rates for treated servicers do not simply reflect differences in loan quality. Third, I address the concern that treated and placebo servicers are not comparable because treated servicers experienced a liquidity crisis that triggered the ownership change.[1] I do not find evidence of changes in liquidation patterns that are consistent with the liquidity crisis being a confounder. If anything, pre-treatment differences between treated and placebo servicers suggest any bias would be *against* the finding of higher loss rates.

Exploring the mechanisms, I find that the higher loan loss rates are due to lower sales prices for assets liquidated by treated servicers. Another concern is that treated servicers could be charging higher fees, but I do not find evidence that liquidation expenses are higher.

Interestingly, I estimate that monthly liquidation volumes increase by 210% for treated servicers relative to placebo servicers. This represents an increase of $96 million per special servicer per month. This rise in liquidation volume resonates with concerns that special servicers may be liquidating more loans to maximize fee streams to affiliated service providers (such as lenders for buyers, brokerages and online sales platforms). Servicers may liquidate more because each liquidation is a property transaction with the potential to deliver a bundle of fee streams to these affiliates.

To further quantify the extent of tunneling, I complement the reduced form estimates for liquidation outcomes with a case study that provides the first transactions-level measure of tunneling in securities markets in the United States.[2] I construct a novel dataset that identifies sellers, buyers, lenders and brokers for a sub-sample of liquidated CMBS properties. While it is hard to track assets after securitization, a few features in the CMBS market help in this regard. First, most real estate transactions are recorded publicly. The recorded owners are often limited liability companies. Given that commercial properties are high value assets, data providers are willing to invest resources to collect information about the true identities of property owners (amongst other information). Linking the CMBS data to the property transactions data using property addresses allows me to track what happens to securitized assets for this sub-sample.

My analysis indicates that self-dealing purchases (as measured in this paper) seem to be limited but there is a marked increase in the use of affiliate service providers. This case study at the property level hand-matches more than 1000 commercial real estate transactions to properties underlying the CMBS loans data for all loans liquidated by one of the four treated special

[1] Like many debt firms, the balance sheet of these servicers worsened dramatically when credit spreads widened during the recent crisis, which triggered the need for capital infusion by new owners.

[2] Previous studies include analyses for markets in China (Jiang et al., 2010), Hong Kong (Cheung et al., 2006), Korea (Baek et al., 2006) and Bulgaria (Atanasov, 2005). Kroszner and Strahan (2001), Engelberg et al. (2012) and Porta et al. (2003) examine lending behavior amongst connected lenders but focus on non-securitized debt.

servicers.[3] Fourteen transactions are purchased by affiliates of the special servicer. Notably, the special servicer increased the use of affiliated brokers from 30% of REO sales in 2011 to 90% in 2014 (Morningstar, 2015). About half of the total transactions by the brokers ($2.8 billion) are transactions that are affiliated with the special servicer ($1.5 billion). Of course, the use of affiliated brokers may be efficient and may not lead to higher loan loss rates, per se. However, I do not find evidence of significantly faster liquidations.

Put together, these findings shed light on the classic tension between the benefits from scale efficiencies of these vertically integrated servicers contrasted against the costs due to self-dealing conflicts. On balance, I find the ownership changes lead to higher loss rates, lower sales prices and more liquidations, with no significant offseting benefits in the form of faster liquidations. These empirical findings are consistent with self-dealing concerns raised by market participants. The case study of property transactions only indicated a few direct purchases by affiliates but a steady increase in the use of affiliated service providers. Finally, I find suggestive evidence that these ownership transfers have reduced trust in the CMBS market.[4]

These issues in CMBS have important implications for the RMBS market as well, where regulators have raised concerns over RMBS servicers that have conflicted relationships with financial institutions (FHFA, 2014). In fact, self-dealing conflicts amongst RMBS servicers and their business affiliates are under scrutiny by regulators and are part of on-going lawsuits alleging servicers directed businesses to benefit affiliates. For example, the Superintendent of the New York Department of Financial Services has raised "the possibility that management has the opportunity and incentive to make decisions ... that are intended to benefit ... affiliated companies, resulting in harm to borrowers, mortgage investors..." (see Goodman (2011) and Lee (2014) for a discussion).

This paper makes progress in addressing two empirical challenges in the literature on self-dealing and tunneling (Shleifer and Vishny (1997), Djankov et al. (2008)). I construct the first transactions-level dataset that tracks self-dealing of securitized assets in the United States. My

[3]The number of transactions is comparable to other studies on tunneling. Baek et al. (2006) study the private sales of equity-linked securities by 262 issuing firms and 70 purchasing firms in Korea. Cheung et al. (2006) study pricing for connected transactions in 375 filings by 261 publicly listed firms in Hong Kong between 1998 to 2000.

[4]As an example, Jack Taylor, Head of the Global Real Estate Finance Group for Prudential Real Estate Investors commented during an industry-wide panel that these ownership transfers are "a very important topic for the CMBS market's growth and resurgence. A fundamental lack of trust in the CMBS market and deal structures has grown in what I will call "end user" or "ultimate investor" as opposed to day traders. For the CMBS market to significantly grow again, this trust needs to be reinvigorated. One of the pillars of that reinvigoration will be resolution of the conflict issues...." (Lancaster et al., 2012).

research design uses the sharp change in links to affiliates due to the ownership change as a source of quasi-experimental variation in self-dealing incentives. This circumvents the common problem that outcomes and self-dealing incentives are endogenous and often confounded by omitted variables. I present robustness checks that demonstrate that potential biases due to changes in unobserved economic conditions, loan quality or special servicer attributes are either not large or biased *against* the finding of higher loss rates for treated servicers.

This paper is also related to the literature on mortgage-backed securities. Most of the papers on adverse selection investigate whether securitized assets are adversely selected compared to non-securitized assets (see Gorton and Metrick (2013) for a review). However, there is relatively less work on agency conflicts *after* securitization (Keys et al., 2013), despite the fact that a large share of the securitized market is actively managed by intermediaries, including all MBS debt and some collateralized loan obligations (Gorton and Metrick, 2013).[5]

The rest of the paper proceeds as follows. Section 2 provides background of the CMBS market, section 3 describes the data, section 4 lays out the empirical framework, section 5 describes the results. Section 6.4 discusses mechanisms and section 7 concludes.

2 Background

2.1 CMBS and role of special servicer

A typical CMBS trust comprises a pool of mortgages collateralized by income-producing commercial property, including apartments, hotels, warehouses and retail property. As in RMBS, each CMBS trust has a master servicer which services all loans that are current or expected to be recoverable.

In CMBS, the *special servicer* manages distressed assets. The objective is to maximize the net present value of assets for CMBS bondholders. In contrast to RMBS, special servicers are needed because commercial properties require active management in the event the borrower de-

[5] Agarwal et al. (2011) and Piskorski et al. (2010) study the effects of securitization on how RMBS servicers resolve distressed residential mortgages by comparing securitized loans against bank-held loans. Agarwal et al. (2015) and Maturana (2014) study the incentives of servicers to workout distressed residential mortgages. Within the CMBS literature, Ghent and Valkanov (2014) and An et al. (2009) investigate whether securitized loans are adversely selected, Stanton and Wallace (2012) studies CMBS subordination levels and ratings. Gan and Mayer (2006), Titman and Tsyplakov (2010), Ashcraft et al. (2014), and Ambrose et al. (2015) study other aspects of agency problems in CMBS.

faults. They are appointed by the controlling class holder (usually the most junior tranche in the CMBS structure, commonly known as the B-piece or the equity tranche). B-piece buyers often appoint themselves as special servicers.[6] Special servicers usually earn 25 basis points on loans in special servicing, 1% of the resolved loan balance for loan resolutions (modifications or liquidations), and other fees, as stated in the pooling and servicing agreement.

Special servicers are often debt firms. Besides servicing, some firms also originate and buy and sell debt. It is a concentrated industry with 5 key players (Berkadia, C-III, CW Capital, LNR, Midland) servicing 73 % of loans (by loan amount) in my data. Special servicers have grown in importance in light of the rise in delinquent loans after the crisis. CMBS 30-day delinquency rates rose from less than 2% before 2008 to around 9% in 2011 (PREA, 2015). Loans in special servicing grew from $5 billion dollars in 2007 (0.5% of CMBS loans) to $90 billion dollars (12%) in 2012.

