

Mutual Funds and the Price of Mortgage Credit Risk*

Chuqiao Bi[†], Pedro Gete[‡], Susan Wachter[§]

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Abstract

In this paper, we show that investor composition shapes both the pricing of mortgage credit risk and the extent to which prices reflect underlying credit fundamentals. Using a novel dataset of Credit Risk Transfer (CRT) securities issued by the Government-sponsored Enterprises (GSEs), we find that mutual funds, which account for more than 55% of CRT purchases at issuance, lower CRT spreads and weaken the relationship between underlying default risk and prices. A one-standard-deviation increase in mutual fund share reduces spreads by 8.2%, translating into a 3% reduction in the credit-risk component of guarantee fees. More importantly, mutual fund participation attenuates the pass-through of expected default risk into prices, showing that investor composition affects the cost of risk transfer and the mapping between fundamentals and market prices. As policymakers weigh GSE privatization, our results show that who bears mortgage credit risk can be as important as how much risk is transferred.

Keywords: Credit Risk Transfers, Mutual Funds, Mortgage Credit Risk, Housing Finance System.

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[†]Cornell University. Email: cb868@cornell.edu.

[‡]IE University. Email: pedro.gete@ie.edu.

[§]The Wharton School of the University of Pennsylvania. Email: wachter@wharton.upenn.edu.

1 Introduction

A central question in modern asset pricing is whether investor identity affects equilibrium prices. Demand-based asset pricing models predict that heterogeneous investors apply different discount rates to the same cash flows, implying that prices depend not only on fundamentals but also on who holds risk. Empirical tests of this prediction are challenging because investor participation is rarely observed at issuance. Credit Risk Transfer (CRT) securities provide a unique setting to study this question. The identity of primary market investors is observable, the underlying mortgage risk is transparently measured, and the pricing of these securities feeds directly into the guarantee fees that determine mortgage rates for millions of borrowers.

The importance of this question is heightened by the future of the U.S. housing finance system. The bailout of Fannie Mae and Freddie Mac was among the largest taxpayer costs of the 2008 financial crisis, and both Government-sponsored Enterprises (GSEs) have remained under federal conservatorship since, with renewed discussion of privatization.¹ A central design question in any transition concerns how much mortgage credit risk should be transferred to private investors, and at what cost. CRT securities were introduced following the Dodd-Frank Act to facilitate this transfer. CRT investors receive cash flows linked to pools of mortgages held by the GSEs and directly share in mortgage credit losses alongside Fannie Mae and Freddie Mac.²

We construct a novel database of CRT issuances that includes detailed information on investor participation.³ Using these data, we show that investor composition significantly influences the pricing of mortgage credit risk. Mutual funds, which account for more than half of CRT purchases at issuance, are associated with lower CRT spreads and weaker sensitivity of spreads to underlying mortgage default risk.

To identify these effects, we combine a highly saturated specification that compares otherwise similar CRT issuances with different investor compositions, following the broader investor-demand literature (Kojien and Yogo, 2019) and recent empirical work on investor composition and asset pricing (Coppola, 2021; Kubitzka, 2023), with an instrumental variables strategy that exploits quasi-random variation in mutual fund participation across CRT issuances. Both ap-

¹For example, Lucas (2019) estimates that the total direct cost of crisis related bailouts in the United States was approximately \$500 billion, or 3.5% of 2009 U.S. GDP.

²CRTs and mortgage-backed securities (MBS) are both exposed to mortgage prepayment risk. However, they differ fundamentally in credit risk. MBS investors bear no credit risk because payments are guaranteed by the GSEs.

³Freddie Mac issues CRTs under the Structured Agency Credit Risk (STACR) program, while Fannie Mae issues them as Connecticut Avenue Securities (CAS).

proaches yield similar estimates. A one-standard-deviation increase in mutual fund share, equivalent to a 14.6 percentage point increase, reduces CRT spreads by approximately 8.2%.

