Online Appendix

CMBS and Conflicts of Interest: Evidence from Ownership Changes for Servicers

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A Empirical appendix

A.1 Data construction

Deals

The deal dataset comes from Realpoint, downloaded on November 11th 2010. The raw dataset consists of 1082 deals, securitized between July 1991 and November 2010. The deals affiliated with the United States government (N=186) and deals originated in Canada or have a trustee in Canada (N=60) are dropped. I also drop deals securitized after 2008 as these deals tend to have different governance structures. This results in a final sample of 787 deals.

All securitized loans

The raw data has a total of 141,976 loans coming from the same 1082 deals in the Realpoint deal data. Each loan has an identifier for the deal it belongs to and an unique loan ID. After dropping the deals discussed above, the full sample of securitized loans includes 120,495 loans.

Realpoint does not report historical values for most loan attributes. Each month, it reports fixed at-origination loan attributes for all loans. For attributes that change over time (delinquency status, current LTV, current DSCR, current balance), Realpoint only updates and report the updated value for loans with a positive balance that month.

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For time-varying attributes, I construct a *loan-report month* level panel for 71,000 loans that have a positive loan balance in November 2010. The ownership changes span November 2009 (Berkadia) to September 2010 (CW Capital). Therefore, the first relative month where I have current loan information for Berkadia is month 11. Month 26 is the last relative month where I have current loan information for CW Capital. For liquidated loans, I downloaded one cross-section of data in January 2010, which allows me to track current LTV and current DSCR for loans liquidated between January and November 2010. However, I do not have monthly data between January and November 2010, and cannot construct a loan panel of current loans between these two months.

Realized loss dataset

This is the core dataset used to estimate the effect on loan loss rates. In a separate dataset called the realized loss report, Realpoint lists the history of all loans that have realized losses to the CMBS trust. The realized loss report includes a sample of 11,332 liquidated loans with liquidation months ranging from September 1997 to November 2012. I dropped around 1400 loans with missing liquidation dates. The primary estimation sample includes 9,272 loans liquidated between 2003 and 2012.

Bloomberg data on liquidated loans

In August 2016, I downloaded auxiliary data from Bloomberg that includes 12,000 loans liquidated from 2000. The data reports the termination date, special servicer, and realized losses in dollars, but not the loan balance before losses.

Bloomberg data on bond-level loss rates

In April 2016, I also downloaded data from Bloomberg that reports bond-level loss rates. Bloomberg reports the cumulative loss rates for each bond, up to April 2016. Bloomberg did not have loss rates for a few bonds. I supplemented this with bond-level loss rates from Realpoint (I have some bond-level loss rates from February 2011). The conclusions are similar with and without the supplemented data. In total, I have bond loss rates for 14,000 bonds, with 7,000 bonds with an original rating of A or better, and 4,000 bonds with an original rating of AAA or better.

Variable construction

The loss rates at the loan level are reported as a ratio of the total realized loss for the loan (in dollars) divided by the loan balance before losses. Some outliers appear to be loans from the same portfolio where the realized loss in dollars for the entire *portfolio* was divided by the loan balance for each *loan*, resulting in loss rates that seem implausibly high. The core analysis winsorizes loan loss rates at the top 1% to drop these outliers. I checked the other loans with high loss rates against other sources to determine they are not data errors. As a robustness check, I also report another specification where I further winsorize loss rates at the top 1%. For a subset of loans in the loan-month panel (downloaded after November 2010), I check that the special servicer does not change from month-to-month. For my estimation sample, I only observe switching for fewer than 100 liquidated loans. In the analysis, the month of liquidation is centered around event dates. All ownership changes happened within the span of a year (December 2009 to September 2010). Centered months of liquidation and calendar months are not very different. Additionally, the initial DSCR and initial LTV are winsorized at the top 1%. Property age is set to missing if the year the property was built is before 1700 or after 2010.

A.2 Additional results

A.2.1 Different time controls

Table A1 repeats the main specification but uses coarser time controls instead of month of liquidation fixed effects. Column 1 includes quarter of liquidation fixed effects (centered around the event dates), column 2 includes year of liquidation fixed effects and column 3 includes a post indicator and quadratic monthly time trends. The estimated effects are slightly larger but not statistically different from the main specification (8 p.p.).

Table A1: Effect on loan loss rates with different time controls

Specification:	**Quarter FE**	**Year FE**	**Time trend**
	(1)	(2)	(3)
Post × Ownership change	0.10***	0.10***	0.10***
	(0.03)	(0.03)	(0.03)
N	9272	9272	9272
R^2	0.12	0.11	0.11
Quarter FE	Y	N	N
Year FE	N	Y	N
Trend	N	N	Y
Special servicer FE	Y	Y	Y
Controls	Y	Y	Y

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

A.2.2 Heterogeneous samples

Table A2 estimates the effect of ownership changes on loan loss rates for heterogeneous samples. Given the smaller sample sizes, instead of including both special servicer and month of liquidation fixed effects, I only include special servicer fixed effects, a post indicator, and quadratic time trends. Column 1 presents the results for the full sample, but using time trends only. Columns 2 to 6 repeat this specification but restricted to loans with balloon payments, fixed interest rates, for apartments, offices, and retail properties respectively.