This paper studies the liquidation behavior of special servicers. Loans that are delinquent beyond applicable grace periods (typically 60 days) are transferred to the special servicer. It then decides whether to modify the loan or to foreclose on the loan. If it decides to foreclose, the special servicer puts the foreclosed property up for sale.

2.2 Ownership changes and self-dealing concerns

I study the following four events: The transfer of ownership for Berkadia (December 2009), C-III (March 2010), LNR (July 2010) and CW Capital (September 2010). These firms were four of the five major special servicers before the crisis. Their balance sheets were heavily-ladened with high risk debt that plummeted in value when spreads widened in late 2008. Soon after, they required capital infusion. The fifth major special servicer, Midland, is part of PNC bank and did not require capital infusion from outside investors. There are 4 treated special servicers and 31 placebo special servicers (Midland is the largest placebo special servicer).

These events raised concerns over self-dealing conflicts amongst CMBS participants. For example, Standard and Poor issued a comment on these events in March 2012 that stated that "... combined with several ownership changes pertaining to some of the largest commercial mortgage servicers, the rise in special servicing activity has drawn increased market focus on potential conflicts of interests, several market participants, including CMBS investors, have expressed concern

[6]See Gan and Mayer (2006); Ashcraft et al. (2014) for studies related to this issue.

over special servicers' exercising "fair market value" purchase options, their use of affiliates, and the practice of charging additional fees in connection with loan restructurings." (Steward et al., 2012). See also Lancaster et al. (2012), Wheeler (2012), Berger (2012) for related commentary on potential agency conflicts.

The concerns amongst market participants center around two types of self-dealing mechanisms that could potentially hurt bondholders. First, special servicers may directly purchase the foreclosed property by exercising a *fair value option*. This option allows the special servicer to purchase any foreclosed property in the CMBS trust at a fair value.

Second, special servicers could direct services associated with the liquidation to its affiliates and earn fees for these services. Since the ownership changes, special servicers have acquired or created affiliated service providers. These services include lending to buyers, brokerage, online auctions and titling.While vertical integration presents benefits from scale efficiencies which could lead to faster liquidations, such affiliations inadvertently raise concerns over exclusive dealing or self-dealing conflicts.

The concern is that servicers might use fees to tunnel cash flows to parent firms, at the expense of distant bondholders. For example, affiliated service providers might charge bondholders higher fees.[7] Also, special servicers may be incentivized to liquidate more properties in an effort to steer business opportunities to their affiliates. Moreover, they might be incentivized to accept lower bid prices from buyers who promise to use their services.

3 Data

3.1 CMBS loans

I downloaded CMBS loans data from November 2010 through November 2012 from Realpoint (since owned by Morningstar). It is similar to the data provided by Trepp that has been used in the CMBS literature. This dataset includes the universe of all securitized loans. The appendix provides more details of the sample construction. After dropping government and international CMBS deals, the sample includes close to 120,000 loans securitized between 1991 and 2008.

[7] For example, Ocwen, an RMBS servicer, used an affiliated online auction platform (Hubzu) to auction off foreclosed homes. Hubzu allegedly charged these affiliated auctions a fee of 4.5% (paid by bondholders) but charged fees as low as 1.5% for non-affiliated auctions it competes for in the open market (Lee, 2014).

The Realpoint dataset includes loan attributes at origination (such as loan-to-value (LTV), the loan amount, the loan term, the origination date, the master servicer, and the special servicer) and information about the collateral (such as the property type, age and the street address of the property). In addition to these attributes that are known at securitization, some loan attributes are updated every month (such as current LTV, current balance), beginning November 2010 through November 2012. I use these variables to construct post trends for treated and control group special servicers. One constraint of this dataset is I do not have pre-2010 data for current attributes.

Crucially, Realpoint also publishes a historical realized loss report that includes all securitized loans that report realized losses. There are 11,332 loans liquidated between September 1997 and November 2012. The primary estimation sample uses 9408 loans liquidated within 72 months of the events. I show later that the results are similar across different estimation samples, except shorter event windows have fewer observations and less power to include many controls while longer event windows will include loans liquidated long ago that may be different from more recent liquidations.

One common data constraint in the commercial real estate context is the small sample size. Since commercial properties are expensive, there are few transactions each year. For example, the sample of 11,332 liquidated loans is small compared to the residential context where millions of homes were foreclosed in a similar timeframe, but the total value of these liquidated CMBS loans (close to $60 billion in my sample) remains sizable. Also, liquidations are infrequent. So, it is not possible to have a very short event window if we want to study liquidation behavior. Table 1 reports the summary statistics for the sample of 120495 loans securitized before 2008 and 9408 liquidated loans in the estimation sample.

3.2 Measuring self-dealing using property transactions

Direct purchases

One benefit of studying securitized real estate assets is that we can trace the chain of ownership for the liquidated mortgages because each liquidation is essentially a sale of the collateral underlying the mortgages (non-residential properties) and most real estate transactions are recorded publicly. Relative to houses, commercial properties are higher value assets. Therefore, data firms are willing to invest resources to collect information about the true identity of buyers. Most publicly recorded buyers of commercial properties are limited liability companies (LLC). However, data firms make significant attempts to identify the true owner. These include calling brokers, property owners or looking up online deeds.

The goal of the analysis is to link the CMBS dataset of liquidated loans to property transactions to identify affiliates of special servicers that bought foreclosed properties liquidated by the same special servicer. I use two databases of property transactions, CoStar and Real Capital Analytics. Both databases include information such as the transaction price, transaction date, address as well as the identity of the buyer, seller, broker and lender. These databases focus on large transactions (typically greater than $2.5 million) but also report most transactions affiliated with CMBS since information for CMBS property transactions is easier to find compared to private transactions.

The process of merging loan transactions in the CMBS dataset with property transactions for non-residential properties is time consuming. I restrict my analysis to liquidations by one of the four treated special servicers, C-III (which changed owners in March 2010). I chose this special servicer because regressions by special servicer indicate that the patterns are most robust for this special servicer. The sample for the property-level analysis includes 1,074 properties that were liquidated from 2010 to 2012 by C-III.

I begin by handmatching properties liquidated by C-III (in the CMBS data) with property transactions in CoStar and Real Capital Analytics (to match properties associated with liquidated loans with property transactions). Since both property databases are proprietary, each property address for the 1,074 properties had to be entered individually into these databases. This process was time consuming because most properties have addresses that are not standardized and they also have relatively larger footprints compared to single family homes (latitudes and longitudes for the same property in different databases are unlikely to be identical making it hard to match properties using mapping software).

Most transactions are structured so that buyers are limited liability companies (LLC). For example, the buyer for an apartment complex, Cherry Grove, is recorded publicly as RFI Cherry Grove LLC. Oftentimes, the address of the LLC's can be linked to the true owner. For example, the address for RFI Cherry Grove LLC is written in the deed as "RFI Cherry Grove LLC, c/o C-III Acquisitions LLC, 717 Fifth Avenue in New York". Another commonly used address by C-III affiliates is 5221 North O'Connor Blvd, Suite 600, Irving, Texas. CoStar and Real Capital Analytics also utilize other resources (including having their analyst call brokers and owners) to identify the true seller and buyer of each transaction. For transactions that were identified as being bought by C-III, I also obtained deeds of sale to confirm that the buyer is affiliated with C-III.

Other affiliates

Finally, Real Capital Analytics also reports the broker and lender of each transaction, whenever available. I searched for all transactions from 2010 to 2015 that used an affiliate of C-III as the lender or the broker.

4 Empirical framework

To estimate the causal impact of the ownership change on bondholder losses, I use a panel data specification that compares the changes in loan outcomes for treated special servicers after they were sold, relative to changes in loan outcomes for placebo special servicers. Specifically, I estimate

$$y_{lit} = \alpha + \beta OwnershipChange_i \times POST_{it} + \gamma X_{li} + \tau_t + \delta_i + \varepsilon_{lit} \tag{1}$$

where y_{lit} is the outcome for loan l liquidated by special servicer i in month t (centered around event dates), $OwnershipChange_i$ is 1 if servicer i is Berkadia, C-III, CW Capital or LNR and $POST_{it}$ is 1 if month t is after the event date for special servicer i. For treated servicers, the event date corresponds to the month they changed owners. For placebo servicers, $Post_{it}$ is 1 if month t is after July 2010 (the placebo date). The results are similar using other placebo dates. Additionally, X_{li} represents pre-determined controls for loan l, τ_t is month fixed effects, δ_i is special servicer fixed effects and ε_{lit} is an idiosyncratic error term.