Mutual fund participation affects not only the level of prices but also how mortgage credit risk is incorporated into prices. We find that CRT spreads increase with the predicted default risk of the underlying mortgage pool, consistent with rational pricing of credit risk. However, this relationship weakens as mutual fund participation rises. In other words, mutual funds attenuate the pass-through of expected default risk into prices. These findings imply that investor composition affects both the cost of risk transfer and the extent to which market prices reflect underlying credit fundamentals.

The economic implications are substantial. Because CRT spreads influence the guarantee fees charged by the GSEs, changes in investor composition affect borrowing costs for households. Our estimates imply that greater mutual fund participation reduces the credit risk component of guarantee fees by approximately 3%. Given the volume of mortgages acquired annually by Fannie Mae and Freddie Mac, this translates into roughly \$78 million in annual borrower savings. More broadly, our results suggest that the pricing of mortgage credit risk depends not only on the quality of the underlying mortgages but also on who ultimately bears that risk.

Related literature. Our paper contributes to the literature showing that investor heterogeneity shapes asset prices. The demand system approach of [Kojen and Yogo \(2019\)](#) shows that heterogeneity in investor mandates, benchmarks, and risk tolerance is a key determinant of equilibrium asset prices, and that ignoring this heterogeneity can lead to misspecified asset pricing models. [Vayanos and Vila \(2021\)](#) and [Greenwood and Vayanos \(2014\)](#) show that investor clienteles with different maturity preferences face downward sloping demand curves, implying that prices reflect not only fundamentals but also the composition of investors holding an asset. Prior studies have applied this framework to equities, corporate bonds (e.g., [Kubitza 2023](#); [Li et al. \(2026\)](#); [Bretscher et al. 2026](#)), and sovereign bonds (e.g., [Fang et al. 2022](#); [Jansen et al. 2024](#)).

Our results also contribute to the literature on the role of mutual funds in financial markets. Existing work shows that mutual fund flows affect asset prices and the supply of capital. For example, [Zhu \(2021\)](#) finds that mutual fund flows increase the supply of capital to firms and reduce yield spreads in corporate bond markets, while [Adelino et al. \(2023\)](#) shows that exogenous fund flows stimulate municipal bond issuance and raise bond prices. We complement this literature by showing that mutual funds influence not only the level of prices but also their sensitivity to risk. Greater mutual fund participation weakens the relationship between CRT spreads and underlying mortgage default risk, implying that investor demand can affect how

credit risk is incorporated into prices.

Our paper also contributes to the growing literature on credit risk transfer securities. Early work by [Finkelstein et al. \(2018\)](#) characterizes CRT programs as a form of GSE reform and shows that CAS and STACR securities successfully transferred substantial mortgage credit exposure to private investors without disrupting agency MBS liquidity. [Wachter \(2018\)](#) argues that liquid and transparent CRT markets can improve market discipline by generating informative prices for mortgage credit risk. More recently, [Gete et al. \(2024\)](#) show that investors incorporate climate disaster risk into mortgage credit markets through CRT pricing.

Finally, we contribute to the literature on the structural pricing of CRT securities. Existing models make substantial progress in capturing the complex cash flow structure of CRTs and incorporating realistic sources of risk. [O’Neill \(2022\)](#) extracts risk neutral mortgage loss distributions from CRT prices, [Flanagan \(2025\)](#) prices CRT cash flows using traded securities with similar risk characteristics, and [Capponi et al. \(2026\)](#) develops a structural model with Treasury, corporate bond, housing, and labor income risk factors. A common feature of these models is the assumption that all investors apply the same discount factor. Our evidence suggests that this assumption is consequential. After controlling for the risk factors emphasized in [Capponi et al. \(2026\)](#), mutual fund participation remains strongly associated with CRT spreads. This finding implies that investor identity, in addition to risk fundamentals, is an important determinant of mortgage credit risk prices.