Table A2: Effect of ownership changes on loan loss rates for heterogeneous samples

	All	**Balloon**	**Fixed rate**	**Apartment**	**Office**	**Retail**
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Ownership change	0.10***	-0.01	0.11***	-0.07**	0.08*	0.09**
	(0.03)	(0.04)	(0.04)	(0.03)	(0.05)	(0.04)
N	9272	6372	8073	2444	1301	1876
R^2	0.11	0.13	0.11	0.21	0.13	0.17
Time trend	Y	Y	Y	Y	Y	Y
Special servicer FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

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

A.2.3 Trends in pre-determined loan attributes for liquidated loans

Each figure repeats the main loan-level analysis (equation 1) with annual estimates of the differences between treated and placebo servicers (β), controlling for month and servicer fixed effects (without loan controls). Standard errors are double clustered by servicer and month and 95% confidence intervals are included. The omitted group is year -6.

Importantly, the trend for the balloon indicator (second panel in Figure A-1) is decreasing, which indicates that fewer balloon loans are liquidated over time. While the cross-sectional analysis indicates treated loans are more likely to have hotel, office, or retail loans, the trends do not indicate that more of these loans are being liquidated in the post period. Relative to year -6, the trend for initial loan balance is also not increasing steadily over time. Overall, the trends are relatively stable and not large enough to explain the 8 p.p. effect after ownership changes.

Figure A-1: Trends in fixed rate loans, balloon loans, and year of securitization