The primary outcome is *loss rate*$_{lit}$ for loan l liquidated by special servicer i in month t, calculated as the realized loss for loan l divided by the balance before loss. This measure captures the severity of losses suffered by bondholders and is motivated by concerns that treated special servicers might tunnel cash flows to their parent companies at the expense of distant bondholders.

The parameter of interest is β which tests whether outcomes change differentially after treated special servicers were sold compared to placebo special servicers.[8] The key identification assumption is that unobserved determinants of y_{lit} did not change differentially around the event dates for treated versus placebo special servicers, conditional on the controls.

The ownership change was perceived to sharply increase the likelihood of self-dealing conflicts.

[8] Ideally, another potential regressor would be an indicator for whether a loan involves an affiliate of the special servicer. This will involve matching more than 9000 liquidated loans to the commercial property databases, but I was only able to do so for the sub-sample of 1000 loans liquidated by C-III due to time and data constraints.

First, there was little potential for self-dealing before the crisis because very little CMBS debt was distressed and liquidated (Figure 1). Second, the new owners are buyers of CRE assets. In other words, the change in ownership linked potential sellers (special servicers) with potential buyers and affiliated service providers. Moreover, media and analyst reports of several high-profile connected transactions also increased investors' concerns over self-dealing conflicts. At the same time, special servicers in the placebo group did not experience a sharp change in demand for CMBS debt (liquidated by them) around the event dates because there was no change in ownership and the major special servicer in the placebo group (Midland) is not an active buyer of CRE assets. The appendix provides more details on who the new owners are.

below $2 billion through early 2009 in my data. As commercial real estate prices plummeted between late 2007 and 2009, total liquidation remains low. Special servicers (in fact, most lenders) were more likely to extend the maturity date of distressed loans during the most recent crisis instead of liquidating at fire sale prices. After 2009, the total value of liquidation increases as more loans are liquidated and at higher prices, coinciding with the uptick in commercial real estate prices.

5 Effect of ownership change

5.1 Effect on loan loss rates

Table 2 reports estimates of the effect of the ownership change on loan loss rates (β in equation 1). Each column corresponds to a regression where the dependent variable is the loss rate for loan l, liquidated by special servicer i in month t. Standard errors are clustered by special servicer and month of liquidation (centered around event dates).

Column 1 presents the main specification which indicates that loss rates for loans liquidated after special servicers changed owners are 8 percentage points higher than before, relative to placebo special servicers that did not change owners. The magnitude of the effect is sizable, representing 16% of the mean loss rate in the pre-period (50%) and translating into aggregate losses of $2.3 billion.[9] As a benchmark, between 2008 and 2013, special servicers liquidated approximately $65 billion in loans with total losses of $28 billion (O'Callahan, 2013).

[9]To calculate the total losses implied by the 8 p.p. effect on loss rates, I multiply it by the total loan balance before losses for all loans liquidated by treated servicers after the ownership changes ($29 billion, liquidated between 2010 and 2012).

The main specification includes controls that mitigate three sources of omitted variable bias. First, month of liquidation fixed effects circumvents potential confounding due to changes in general economic conditions. This is important as the ownership changes happened in 2010, coinciding with the recent crisis. Second, special servicer fixed effects address concerns that treated and placebo servicers are not comparable. Third, loans serviced by treated versus placebo servicers could be different. I control for pre-determined loan attributes reported in Table 1, including the initial debt service coverage ratio (DSCR) and initial loan-to-value (two loan quality measures commonly used to underwrite commercial real estate loans),[10] initial loan balance, indicators for loans with balloon payments, with fixed interest rates, five indicators for property types (hotels, industrial properties, apartments, offices, retail), year of securitization, the number of properties, and an indicator for loans with a portfolio of properties (more than five), property age, and an indicator for loans with missing loan attributes.[11] Column 2 repeats column 1 but winsorizes potential outliers in loss rates (loss rates above five) to show that the results are not driven by outliers.

Finally, the last two columns further address the concern that β could be biased by unobserved changes over time that are different for treated versus placebo special servicers. Column 3 adds interactions between loan attributes and the post indicator, to allow for the effects of loan attributes on loss rates to be different before and after 2010. Column 4 adds special servicer-specific quadratic time trends and a post indicator (but drops month fixed effects).[12] This alleviates the concern that loan quality is worsening over time differently across special servicers. Reassuringly, the results remain similar and the effects are not statistically different across the columns.

5.2 Threats to identification

5.2.1 Differences in loan quality

Table 3 shows that while the composition of loans are different along some dimensions, treated servicers do not appear to service loans that have systematically worse quality. This alleviates concerns that the higher loss rates may be driven by worse loan quality for treated servicers. Each

[10]The debt service coverage ratio is calculated by dividing the net operating income of a property by the debt service payment. Ratios above 1 correspond to loans that have enough operating income to cover debt service payments.

[11]This list of loan attributes covers most controls used in loan-level analyses in the CMBS literature (see Ghent and Valkanov (2014) for an example), whenever the attributes used in the literature are available and appropriate for this context.

[12]For placebo special servicers, I estimate a separate trend for Midland and a common trend for the smaller placebo servicers.

row reports results from an OLS regression with the loan attribute as the dependent variable and the treatment dummy as the regressor. I focus on at-origination loan attributes (determined before the change in ownership). The sample comprises all loans in the CMBS dataset that were securitized before the event dates. Standard errors are clustered by special servicer and month of securitization.

Notably, the differences in initial LTV and initial debt service coverage ratios are small. Loans serviced by the treatment group have LTV's that are higher by 3% (compared to a mean of 67%) and DSCR's that are lower by 0.02 (compared to a mean of 1.49). One concern is that treated servicers are 41% more likely to have loans with balloon payments (relative to a mean of 74%), which could indicate worse loan performance. However, the results are robust to controlling for the balloon loan indicator. Finally, loans serviced by treated special servicers have larger loan balances, are more likely to have fixed interest rates, slightly more likely to be a hotel, office or retail loan and are newer. Taken together, these differences in loan attributes do not systematically point to treated special servicers having loans of significantly worse quality.

Next, I present evidence that loan quality also does not change differentially *over time* for treated versus control groups. While loans do not appear to be much worse for treated servicers at origination, the concern remains that loss rates could be higher over time because loan quality is worsening. Figure 2 shows that current LTV's and DSCR's appear to be parallel between treatment and placebo special servicers. The last two rows of 3 show that the differences do not appear to be large, on average. This is a loan-month level analysis where I first regress *current LTV* for loan l in month t on the ownership change dummy and month fixed effects. Standard errors are clustered at the special servicer-month level. The sample includes loans that are current in month t. I do not control for current LTV and current DSCR when estimating equation (1) as these attributes are not pre-determined and I do not have pre-treatment data for current LTV and current DSCR. This analysis uses data on current loan attributes that was collected monthly between December 2010 and November 2012 (there is no pre-data for current loan attributes).

Finally, Figure 3 reinforces the findings above that loan quality did not worsen more over time for treated servicers. This figure plots the share of loans that are current in month t that first became 60-day delinquent in month t. This represents a relatively exogenous measure of loan quality as special servicers have less control over these loans because most loans are only transferred to special servicers after they become delinquent for more than 60-days.

5.2.2 Credit crisis for treated servicers before ownership change

Naturally, treated special servicers could be different from placebo servicers simply because treated servicers experienced a credit crisis which triggered their sale. This could mean that before their sale, these special servicers were capacity constrained and had not time to liquidate loans. But, after their sale, the capital infusion from the new owners allowed them to hire more staff and spend more time servicing their portfolio.

Once the capital crisis was addressed, treated servicers could have liquidated the worst loans first. Therefore, losses could be higher after the ownership change due to the lower loan quality of liquidated loans, instead of self-dealing conflicts.