Structure of the paper. Section 2 provides institutional background on the CRT market. Section 3 describes the data construction and presents summary statistics. Section 4 documents the negative relationship between mutual fund participation and CRT issuance spreads, using a stepwise OLS strategy. Section 5 establishes causality via an instrumental variables approach that exploits quasi-random variation in the number of mutual fund portfolios participating in each issuance. Section 6 presents robustness checks. Section 7 examines how mutual fund participation shapes the sensitivity of CRT spreads to underlying default risk and quantifies the implied effect on guarantee fees and mortgage rates. Section 8 concludes. The Appendix details data sources, variable construction, and supplementary results.

2 The Credit Risk Transfers

Freddie Mac introduced STACR bonds in 2013, followed by Fannie Mae with CAS bonds, together forming the GSE CRT market. CRTs are issued at par and linked to pools of mort-

gages. As shown in Table 1, each pool typically contains over 100,000 mortgages, with an average issuance size of USD 850 million. The GSEs also provide detailed pool data to enable investors to assess the credit quality of the underlying mortgage pool. CRTs pay a floating interest rate that is priced at a spread to a benchmark interest rate, such as LIBOR or SOFR. Table 1 shows that the average credit spread across all tranches is around 307 basis points.

CRT investors bear mortgage losses based on a tranche structure that establishes a hierarchy of seniority⁴. Losses hit the lowest tranches first, while senior tranches are affected last. However, mortgage prepayments are applied to the most senior tranche first. In addition, credit enhancement thresholds, which cap the share of default losses covered by a given CRT deal, provide further protection for upper tranches, averaging around 4% across deals in our sample, as shown in Table 1.

Table 2 presents the distribution of CRT purchases at issuance across different investor types. Mutual funds are the dominant participants, accounting on average for more than half of total issuance (55.7%), followed by hedge funds with approximately 30.5%. Other investor types, such as insurance companies, REITs, sovereign funds, and banks or credit unions, hold comparatively smaller shares, each averaging below 5%. The relatively low participation of banks and credit unions (mean of 1.2%) suggests limited direct exposure of depository institutions to CRTs because of their high regulatory capital weights (Finkelstein et al. 2018). The variation across investor types—as reflected in the standard deviations—indicates heterogeneity in market participation, particularly among institutional investors such as hedge funds and mutual funds.

Figure 1 plots mutual fund purchase shares alongside deal-level average CRT issuance spreads. Between 2013 and 2019, mutual funds purchased approximately 40% of newly issued CRTs. Between 2019 and 2021, this share increased to nearly 75%. Then, in 2022, the share fell back to approximately 40%. Meanwhile, CRT spreads moved in the opposite direction to mutual fund participation. In the post-COVID period, the negative relationship between MF participation and CRT spreads was particularly pronounced. In late 2021, the CRT spreads reached a local trough when mutual fund participation was high, but they rose sharply by the end of 2022 when mutual funds exited the market, coinciding with the monetary policy tightening cycle that began in early 2022.

Figure B1 shows the size of the GSEs' CRT market, in terms of bond issuance volume and unpaid principal balance of mortgages covered. Between 2013 and 2019, both Fannie and Freddie issued a similar volume of CRTs. However, since 2019, Freddie has issued a larger

⁴We refer to tranches A-1, M-1A, M-1B, M-1, M-2 and M-3 as mezzanine tranches. We denote tranches B, B-1 and B-2 as junior tranches.

volume of CRTs. For example, in 2022, total CRT issuance was approximately \$20 billion, of which Freddie accounted for \$12 billion and Fannie for \$8 billion. By the first quarter of 2025, the combined CRT issuance of both GSEs has reached approximately \$150 billion, which covers an unpaid principal balance of conforming mortgages close to \$6 trillion. By comparison, the total mortgage debt outstanding of one-to-four-family residences in the U.S. by 2025Q1 was around \$14.4 trillion (FRED, 2026). CRT securities therefore provide credit loss coverage for approximately 41.6% of single-family mortgages in the United States. The scale of the CRT market underscores the importance of understanding what drives its pricing, the question at the heart of this paper.

3 Data

To conduct our analysis, we construct a novel database by merging data from several sources. Table 1 presents summary statistics for the main dependent and control variables, while Table 2 reports investor participation at the deal level. We briefly describe the data sources below; Appendix A describes the data sources, data-processing procedures, and variable construction in detail.