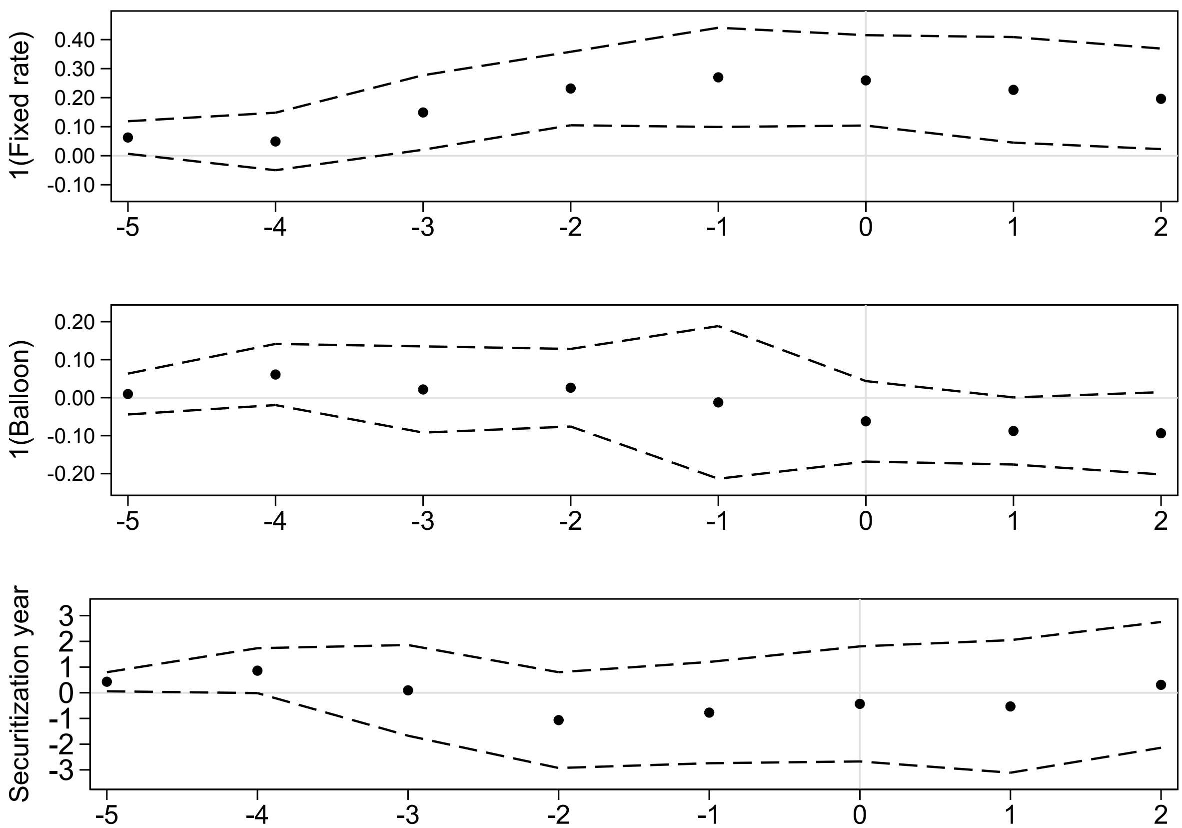


Figure A-2: Trends in hotel, apartment, and retail loans

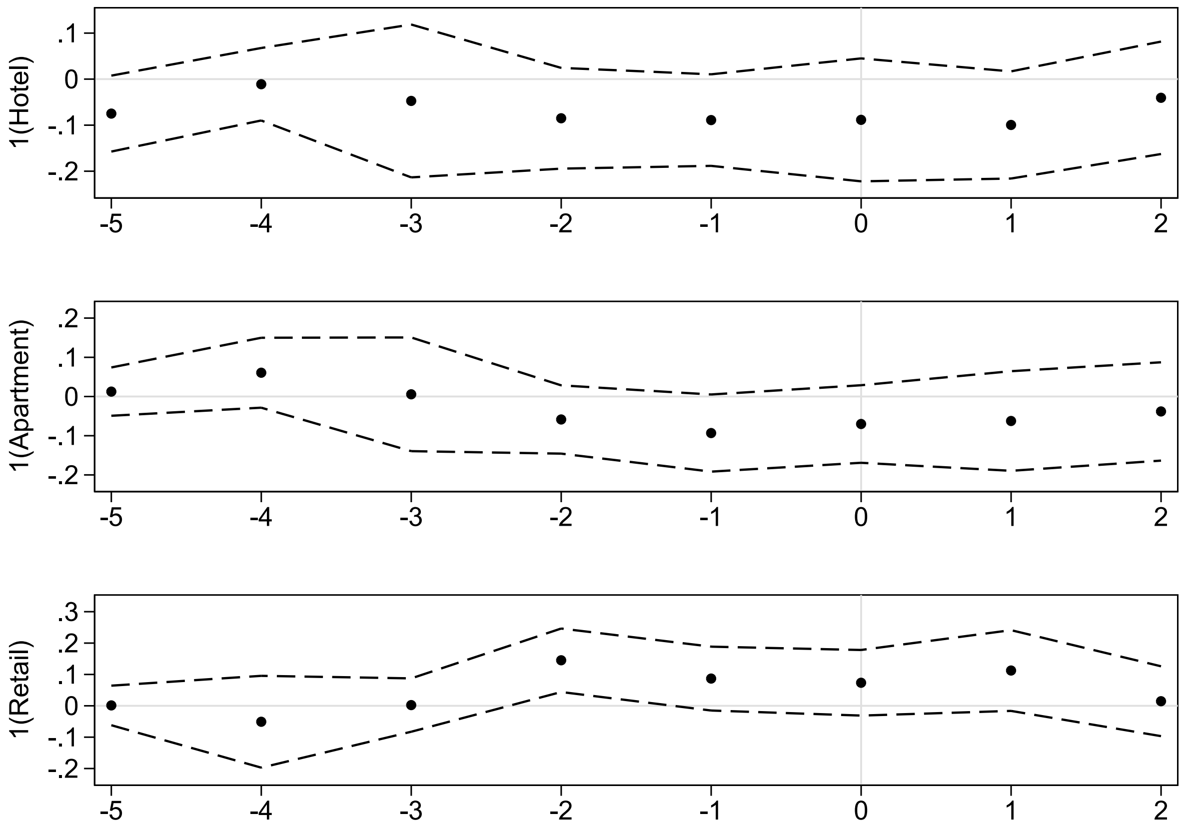
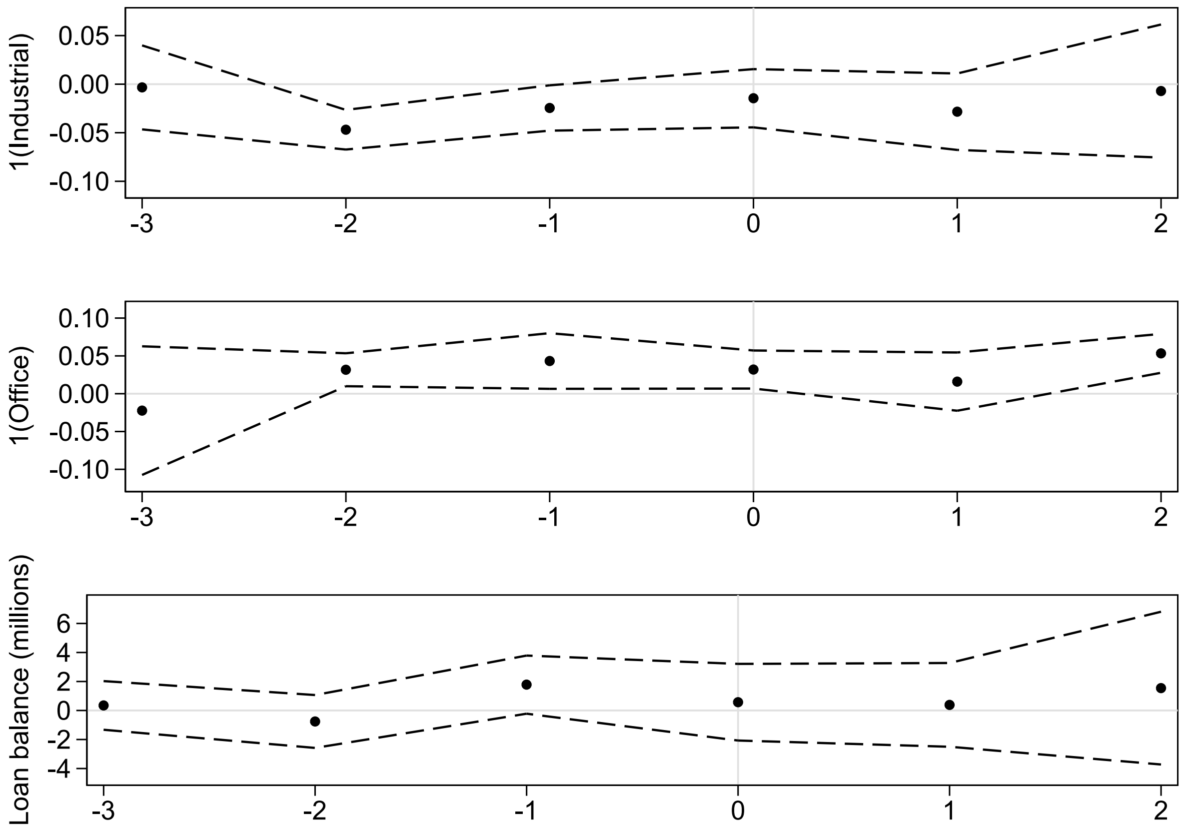