Third, I present evidence that my findings are not driven solely by the credit crisis experienced by treated servicers that triggered their ownership change. Like many debt firms, the balance sheet of these servicers worsened dramatically when credit spreads widened during the recent crisis, which triggered the need for capital infusion by new owners. The concern is treated servicers were capacity constrained before the ownership changes as they were too occupied with their own problems and built a stockpile of very distressed loans that should have been liquidated. After the ownership change, treated servicers expanded capacity, which allowed them to start liquidating more assets. Therefore, one concern is that the higher loss rates for loans liquidated after the ownership change are driven by servicers liquidating differentially worse loans first. However, if the higher loan loss rates are driven by compositional differences in the quality of liquidated loans, I should find different post trends in loan quality for treated versus placebo servicers. In particular, there should be a spike in current LTV (measured in the month of liquidation) for loans liquidated right after the ownership change relieved the capacity constraint. Instead, I find relatively similar trends in both current LTV and current debt service coverage ratio for liquidated loans.

Figure 4 provides evidence that treated special servicers did not liquidate differentially worse loans compared to placebo servicers. Each figure plots the current LTV and DSCR at the month of liquidation. If treated servicers were capacity constraint before and then liquidated the worst loans first, we should see a spike in LTV (and the opposite for DSCR) for treated servicers, but we do not.

5.2.3 Timing of liquidation

A related concern is that the higher average loss rates after the changes in ownership arises not because of adverse selection and self-dealing concerns that change sharply around the event date but because treated special servicers liquidate the worst loans first and the better loans later and I only have at most three years after the first ownership change (December 2009). Perhaps, over a longer horizon, the post versus pre average loss rates would be similar for treated versus placebo servicers.

However, three years is quite long compared to the reported REO hold time of 12 months for 2012 (Heschmeyer, 2014). Also, I confirmed that the patterns survive with a longer post period. I collected Bloomberg data on CMBS loans liquidated between 2000 and January, 2016, complementing the primary data on liquidation outcomes that ends in 2012. Unfortunately, the Bloomberg data does not report balance before losses but it does report losses in dollars. I continue to find larger losses for treated special servicers.

5.3 Further robustness checks

Table 4 further probes the robustness of the results on loss rates. The first row repeats the main specification in Table 2 (column 1) but includes all months instead of a 72-month window. The second row includes a 48-month event window, including a post indicator and quadratic time trends centered around event dates (instead of month fixed effects). The third row repeats the main specification, restricting the sample to loans matched using propensity scores.[13] The fourth row aggregates the loan level data to the special servicer-month level data to address concerns of over-rejection (Bertrand et al., 2004; Donald and Lang, 2007; Cameron et al., 2008). The specification is analogous to that of the main loan-level estimation, with robust standard errors. I include a 72-month event window, averages of loan controls, month fixed effects, and special servicer fixed effects.[14] Finally, the last three rows repeat the main specification but use the event dates for Berkadia, C-III and CW Capital as placebo dates respectively, instead of LNR. Reassuringly, the effect of the ownership changes on loan loss rates are stable across these robustness checks.

[13] I first predict the probability of treatment using a logit model with the treatment indicator as the dependent variable, loan controls and month of liquidation fixed effects. I then drop the 25% of loans in the control group with the lowest predicted probability of treatment.

[14] For the placebo servicers, I estimate a fixed effect for Midland and a common fixed effect for the smaller servicers.

6 Mechanisms

6.1 Why are loan loss rates higher?

Table 5 shows that the higher loss rates appear to be due to assets being liquidated at lower prices. Loan losses can be greater either because assets are liquidated at lower prices or liquidation expenses are higher. Column 1 explores the sale price channel using a hedonic regression with log sale price as the dependent variable, special servicer fixed effects, MSA fixed effects, and predetermined controls. Unfortunately, the sale prices are missing for close to a third of the sample. Instead of month fixed effects, I include an indicator for the post period and quadratic time trends.[15] Column 2 repeats the same specification using log of liquidation expenses as the dependent variable.

The results suggest prices are 15% lower, on average, for assets liquidated by treated servicers after ownership changes, but there is no significant effect on liquidation expense. A further analysis of a limited sample of around 3500 loans with non-missing information about time to liquidation shows that this lower sale price is accompanied by faster liquidations by 1.5 months.

Next, column 3 shows that treated special servicers are liquidating more loans after ownership changes. The dependent variable measures the volume of liquidation by special servicer i in month t using $ln(\sum_l BalanceBeforeLoss_{lit})$, where I sum over the balance befoer losses for all loans liquidated by special servicer i in month t. This aggregates the data to the special-servicer month level, includes only months within the 72-month window, and controls for month fixed effects, special servicer fixed effects and averages of loan controls. The results are similar with and without loan controls.

The estimate represents an increase in the liquidation volume by 113 log points (210%), or an increase of \$96 million per special servicer per month, using the pre-event average of \$46 million. This is consistent with concerns discussed in section 2.2 that special servicers may be liquidating more loans and directing business opportunities to affiliated service providers which has the potential to deliver more fee streams. For example, if special servicers choose not to liquidate, they will continue earning the stream of special servicing fees. If they choose to liquidate and sell through an affiliated broker or online platform, and the buyers also use affiliated lenders and brokers, liquidating could deliver more private benefit to servicers through the bundle of fee

[15] For the main estimation sample of 9408 liquidated loans in Table 2, the estimates are similar using month fixed effects (0.08) or quadratic time trends plus an indicator for the post period (0.10, s.e. 0.03).

streams.

6.2 Direct purchases

This sub-section directly measures the number of property transactions that connect special servicers with their affiliates. The data identifies whether special servicers directed transactions of liquidated mortgages to affiliated buyers, lenders and brokers. The objective of this exercise is to quantify the extent of self-dealing transactions and whether they can explain the patterns above. This exercise abstracts away from efficiency considerations. For example, self-dealing transactions can improve efficiency and benefit bondholders in a setting where there are no bidders for liquidated assets, except affiliates of special servicers. As discussed in section 3, I only focus on the sub-sample of liquidations by C-III.

There are fourteen property transactions, valued at $171 million, between March 2011 and 2012 that are affiliated with C-III. Table 6 lists these properties.[16] Column 1 indicates the property, column 2 lists the transaction price, column 3 calculates the counterfactual price using the 8 p.p. change in loss rate estimated in column 1 of Table 2. This assumes the counterfactual price will deliver a loss rate that is 8 p.p. lower than the actual loss rate.[17] Column 4 calculates the benefit to C-III which is the savings from paying a lower transaction price instead of the (higher) counterfactual price. Column 5 calculates the equity multiple (the total benefit divided by the total equity for properties that were bought by C-III). The total benefit is $27 million.

6.3 Affiliated service providers

In contrast to the few purchases identified above, C-III steadily increased the use of affiliates. For example, from 2011 to 2014, the share of Real Estate Owned (REO) sales using an affiliated broker increased from 30% to 90% (Morningstar, 2015). In the Real Capital Analytics data on brokers, I am able to identify 166 transactions between 2011 and 2015 where C-III is the special servicer and

[16] Six of these properties are part of a portfolio sale.

[17] To solve for the counterfactual price, P', as a function of the actual transaction price, P^*, and the loss rate, L, I first solve for the initial price (P_0) as a function of P^* and L, using $L = \frac{P^*-P_0}{P_0} \Rightarrow P_0 = \frac{P^*}{(1-L)}$.The counterfactual price is the price that delivers the counterfactual loss rate ($L+0.08$), where $L<0$. Therefore, I set P' such that $\frac{P'-P_0}{P_0} = L+0.08$, which implies that $P' = (1-L+0.08)*P_0 = (\frac{1-L+0.08}{1-L})P^*$. When the actual loss rate is not available, I use the average post event loss rate for C-III (51%).

the broker. These affiliated transactions (total value of $1.5 billion represent a significant share of the brokerages' transaction volume ($2.8 billion).

According to Morningstar (2015), average resolution times were 1 to 5 months longer for sales using affiliated brokers in 2013, compared to non-affiliated brokers. In 2014, loan sales using affiliates were 6 months longer but REO sales were 5 months faster. These differences do not adjust for loan compositions. Using data on months to liquidation for a limited sample, I find that treated servicers have faster liquidations (1.5 months) relative to placebo servicers, conditional on loan controls, time trends and MSA fixed effects.