Data from the GSEs’ webpage: We collect all CRTs issued from July 2013 to February 2025⁵. The dataset contains detailed information about each CRT’s characteristics as a bond security and about the characteristics of the underlying mortgage pool. We compute deal-level issuance spreads by taking the issuance amount-weighted average of tranche-level spreads, reflecting the relative size of each tranche in the deal. We observe origination purchases made by different types of investors: mutual funds (including money managers), hedge funds, insurance companies, REITs, sovereign wealth funds, banks and credit unions, and others⁶.

Data from the CRSP Mutual Fund Database: The CRSP survivor-bias-free U.S. mutual fund database allows us to identify individual mutual fund portfolios that purchased CRTs in the primary market. It provides monthly security holdings for individual mutual fund portfolios. We identify 788 mutual fund portfolios that purchased CRTs from Fannie Mae or Freddie Mac during our sample period (July 2013 – February 2025)⁷. Appendix A.2 describes the methodology we use to identify primary market purchases by these mutual funds. Table C3 decomposes mutual fund buyers from the CRSP database by investment style. The majority

⁵There are 176 deals in this period, but we drop a small number of deals due to missing values in some variables. Appendix A.1 describes the sample selection in detail.

⁶Fannie Mae labels this last group as pension, local, and state government investors.

⁷An individual mutual fund portfolio is identified with the ID variable `crsp.portno`.

of CRT purchases by value, 78%, were made by bond mutual funds that invest in fixed-income assets.

Data from other sources: We obtain CRT secondary market trading volume from TRACE, house price growth from the Federal Housing Finance Agency (FHFA), and the following variables from Federal Reserve Economic Data (FRED): the Federal Funds Effective Rate, the 10-Year U.S. Treasury yield, real GDP, and corporate bond spreads for BBB, BB, and C ratings.

4 Mutual Funds and CRT Pricing

In this section, we uncover a robust pattern: mutual fund (MF) participation is associated with lower CRT spreads. We then explore this result with an identification strategy that compares otherwise similar CRT deals within the same time period and issuer context, where the only systematic difference is the degree of mutual fund participation. Saturating the regression with detailed controls helps approximate this comparison by absorbing the main sources of confounding variation, though we acknowledge it cannot address unobserved endogeneity, which motivates our IV approach in Section 5. By contrast, participation by any other investor type does not show a significant relationship with CRT issuance spreads.

4.1 The Regression on MF Shares: Saturation with Controls

We estimate deal-level OLS regressions using the following specification:

$$\text{Spread}_i = \alpha + \beta_1 \text{Share}_i^{inv} + \boldsymbol{\gamma}' \mathbf{X}_i + \Theta_q + \Theta_g + \epsilon_i \quad (1)$$

where i indexes individual CRT deals. Spread_i denotes the average spread at the deal level, and Share_i^{inv} represents the percentage share of purchases for CRT deal i by investor type inv . In this subsection, we focus on mutual funds; in the following subsection, we also consider other investor types: hedge funds, insurance companies, REITs, sovereign wealth funds, banks, and others. Θ_q and Θ_g are year-quarter and issuer (Fannie Mae or Freddie Mac) fixed effects; ϵ_i captures unobservable characteristics that could explain variation in CRT spreads. We consider a wide range of deal-level risk factors in \mathbf{X}_i , consistent with the bond pricing literature.

- **Deal characteristics:** These include the dollar issuance amount, size of the underlying

mortgage pool, minimum credit enhancement, call terms in years, maturity terms in years, and the characteristics of the underlying reference mortgage pool of each CRT deal, including the number of loans, average interest rate, average LTV, average FICO score, average debt-to-income ratio, and credit ratings.⁸ Controlling for bond characteristics is standard practice in the bond pricing literature. For example, [Coppola \(2021\)](#), studying the role of insurance companies in corporate bond pricing during market downturns, controls for bond credit ratings, bond size, bond seniority, and bond callability; [Siani \(2022\)](#) maps the demand curves of different investor types (short-term versus long-term) in the corporate bond primary issuance market, controlling for bond size and credit ratings. These variables ensure that MF share is not simply proxying for deal design or size: for example, larger, simpler, or more senior deals might attract more mutual funds and also price at lower spreads.