Figure A-3: Trends in industrial loans, office loans, and loan balance



Notes: The omitted group pools together years -4 to -6, to reduce the number of coefficients to estimate double clustered standard errors.

Figure A-4: Trends in number of properties and property age

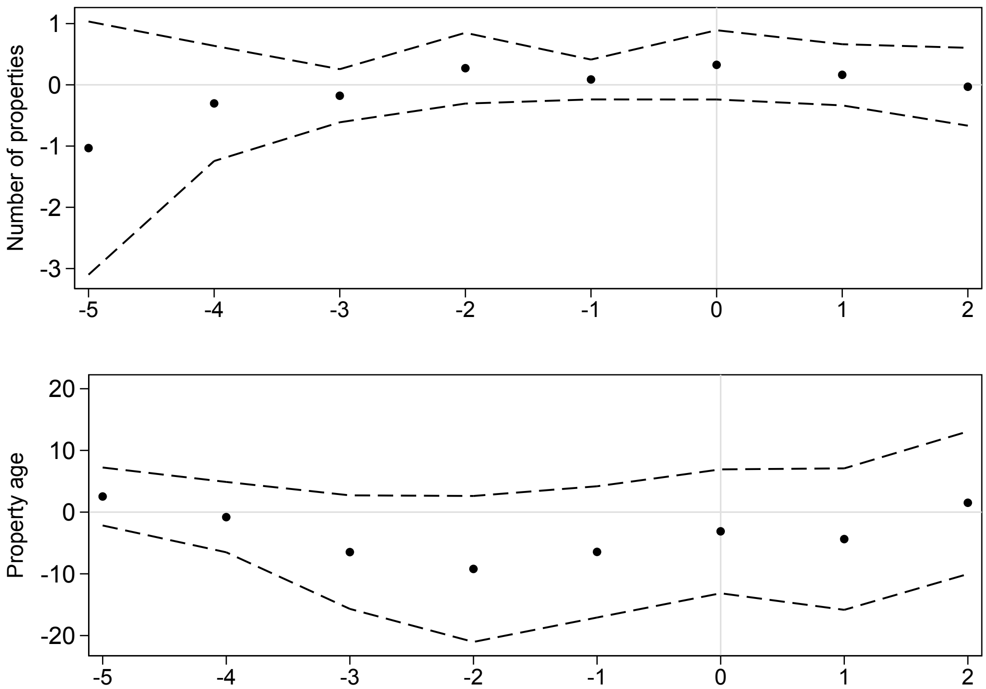
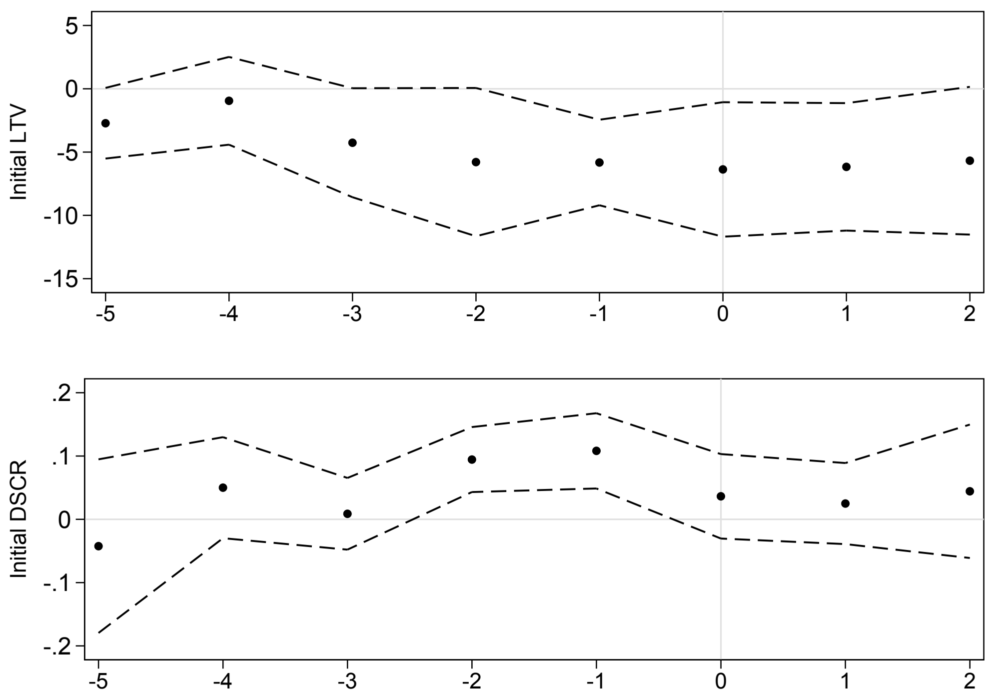