6.4 Alternative interpretations

The preceding analysis shows that special servicers that changed owners liquidated more and had higher loss rates after the change in ownership. These patterns are consistent with investors' concerns that the change in ownership could hurt bondholders. However, measures of direct purchases cannot fully explain these patterns. This section examines alternative interpretations.

Unmeasured affiliations

There could be other tunneling benefits that are not measured as well as unmeasured affiliations. The Investor Reporting Package (IRP) developed by the Commercial Real Estate Finance Council provides a standardized reporting template used widely by servicers, trustees and data providers in CMBS. At present, there are plans to add new report templates that include more information about liquidations. For example, the Loan Liquidation Report would detail the use of affiliates and the fees charged. However, this report will be filed at the discretion of the special servicer.

Adverse selection concerns

Besides direct purchases, self-dealing can also lead to higher loss rates for assets sold by treated servicers if unaffiliated buyers price all assets liquidated by these servicers at a discount because they are concerned that servicers could be cream-skimming (and not disclosing these purchases), leaving adversely selected assets to unaffiliated buyers. In other words, losses can result from actual self-dealing or adverse selection due to heightened concerns over self-dealing conflicts. This indirect effect can lead to higher loss rates even absent any connected transactions between special servicers and affiliated buyers as long as buyers believe there are agency problems due to the link between special servicers and their new owners. Several media and analyst reports of transactions that linked these special servicers with their new owners fueled concerns amongst investors.

Figure 5 shows that treated special servicers have lost market share. The numbers above the bars indicate market shares for treated (dark blue) and placebo (light blue) special servicers. The pattern of treated servicers commanding more than half of the market share persists through 2007, but is notably different for issuances after the crisis (the size of the bolded box is smaller). The market share of a control group special servicer (Midland) appears to have grown. Discussions with industry participants suggest that Midland has the reputation of being a neutral special servicer because it has no proprietary investment activity. While these are short run patterns only, they are consistent with the interpretation that investors' concerns with agency conflicts amongst treated special servicers could lead to real effects on broader investment activity.

Changes in management practices and beliefs

In addition, changes in management practices could also explain changes in liquidation patterns and loss rates. The new management may have different returns expectations or beliefs about future market trends which would lead them to structure liquidations differently.

Even though the special servicers changed owners, the contract between bondholders and special servicers stayed the same. The responsibility of the special servicer is to maximize the net present value for bondholders, regardless of who their owners are. The sizable losses as a result of the change in ownership remains notable and consistent with bondholders' concerns about the change in ownership.

7 Conclusion

This paper uses a natural experiment that involved a sharp change in agency conflicts in the CMBS market. I study four events that resulted in the change in ownership of CMBS special servicers who are in charge of liquidating distressed CMBS assets on behalf of bondholders. These events were highly controversial in the industry and led to concerns of tunneling and self-dealing because investors raised the possibility that special servicers could sell distressed CMBS properties at lower prices to their new owners, at the expense of bondholders.

I find that after special servicers changed owners, they have liquidated loans with higher loss rates, lower sales prices and they have more liquidations, relative to placebo servicers. I do not find significant offseting benefits in the form of much faster liquidations. These empirical findings are consistent with self-dealing concerns raised by market participants.

To further quantify to what extent tunneling can explain these patterns, I provide a case study that directly identifies sellers, buyers, lenders and brokers for a sub-sample of transactions. My analysis indicates that tunneling (as measured in this paper) can only explain part of the patterns above, but I do find a steady increase in the use of affiliated servicer providers. I discuss alternative interpretations, including unmeasured tunneling benefits, adverse selection, and changes in management practice.

These findings have broader implications beyond the CMBS market. Policy makers and researchers have so far focused on adverse selection concerns *before* securitization. For example, the risk retention rule proposed in Section 941 of the Dodd-Frank Act calls for the implementation of credit risk retention requirements in securitized markets.

While the rule targets adverse selection before securitization, one unintended consequence is that it could enhance adverse selection concerns *after* securitization. The high costs of the risk retention requirements could limit competition from small issuers and servicers (Geithner, 2011). As the number of players in the securities market declines, the likelihood of self-dealing conflicts increases because the servicers that remain are likely those with ties to major financial institutions, further exacerbating self-dealing concerns.

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Tables

Table 1: Summary statistics

	All loans			Liquidated loans		
Variable Name:	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**
1(Fixed rate loan)	120495	0.90	0.30	9408	0.87	0.33
1(Balloon loan)	120495	0.74	0.44	9408	0.69	0.46
1(Property is hotel)	120495	0.04	0.20	9408	0.06	0.24
1(Industrial property)	120495	0.07	0.25	9408	0.05	0.22
1(Property is apartment)	120495	0.28	0.45	9408	0.26	0.44
1(Property is office)	120495	0.13	0.34	9408	0.14	0.35
1(Retail property)	120495	0.24	0.43	9408	0.21	0.40
Year of securitization	120495	2002	3.56	9408	2003	3.50
Initial loan balance (in million dollars)	115896	7.78	15.31	8794	6.79	12.39
Number of properties per loan	120495	1.24	4.75	9408	1.21	3.80
1(Number of properties>5 per loan)	120495	0.01	0.10	9408	0.01	0.08
Property age	87616	26.55	21.74	6707	26.24	20.23
Initial loan-to-value	110015	66.72	13.76	8679	71.01	9.71
Initial debt service coverage ratio	83636	1.49	0.54	6705	1.37	0.25

* p<0.1, ** p<0.05, *** p<0.01

Notes: Summary statistics for loan attributes at-origination. The left three columns report the sample size, mean and standard deviation for 120,495 loans securitized before 2008. The right three columns report the same for 9408 liquidated loans in the estimation sample.

Table 2: Effect of ownership change on loan loss rates

Specification:	**Main specification**	**Winsorize loss rates**	**Post × controls**	**Servicer trends**
	(1)	(2)	(3)	(4)
Post × Ownership change	0.08***	0.08***	0.08***	0.12**
	(0.03)	(0.03)	(0.03)	(0.05)
N	9408	9408	9408	9408
R^2	0.14	0.16	0.15	0.11
Month FE	Y	Y	Y	N
Special servicer FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Post × Controls	N	N	Y	Y
Special servicer time trends	N	N	N	Y

* p<0.1, ** p<0.05, *** p<0.01

Notes: This table reports results from OLS regressions using liquidated loans. The dependent variable is the loss rate for loan l liquidated by special servicer i in month t, centered around event dates. The loss rate is the loan losses divided by the loan balance before losses. The key regressor is the interaction between an indicator that is 1 if special servicer i changed owners and a post indicator that is 1 if month t is after the event date for special servicer i. The event date is the month of ownership change for treated servicers. The event date for placebo servicers is LNR's event date. The estimation sample consists of 9408 loans liquidated within a 72-month window of the event date. Column 1 reports the main specification with 106 month fixed effects, 34 special servicer fixed effects and 14 loan attributes (reported in Table 1), plus a dummy for loans with missing values for any loan attributes. Column 2 winsorizes loan loss rates that are above 5. Column 3 repeats column 1 but allows loan attributes to have different effects before and after event dates. Column 4 adds special servicer-specific quadratic time trends (and drops month fixed effects). Standard errors are clustered by special servicer and liquidation months.

Table 3: Loan attributes for treated versus placebo servicers

Dependent Variable:	**Mean**	**SD**	**N**	**Coefficient**	**Std. Err.**
1(Fixed rate loan)	0.90	0.30	120495	0.15***	(0.03)
1(Balloon loan)	0.74	0.44	120495	0.41***	(0.14)
1(Property is hotel)	0.04	0.20	120495	0.03**	(0.01)
1(Industrial property)	0.07	0.25	120495	0.01	(0.02)
1(Property is apartment)	0.28	0.45	120495	0.02	(0.04)
1(Property is office)	0.13	0.34	120495	0.07**	(0.03)
1(Retail property)	0.24	0.43	120495	0.15**	(0.06)
Year of securitization	2002	3.56	120495	0.32	(0.72)
Initial loan balance (in million dollars)	7.78	15.31	115896	3.36**	(1.58)
Number of properties per loan	1.24	4.75	120495	0.04	(0.10)
1(Number of properties>5 per loan)	0.01	0.10	120495	0.004	(0.003)
Property age	26.55	21.74	87616	-1.19**	(0.54)
Initial loan-to-value	66.72	13.76	110015	3.17**	(1.46)
Initial debt service coverage ratio	1.49	0.54	83636	-0.02	(0.02)
Current LTV	59.80	16.46	1349597	4.61**	(2.34)
Current DSCR	1.41	0.62	1249870	-0.002	(0.03)

* p<0.1, ** p<0.05, *** p<0.01

Notes: Each row reports results from an OLS regression with a loan attribute as the dependent variable and the ownership change indicator as the key regressor. The first 14 rows report differences in loan attributes at-origination. The sample includes all loans securitized before 2008. Standard errors are clustered by special servicer and month of securitization. The last 2 rows report results for current loan-to-value ratios for loan l in month t and current debt service coverage ratios. The sample includes all loans that are current in month t. These last 2 regressions add month fixed effects and cluster standard errors by special servicer and months.