- **Risk composition:** These variables remove bias from differences in underlying credit risk: for example, lower-risk mortgage pools might both attract mutual funds and price tighter. This group includes the percentage shares of issuance amounts of M2, B1, and B2 tranches relative to total CRT deal issuance.⁹
- **Year-quarter fixed effects:** These absorb macroeconomic shocks and time trends, including interest rate movements, policy changes, and shifts in risk appetite, so that identification comes from variation within the same quarter.¹⁰
- **GSE fixed effects:** These control for issuer-specific pricing or underwriting policies (e.g., Fannie Mae vs. Freddie Mac).
- **Bond market controls:** The option-adjusted spread of the ICE BofA US corporate bond index (BB-spread) captures overall credit market risk premia, ensuring that the MF and spread relationship is not driven by broader market movements. [Chaudhary et al. \(2023\)](#) demonstrate the importance of controlling for the return on close substitutes when estimating corporate bond demand curves. The intuition is that investors substitute holdings across similar assets, so the pricing of a particular bond is reflected in the pricing of comparable assets. Failure to account for this substitutability would severely bias demand curve estimates. The literature documents close comovement between CRT

⁸Credit ratings were originally recorded in alphabetic form (e.g., A-, BBB, BB, B). We convert them to a numeric scale. The conversion is described in detail in Appendix [A.5](#).

⁹We combine M2 and M3 into the M2 group, and B and B1 into the B1 group. We omit the share of the M1 tranche to avoid collinearity. The M1 group includes the A1, M1A, M1B, and M1 tranches.

¹⁰CRT issuance is announced at the quarterly interval. Since the data structure is not a panel of CRT deals and year-quarters, the year-quarter fixed effects can be interpreted as cohort fixed effects, where deals issued within a quarter are treated as a cohort.

issuance spreads and corporate bond spreads. For example, [Golding and Lucas \(2022\)](#) find that the default cost implied by CRT issuance spreads has a correlation of 0.72 with the BB-spread, higher than their correlation of 0.55 with 90-day delinquency rates. We therefore include the BB-spread in the month preceding each issuance. We also control for the deal-level CRT spread from the previous issuance by the same issuer, to capture the fact that underwriters use recently priced CRT deals as benchmarks when pricing new ones. Direct evidence from CRTCast 5 by Freddie Mac ([Freddie Mac, 2022](#)) confirms that underwriters closely monitor recently priced CRT deals and related assets such as asset-backed securities (ABS) and collateralized loan obligations (CLOs) when gauging prices for new deals¹¹.

- **Potential CRT demand:** We control for the *ex-ante* total assets under management (AUM) of mutual fund investors in the current deal, measured in the month before issuance, and for total CRT secondary market trading volume in the same month, as a proxy for CRT market liquidity. The existing literature shows that mutual fund investments are flow-driven and subject to client redemptions, particularly during periods of poor market performance ([Lou, 2012](#), [Goldstein et al., 2017](#), [Zhu, 2021](#), [Adelino et al., 2023](#)). The assets managed by mutual funds may therefore affect their decision to participate in the CRT market. We adapt the liquidity control from [Siani \(2022\)](#), who uses bid-ask spreads as a liquidity proxy in corporate bond demand curve estimation, replacing it with CRT secondary market trading volume given data availability. Together, these controls ensure that the MF–spread relationship is not driven by deal-level differences in ex-ante investor capacity or market liquidity conditions.
- **Housing and economic environment:** We proxy housing market conditions with two variables: house price growth and the change in the 90-day delinquency rate of mortgages held by the GSEs. These variables capture mortgage default risk, which could affect both CRT spreads and mutual funds’ participation decisions. We also include proxies for the prevailing risk-free rate, the Federal Funds Rate and the 10-year Treasury yield, which are fundamental determinants of bond pricing ([Krishnamurthy and Vissing-Jorgensen, 2012](#); [Siani, 2022](#)) and are explicitly incorporated in structural CRT pricing models ([Capponi et al., 2026](#)).