Figure A-5: Trends in initial LTV and initial DSCR



A.2.4 Exposure to housing bust markets

Table A3 tests whether treated loans are more likely to be located in housing bust markets. I first calculate rate of change in prices between 2006 and 2009, using the Federal Housing Finance Agency (FHFA) house price index (Federal Housing Finance Agency, 2016). Column 1 defines bust markets as MSA's with below-median growth rates, column 2 uses the 25th percentile, and column 3 includes indicators for sand states (MSA's in Nevada, Florida, Arizona, and Inland MSA's in California). Panel A includes all securitized loans where I could merge with the FHFA data. Panel B includes liquidated loans only. Some loans have multiple MSA's (these are dropped). Reassuringly, treated loans are not significantly more exposed to housing bust markets.

Table A3: Exposure to bust markets

Dependent variable:	Bust (p50)	Bust (p25)	Sand States
	(1)	(2)	(3)
	Panel A: All loans		
Ownership change	-0.005	-0.02	-0.001
	(0.02)	(0.02)	(0.01)
N	101514	101514	101514
R^2	0.00002	0.0003	0.000003
	Panel B: Liquidated loans		
Ownership change	-0.01	0.01	-0.01
	(0.03)	(0.04)	(0.02)
N	8065	8065	8065
R^2	0.00003	0.00003	0.00009

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

A.2.5 60-day Delinquency

Column 1 of Table A4 in the appendix shows that treated loans are 0.2% more likely to become 60-day delinquent, relative to a mean of 0.3% and a standard deviation of 1%. The dependent variable is the share of servicer i's loans (in dollars) in month t that first become 60-day delinquent in month t. This is a servicer-month level analysis with month fixed effects and robust standard errors. The higher 60-day delinquency rate for treated servicers is a potential concern, though it would have been ideal to test if this difference is greater relative to the pre-period.

Importantly, columns 2 to 5 in Table A4 provide loan-level analyses demonstrating that the 60-day delinquency is unlikely to be the main driver of the higher loan loss rates. Column 2 regresses an indicator that is 1 if the loan ever becomes 60-day delinquent in my sample period ($EverDelinq$) on the treatment dummy, controlling for all loan controls used in my main specification. The sample includes all loans that are current in November 2010 (when I first obtained access to the data) and standard errors are clustered at the special servicer level. The coefficient on the treatment dummy (0.005) is insignificant and small relative to the mean (0.06). Column 3 shows that the results are similar if I weight observations by their current balances.

Moreover, the last two columns show that loans that become 60-day delinquent in my sample do not have higher loss rates. Column 4 regresses the loss rate on $EverDelinq$ (including controls in my main specification) and finds that these 60-day delinquent loans have loss rates that are 19 p.p. lower. Column 5 shows that the triple interaction (post, treat, $EverDelinq$) is not positive and significant.

Therefore, while the servicer-month level analysis indicates treated servicers are more likely to have loans that become 60-day delinquent, the loan-level analysis suggests this difference is unlikely to explain the higher loan loss rates I find above.

Table A4: Delinquency

Dependent variable:	Fraction becoming delinquent	Ever delinquent	Ever delinquent	Loss rate	Loss rate
Unit:	Servicer-month level	Loan level	Loan level	Loan level	Loan level
	(1)	(2)	(3)	(4)	(5)
Ownership change	0.002***	0.005	0.01		
	(0.0006)	(0.01)	(0.01)		
Ever delinquent				-0.19***	-0.18***
				(0.02)	(0.03)
Post $\times$ Ownership change					0.10**
					(0.04)
Post $\times$ Change $\times$ Ever delinquent					0.004
					(0.02)
N	495	73545	73545	5169	9272
R^2	0.03	0.01	0.01	0.13	0.15
Mean of Dependent Var.	0.003	0.06	0.06	0.51	0.50
Month FE	Y	N	N	Y	Y
Servicer FE	Y	N	N	Y	Y
Controls	N	Y	Y	Y	Y