Table 4: Robustness checks for effect of ownership change on loss rates

Specification:	**Coefficient** (1)	**Standard Error** (2)
Sample: All months	0.10***	(0.03)
Sample: 48 months, trends only	0.09**	(0.04)
Sample: Propensity score	0.09**	(0.04)
Sample: Aggregated data	0.09***	(0.04)
Placebo date: Berkadia date	0.10*	(0.05)
Placebo date: C-III date	0.11**	(0.05)
Placebo date: CW Capital date	0.07***	(0.02)

* p<0.1, ** p<0.05, *** p<0.01

Notes: The first row repeats the main specification in column 1 of Table 2 but includes all months instead of a 72-month window. The second row includes a 48-month event window, including a post indicator and quadratic time trends centered around event dates (instead of month fixed effects). The third row repeats the main specification, restricting the sample to loans matched using propensity scores. The fourth row aggregates the loan level data to the special servicer-month level data, including a 72-month event window, averages of loan controls, 106 month fixed effects, 5 special servicer fixed effects (including a common fixed effect for small placebo servicers), and robust standard errors. The last three rows repeat the main loan-level specification but use the event dates for Berkadia, C-III and CW Capital as placebo dates respectively, instead of LNR.

Table 5: Mechanisms related to higher loan loss rates

Dependent variable:	**Ln(Sale price)**	**Ln(Liquidation expense)**	**Ln(Amount liquidated)**
	(1)	(2)	(3)
Post × Ownership change	-0.15*	-0.09	1.13***
	(0.08)	(0.10)	(0.14)
N	6116	6058	1147
R^2	0.65	0.38	0.61
Special servicer FE	Y	Y	Y
Controls	Y	Y	Y
MSA FE	Y	Y	N
Trends	Y	Y	N
Month FE	N	N	Y

* p<0.1, ** p<0.05, *** p<0.01

Notes: Column 1 reports results from a hedonic regression where the dependent variable is log (Sale price) for the liquidated loan, the key regressor is the interaction between the ownership change and the post indicator, controlling for special servicer fixed effects, loan controls, MSA fixed effects, quadratic time trends (centered around event dates) and a post indicator. The sample includes liquidated loans in the estimation sample of Table 2 that have non-missing values for sales prices. Column 2 repeats the same regression with log of liquidation expenses as the dependent variable. Column 3 aggregates the loan level data to the special servicer-month level. The dependent variable is log of the total amount liquidated by special servicer i in month t, where the total amount liquidated sums over the balance before losses for all loans liquidated by special servicer i in month t. This specification includes special servicer fixed effects, averages of loan controls and month fixed effects and reports robust standard errors.

Table 6: Estimated benefits for purchases by C-III

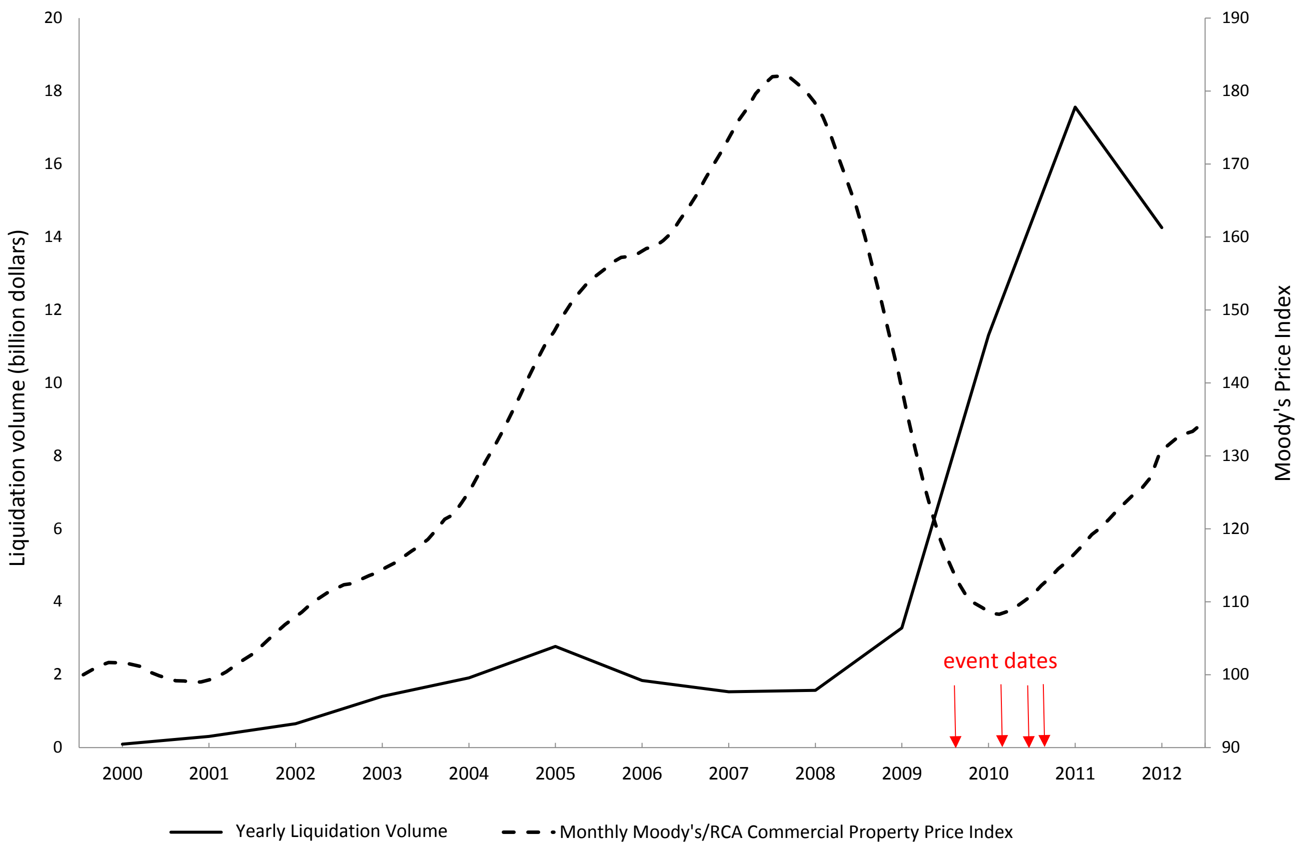
Property	Price	Estimated benefit		
		Counterfactual (8 p.p. lower loss rate)		
		Counterfactual price	Benefit	Equity multiple
[1]	[2]	[3]	[4] = [3] - [2]	[5]
Hampton Inn, Woodbridge, VA	9,050,000	9,894,490	844,490	0.4
Westchase Ranch, Houston, TX	15,500,000	16,787,659	1,287,659	0.3
*Somerset I & II, Houston, TX	8,000,000	9,306,122	1,306,122	6.5
Foxboro, Houston, TX	6,500,000	7,039,986	539,986	0.3
Cherry Grove, Jackson, TN	18,912,000	24,362,485	5,450,485	1.1
*Seven Gables, Richmond, VA	35,571,400	41,378,976	5,807,576	0.2
*Rollingwood, Richmond, VA	9,500,000	11,051,020	1,551,020	3.1
*Hilltop, Dallas-Fort Worth, TX	8,127,935	9,454,945	1,327,010	0.6
*Cambridge, Houston, TX	5,100,000	5,932,653	832,653	0.6
*Audobon Park, Mesquite, TX	7,551,731	8,784,667	1,232,936	0.6
*Knollwood, St Louis, MO	16,681,968	19,405,555	2,723,587	0.8
*Camellia, Jackson, TN	11,300,000	13,144,898	1,844,898	0.6
The Park, Columbia, SC	7,250,000	7,852,292	602,292	0.2
*Portofino, Pittsburgh, CA	11,800,000	13,726,531	1,926,531	0.8
Total	**170,845,034**		**27,277,244**	

Notes: Column 1 lists the property, column 2 indicates the transaction price, column 3 reports the counterfactual price, column 4 estimates the benefit to C-III and column 5 estimates the equity multiple for this transaction (estimated as total benefit divided by total equity paid by C-III).