Results. As shown in Table 3, we employ a stepwise strategy, adding one group of risk factors at a time. Each additional group absorbs alternative channels through which spreads could vary, tightening identification by reducing omitted-variable bias. In the most saturated

¹¹See the discussion by Christy Tintle in paragraph 3 on page 2 of CRTCast 5 by Freddie Mac.

specification, we control for a large number of confounding factors that could affect both mutual fund demand for CRTs and issuance spreads. In column (8) of Table 3, identification comes from cross-sectional and time-series variation in mutual fund participation across CRT deals, after controlling for all observable deal-, risk-, market-, and macro-level factors. The goal is to isolate the effect of MF demand on CRT spreads net of other influences, comparing deals that are otherwise similar in risk, structure, and timing, but differ in the degree of mutual fund participation.

In Table 3, the univariate regression of CRT spreads on mutual fund share (column (1)) explains only a small portion of spread variation, with an R^2 of 16.3%. As successive groups of controls are added, deal characteristics, risk composition, time and issuer fixed effects, and market-level variables, explanatory power rises sharply, reaching an R^2 of 92.5% in the fully saturated specification. This improvement indicates that much of the variation in spreads is driven by systematic deal, risk, and macroeconomic factors. Importantly, the coefficient on MF share remains negative and statistically significant at the 5% level throughout, suggesting that deals with higher mutual fund participation consistently exhibit narrower issuance spreads, even after accounting for these confounding influences.

In the most saturated specification, a one-percentage-point increase in mutual fund share corresponds to an estimated 0.981 basis point reduction in spreads, holding other factors constant. This finding suggests that greater participation by mutual funds, typically perceived as relatively stable, price-insensitive investors, contributes to lower funding costs for issuers.

Table C1 reports the coefficients on control variables from Table 3. Column (8), the most saturated specification, shows: (1) larger deals, measured by deal size and mortgage pool size, are associated with higher spreads, consistent with investors requiring compensation for absorbing greater supply; (2) a negative coefficient on the number of mortgages in the pool, reflecting the diversification benefit that reduces credit risk compensation; (3) a positive coefficient on the credit rating, consistent with higher numeric ratings indicating greater credit risk and requiring higher compensation; (4) positive coefficients on the shares of junior tranches (B1 and B2), reflecting higher spreads required to compensate investors for greater exposure to credit losses; (5) a coefficient of 0.939 on the BB corporate bond index spread, significant and consistent with double-B corporate bonds being a close substitute for CRT bonds at the deal level; (6) a positive coefficient on the CRT issuance spread from the previous closing date, showing that recent pricing history influences current CRT pricing; (7) positive coefficients on the Federal Funds Rate and the 10-year Treasury yield, confirming that risk-free rates are fundamental determinants of CRT pricing; (8) a positive coefficient on the change in the 90-day delinquency rate, confirming that CRT spreads capture housing market default risk.

4.2 Comparing Types of Investors

Table 4 presents the estimated relationship between the composition of CRT buyers and deal-level issuance spreads for all investor types, that is, the estimated coefficients of β_1 in specification (1) for each investor type, using the most saturated controls. The results confirm the unique role of mutual funds in CRT spread pricing.

Note that Table 4 includes only one investor type’s share at a time. Each coefficient therefore captures the difference between the effect of that investor type and all remaining investors combined. For example, the coefficient on mutual fund share compares the effect of mutual fund participation on CRT spreads with the combined effect of all other investors, hedge funds, insurers, REITs, sovereign funds, and others. Only the coefficient on mutual funds is negative and significant, confirming that mutual funds price mortgage credit risk differently from all other investor types.