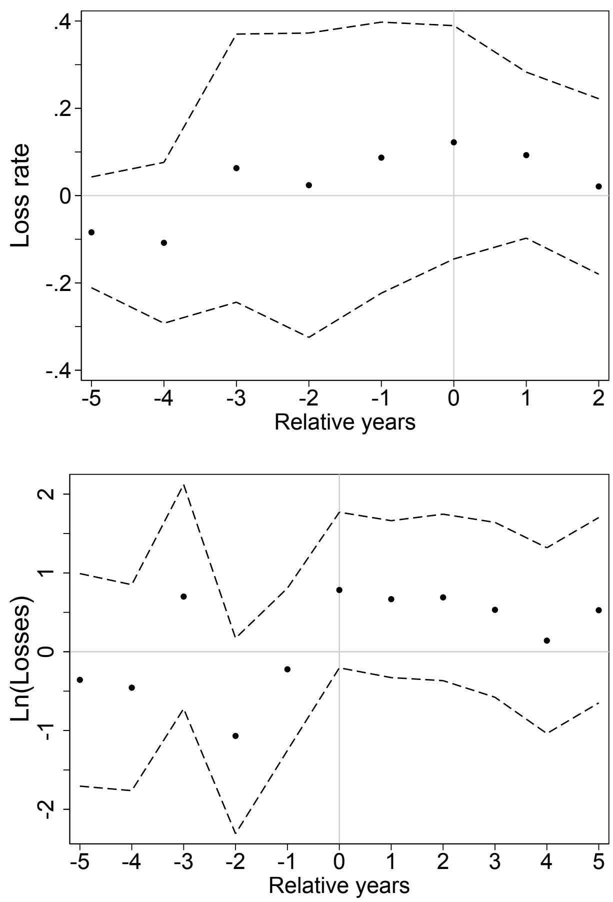
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

A.2.6 Trends in outcomes

The top panel repeats the main loan-level analysis (equation 1) with annual estimates of the differences between treated and placebo servicers (β), controlling for month fixed effects, servicer fixed effects, and loan controls. Standard errors are double clustered by month and by servicer. The omitted group is year -6.

The bottom panel reports annual estimates from the servicer-month level analysis from Bloomberg (equation 2), for the effect of ownership changes on the monthly volume of losses. The controls include month and servicer fixed effects, with robust standard errors. The omitted group is year -6 and the Bloomberg data has a longer post period.

Figure A-6: Trend in effect on loan loss rates and volume of losses



A.2.7 Assessing importance of selection on unobservables

I follow Altonji, Elder, and Taber (2005) and Oster (2016) to calculate how large selection on unobservables will need to be to explain away the entire 8 p.p. effect on loan loss rates. This method depends on the stability of coefficients (β) and on how useful the controls are at explaining the variation in the outcome (R^2). I compare an uncontrolled specification (regressing loss rates on *post*, *treat*, and the interaction, β) to the controlled specification (my most saturated specification in column 3 of Table 2 in the paper). Following Oster (2016), I calculate that $\delta = [\frac{\beta_C}{(\beta_U - \beta_C)}] * (\frac{R_C - R_U}{(0.3 \times R_C)})$, where U denotes the uncontrolled specification and C denotes the controlled specification. Intuitively, δ is high if the coefficients are stable (denominator of the first term in the bracket is small), or the R-squared changes a lot (numerator in the second term proxies for how useful the controls are). In my context, β is more than halved (0.19 to 0.08) because the market conditions also changed significantly around 2010. Importantly, the R-squared increases more than seven-fold (0.05 to 0.38), which suggests the controls are useful.

I calculate that δ is 2.1, twice as large as the heuristic cutoff of 1. This implies that selection on unobservables needs to be twice as important as selection on observables to explain the entire 8 p.p. effect.

Table A5: Assessing importance of selection on unobservables

Specification	(U)ncontrolled	(C)ontrolled
	(1)	(2)
β	0.19	0.08
R^2	0.05	0.38
N	9272	9272
δ		2.1
Month FE	N	Y
Special servicer FE	N	Y
Controls	N	Y
Post × Controls	N	Y
MSA-year FE	N	Y

A.2.8 Dropping years right before and after ownership changes (Bloomberg)

Table A6 demonstrates that the larger losses for loans liquidated by treated servicers after the ownership changes remain using a longer post period. This analysis uses data downloaded from Bloomberg for loans liquidated between 2000 and August 2016. The data from Bloomberg only reports loan losses (the numerator for loan loss rates). I estimate equation 2 at the servicer-month level, with robust standard errors.

Column 1 includes the full Bloomberg sample (6 years pre and post), column 2 restricts to my primary sample period (6 pre years, 3 post years), columns 3 to 5 respectively drop 1 to 3 years around the ownership changes (from the full sample in column 1). Reassuringly, the estimates are not statistically different from each other.

The coefficients in the Bloomberg analysis (servicer-month level) are not directly comparable to the loss rate analysis (loan level). Here, $Loss_{it}$ is greater when the loss rate is greater (Table 2) or when the volume of liquidation is greater (column 3 in Table 6) .