* Some values for these properties had to be estimated. The transaction prices for Somerset, Cambridge, Audobon Park, Knollwood and Park were estimated, either from Real Capital Analytics or from the deeds of sale. Except, the price for Knollwood was estimated by dividing the loan amount by an estimated LTV (79%). Since Knollwood was part of a portfolio sale, the LTV was estimated as the average LTV for other properties in that portfolio. The loss rates were assumed to be 51% for Somerset, Seven Gables, Rollingwood, Hilltop, Cambridge, Audobon Park, Knollwood, Camellia and Portofino.

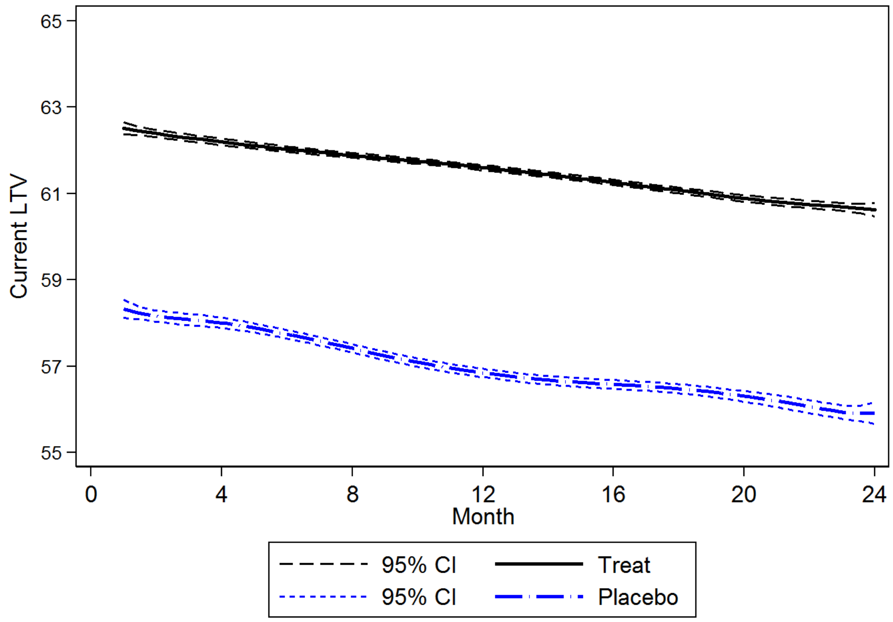
Figures

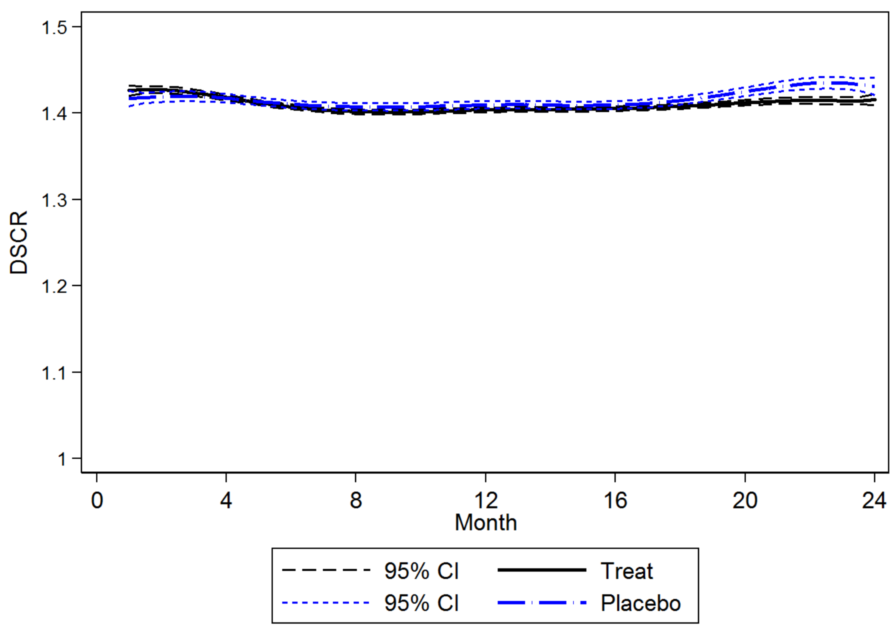
Figure 1: Trends in liquidation volume and commercial property prices



Notes: The solid line plots the total volume of liquidations (billion dollars) each year in my data. The dashed line plots the monthly Moody's/RCA Commercial Property Price Index. The four arrows indicate the four event dates when special servicers changed owners.
Source: Moody's Price Indices–2013 Real Capital Analytics, Moody's RCA/CPPI. Liquidation Value–author's own calculations.

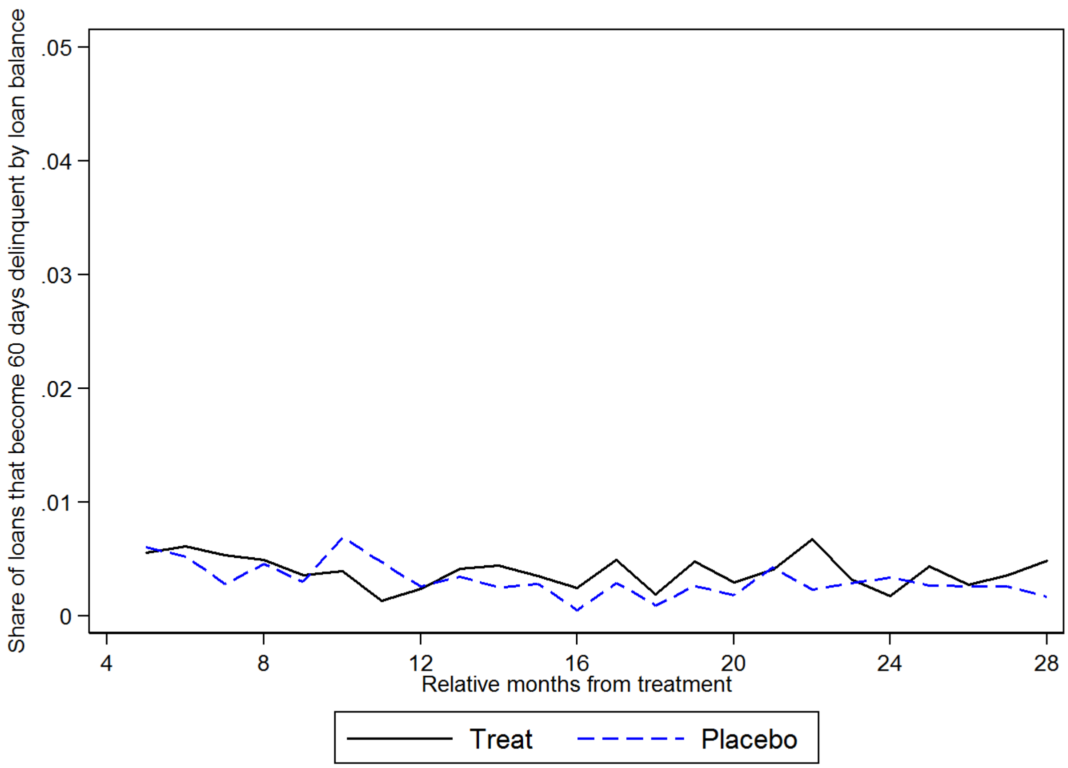
Figure 2: Post trends for monthly loan-to-value and monthly debt service coverage ratios