Table A6: Effect on volume of losses (longer post period from Bloomberg)

Dependent variable:	$Ln(Loss_{it})$				
Years:	6 pre, 6 post	6 pre, 3 post	Drop 1 year	Drop 2 years	Drop 3 years
	(1)	(2)	(3)	(4)	(5)
Post × Ownership change	0.84***	0.87***	0.84***	0.60*	0.92**
	(0.21)	(0.22)	(0.28)	(0.34)	(0.40)
N	1201	875	929	713	521
R^2	0.52	0.56	0.51	0.49	0.45
Month FE	Y	Y	Y	Y	Y
Special servicer FE	Y	Y	Y	Y	Y

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

A.2.9 Bounding exercise for stockpiling effect

Assumptions needed to bound the stockpiling effect

Below are the assumptions for step 1 of the bounding exercise.

1a: I assume the most the treated servicer can liquidate each month is \$101 million (ie. the *height* for Area T corresponds to the maximum from the post trend for the treated servicer).

1b: Second, I assume that the counterfactual step function jumps up 12 months before 0 (ie. the *width* for Area T).

- The ownership changes happened between December 2009 and September 2010.
- A duration of 12 months in the pre-period is plausible. In reality, the 60-plus delinquency rate was still trending down through 2008 and only started rising towards the end of 2008. The delinquency rate was 0.88% in December 2008 and 3.5% in September 2009.
- Moreover, a majority of delinquent loans are not liquidated.

1c: The actual losses for the treated servicer during this time period amount to \$504 million (area under the trend line for the treated servicer, between month -12 and month 0).

1d: So, the additional losses implied by **Area T** $= \$101m * 12 - \$504m = \underline{\$708m}$

1e: For the placebo servicer, the losses corresponding to **Area C** $= \$22m * 12 - \$96m = \underline{\$168m}$.

The assumed heights for Area T and Area C are likely an upper bound. For example, a height of \$101 million for the treated servicer implies that losses would be 2.4 times larger than actual losses ($\frac{101*12}{504} = 2.4$). Similarly, the implied losses for the placebo would be 2.8 times larger ($\frac{22*12}{96} = 2.8$). In other words, this counterfactual assumes the servicers would have more than doubled the losses immediately. Instead, if we assumed the height was equal to the stabilized level after the excess mass (\$85 million per month for treated and \$18 million for placebo), the share explained by stockpiling would be 15% (the stockpiling effect would be (\$85 million - \$18 million)*12 months - (\$504 million - \$96 million)).

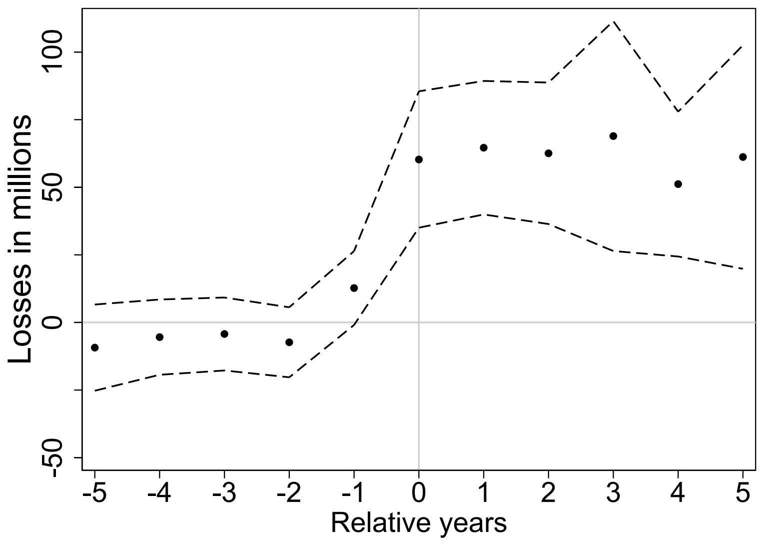
No bunching pattern with conditional trends

Figure A-7 below shows that the conditional differences in the volume of losses do not exhibit a bunching pattern in the post period (controlling for month fixed effects and special servicer fixed effects). Here, I am estimating equation 2 in the paper, but with losses as the dependent variable (instead of logs), and annual estimates for the key parameter (β). The omitted group is year -6.

$$Loss_{ity} = \sum_{y=-5}^{5} \beta_y OwnershipChange_i \times Post_{ity} + \tau_t + \delta_i + \varepsilon_{ity} \quad (1)$$

The lack of any spike between year 0 and year 3 indicate that the main specification likely differences out part of the stockpiling effect. In reality, most servicers were blindsided by the crisis and needed time to overcome their capacity constraints.

Figure A-7: Conditional trends in monthly volume of losses



B Special Servicer Background

This section provides more details about special servicers in the treated and placebo groups.

Berkadia Berkadia's origins can be traced back to 1994, when GMAC Commercial Mortgage Corporation was established. In December 2009, Berkshire Hathaway and Leucadia National Corporation bought Capmark Financial and renamed it Berkadia Commercial Mortgage LLC. One of Berkadia's business lines includes "proprietary lending" to "originate loans for its own balance sheet" (Berkadia, 2016). Berkadia also has a mortgage brokerage business (Leucadia National Corporation, 2014).

C-III In March 2010, Island Capital acquired the commercial mortgage loan servicing business of Centerline Holdings Company and renamed it C-III. Centerline's origins date back to 1972 when it was founded as a subsidiary of Related Companies, providing multifamily finance and investment management services.

Island Capital also owns C-III Investment Management LLC, which manages over $3.8 billion in assets. According to their website, C-III Investment Management funds target "commercial real estate equity, distressed commercial real estate mortgage loans, unrated and below investment grade commercial mortgage-backed securities (CMBS), collateralized debt obligations (CDOs), whole loans, B-notes and mezzanine debt" (C-III Capital Partners, 2016). Island Capital also has affiliated brokerages (C-III Realty, NAI Global) and a titling agency (Zodiac).

LNR LNR began as an operating unit within Lennar Corporation, a national homebuilder. In July 2010, LNR was recapitalized by a consortium of investors including Cerberus, Vornado, Oaktree, iStar, and Aozora. All of these firms are active investors in the commercial property market (Oaktree, 2014; Istar, 2015; Cerberus, 2015). Vornado is a large Real Estate Investment Trust, and Oaktree counts distressed debt and real estate as its major asset class. The primary business segments of i-Star include "real estate finance, net leasing, operating properties and land". Cerberus has over $20 billion under management invested in four primary strategies, including "[d]istressed securities and assets (mortgage-based securities, corporate debt, non-performing loans, structured loans) [and] real estate-related investments". At that time, Cerberus also owned 49% of Aozara Bank. In April 2013 (after my sample period), Starwood Property Trust announced it had acquired LNR.

CW Capital CW Capital was founded in 1972 as a regional, multifamily lender, and a primary servicer. Prior to their sale, CW Capital was owned by a Canadian pension fund manager. In September 2010, Fortress Investment Group LLC acquired CW Capital. Fortress has approximately $67.5 billion of assets under management as of December 2014, with some investments in "distressed and undervalued assets...including...real estate" (Fortress, 2015).

Placebo group As discussed in the main text, special servicers in the placebo group have fewer self-dealing conflicts. Going across the columns in Table A7, treated servicers are more likely to be affiliated with brokerages and online auction platforms. Brokerage and auction fees are relatively fixed, with firms relying more on volume to drive revenue. Some of these businesses are also new brands. Gaining market share and becoming known as the dominant intermediary in the market is important as customers tend to go to firms with large networks and deal flows. Therefore, the large scale of the treated servicers complement these business lines.

By contrast, none of the placebo servicers have affiliated brokerages and online auction platforms. Some are part of banks which were heavily regulated after 2008 and generally do not have brokerage services (Midland, Keycorp, Wells Fargo, Washington Mutual, and Crown Northcorp. GE Capital was systemically important). According to their rating agency reports, several placebo servicers (Situs, Torchlight, Trimont) also claim that they do not engage affiliated service providers to avoid conflicts.

Second, all servicers are lenders as this is how they got into servicing to begin with. But, treated servicers are more likely to be new lenders (Berkadia and C-III are new brands), relative to placebo servicers which are established brands. Investing in new relationships and brand equity are relatively more important for new lenders.

Third, all treated servicers are potential buyers of CMBS liquidations. In particular, the parents of LNR, CW Capital, and C-III have distressed debt investment funds. The parents of Berkadia (Berkshire and Leucadia) do not have distressed debt investment funds per se (to my knowledge), but they are involved in acquisitions. By contrast, only three placebo servicers are potential buyers. The rest do not have proprietary investments (they are banks or the rating agency reports indicate they do not have affiliated buyers).

Some placebo servicers also underwent ownership changes (Wachovia and Washington Mutual), but the new owners do not have affiliated service providers. Dropping the liquidations by these two servicers lead to an identical effect (8 p.p. effect on loss rates). Helios and ING Clarion were renamed during my sample period. The result is identical after dropping these servicers. One of the special servicers in the placebo group, JER Partners, was acquired by Island Capital towards the end of my sample period (August 20, 2011). The analysis does not include liquidations by JER that are after August 2011 ($1.7 billion). The results are similar if I drop all liquidations from JER.

Table A7: Affiliates

Special servicer		Brokerage	Online auction	Titling	Lender	Potential buyers
Berkadia	Treated	Yes	-	-	Yes	Yes
LNR	Treated	-	Auction.com	-	Yes	Yes
CWCapital	Treated	REDS	Auction.com	-	Yes	Yes
C-III	Treated	NAI Global, C-III Realty	Real Capital Markets	Zodiac Title Insurance	Yes	Yes
Midland	Placebo	-	-	-	Yes	-
GE Capital	Placebo	-	-	-	Yes	-
Crown Northcorp	Placebo	-	-	-	Yes	-
Helios/Situs	Placebo	-	-	-	Yes	-
Orix	Placebo	-	-		Yes	Yes
ING Clarion/Torchlight	Placebo	-	-	-	Yes	Yes
Keycorp	Placebo	-	-	-	Yes	-
CNL Financial Services	Placebo	NA	NA	NA	Yes	Yes
Washington Mutual	Placebo	-	-	-	Yes	-
Wachovia/Wells Fargo	Placebo	-	-	-	Yes	-

Notes: I could not find information on whether CNL has affiliated brokerages or auction platforms (NA indicates not available). CW Capital has a minority interest in Auction.com (renamed Ten-X).

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