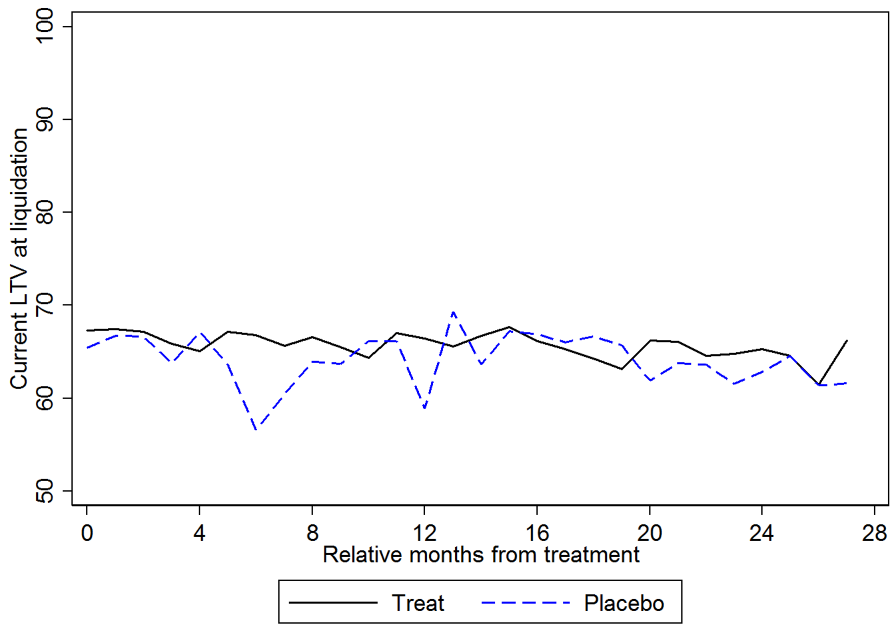
Notes: Estimated trends in current loan-to-value (LTV) and current debt service coverage ratio (DSCR), by treated (solid line) and placebo (dashed line) special servicers, with associated 95 percent confidence intervals. DSCR equals net operating income divided by debt service payments. Each of the time series trend lines was estimated using a fourth order local polynomial regression at the loan-month level. The sample includes all current loans, each month from December 2010 to November 2012.

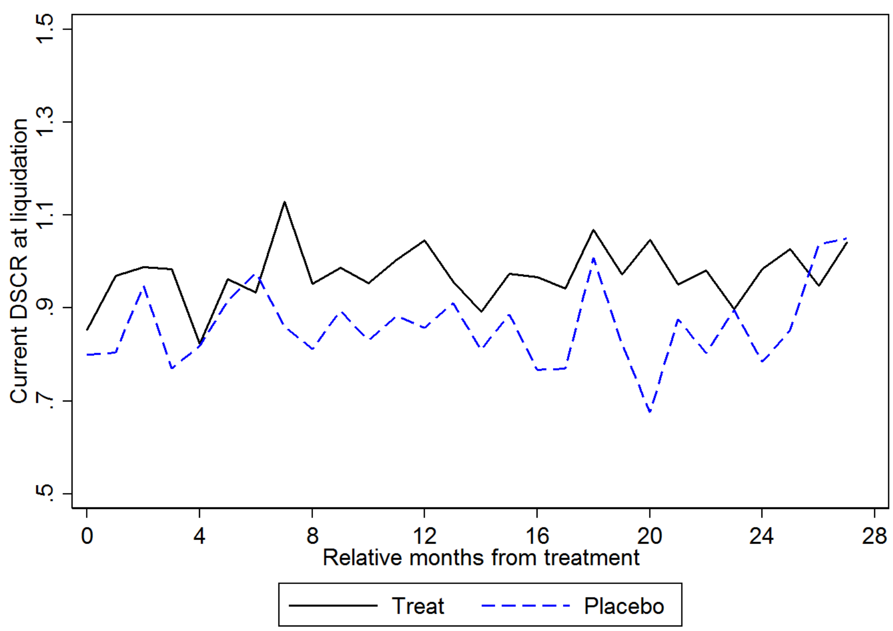
Figure 3: Share of current loans that become 60-day delinquent



Notes: Share of loans (by dollar amount) that become 60-day delinquent in month *t* for treated (solid line) versus placebo servicers (dashed line). Each month, I report the share of current loans that just became 60-day delinquent in that month. Loans are transferred to special servicers after they become 60-day delinquent.

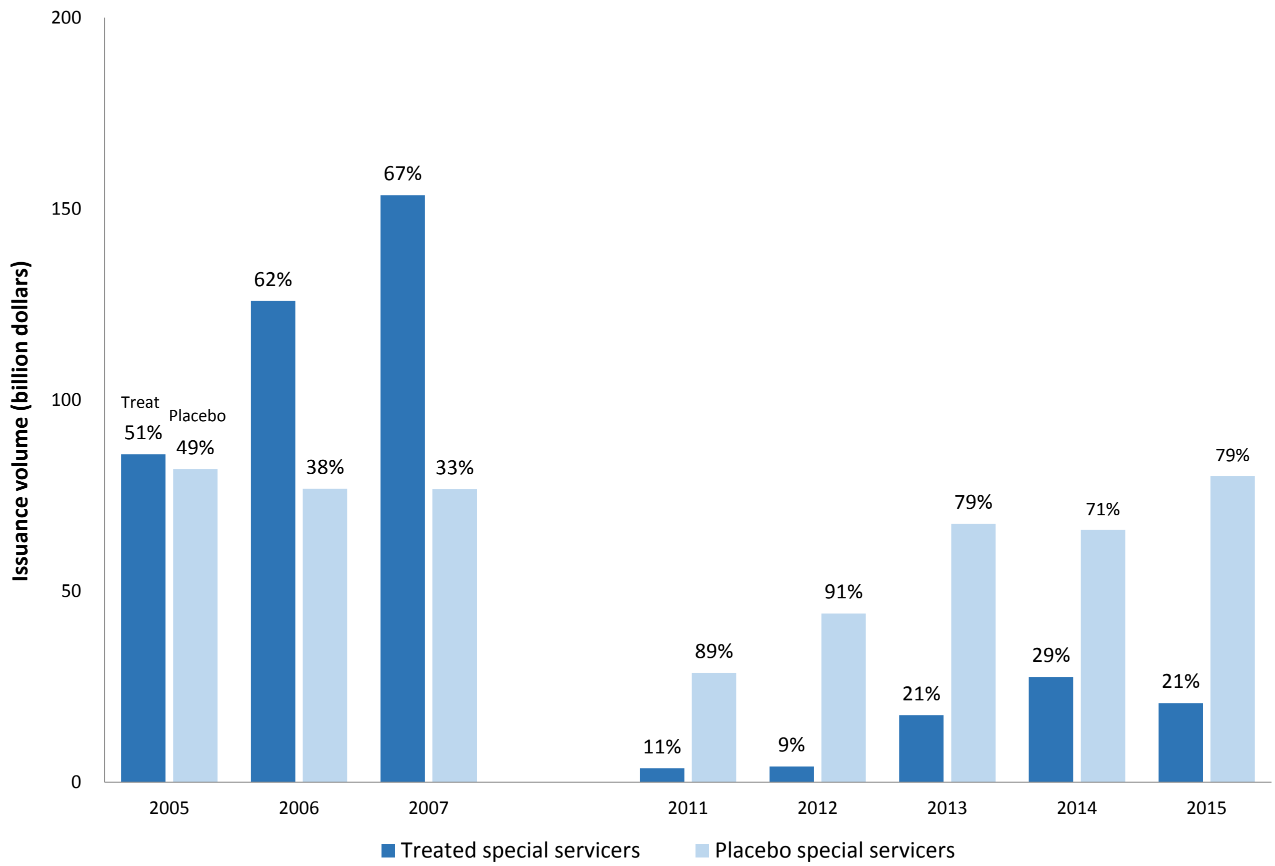
Figure 4: Current loan to value and current debt service coverage ratio on the month of liquidation





Notes: Monthly averages of current loan-to-value and monthly averages of current debt service coverage ratios for liquidated loans, by treated (solid line) and placebo (dashed line) servicers.

Figure 5: CMBS issuance by year and market shares of special servicers



Notes: Each bar represents the total volume of CMBS debt issued each year between 2005 and 2007 and between 2011 and 2015 for treated (darker bar) and placebo (lighter bar) special servicers, respectively. The annual issuance volumes between 2008 and 2010 (ranging from $3 billion to $12 billion) have been suppressed. The numbers above the bars correspond to the market shares for the treated and placebo special servicers.