5 Instrumental Variable Identification Strategy

In this section, we explore an alternative identification strategy to isolate the contribution of mutual funds. We instrument the share of purchases by mutual funds with the *number* of mutual fund portfolios participating in each CRT deal, where individual mutual fund purchases are identified through the CRSP mutual fund database¹². The total amount of mutual fund CRT purchases is composed of the number of participating mutual funds (*the extensive margin*) and the purchase amount per mutual fund (*the intensive margin*). In the CRSP mutual fund database, we find that the independent purchasing unit for CRTs is the portfolio¹³. We use the number of portfolios buying CRTs, *the extensive margin*, as the instrument, while retaining the controls, year-quarter fixed effects, and GSE fixed effects specified in equation (1). The intuition for this instrument is that the extensive margin of mutual fund portfolio participation is difficult to predict and appears nearly random within a short horizon, such as a quarter. It therefore provides exogenous variation in mutual fund presence that is plausibly unrelated to other factors driving spreads. We discuss these assumptions below.

Table 1 reports descriptive statistics for the *instrumental variable*. On average, 73 mutual fund portfolios purchase a positive amount in a given CRT deal, with a minimum of 3 and a maximum of 161. Table 5 compares the OLS and IV estimates. The IV coefficient is larger

¹²The CRSP mutual fund database contains only U.S.-domiciled funds; their aggregate purchases from the CRT primary market account for approximately 50% of the entire mutual fund group.

¹³One portfolio can be held by several mutual funds, and one fund can hold several portfolios.

in magnitude than the OLS coefficient. Quantitatively, the instrumented coefficient implies that a one-standard-deviation increase in the mutual fund purchase share of CRTs (14.61%, as reported in Table 2) lowers CRT spreads by 25 basis points, or approximately 8.2% of the average CRT deal spread (307 basis points, as reported in Table 1).

Table C4 reports the first-stage results of the two-stage least squares (2SLS) regression based on equation (1), confirming the relevance of the instrument. The instrument is significantly correlated with the mutual fund share of CRT purchases, and the Kleibergen-Paap F -statistic of 17.87 allows us to reject the null of a weak instrument¹⁴.

Instrument Validity. Denote the instrument as Z_i . The exclusion restriction requires that $\mathbb{E}[Z_i\epsilon_i \mid \mathbf{X}_i, \Theta_q, \Theta_g] = 0$, where \mathbf{X}_i , Θ_q , and Θ_g are the controls and fixed effects specified in equation (1). This assumption implies that, *within a quarter*, the matching between individual mutual fund portfolios and a particular CRT issuance is uncorrelated with unobservable determinants of spreads not captured by the controls and fixed effects. Consequently, the aggregate number of mutual fund portfolios participating in a CRT issuance is orthogonal to spreads, conditional on the observable controls.

We validate this assumption by estimating regressions at the mutual fund portfolio level to understand which factors determine a portfolio’s decision to participate in a given CRT issuance. In addition to the control variables in specification (1), we include dummies for each portfolio’s past CRT purchasing history prior to the current issuance.

We estimate Logit regressions with the following specification at the mutual fund portfolio level:

$$\Pr(D_{i,j} = 1) = \Lambda(\alpha + \beta_1 \text{EverPurchased}_j + \beta_2' \text{PurchasingHistory}_j + \gamma' \mathbf{X}_{i,j} + \Theta_j + \Theta_q + \Theta_g) \quad (2)$$

where $\Lambda(\cdot)$ denotes the logistic CDF, and $D_{i,j}$ is a binary indicator equal to one if mutual fund portfolio j purchases CRT deal i . EverPurchased_j indicates whether portfolio j has ever purchased CRTs in the primary market from a given issuer (Fannie Mae or Freddie Mac). $\text{PurchasingHistory}_j$ is a vector of thirteen dummies indicating whether portfolio j purchased CRTs at each of the past thirteen closing dates from the same issuer.¹⁵ The vector $\mathbf{X}_{i,j}$ collects all remaining covariates: the most recent CRT issuance spread (LastCRTSpread_i); the ICE BofA US Corporate BB index spread (BBSpread_i); deal characteristics and risk composition ($\text{DealCharacteristics}_i$, RiskLayers_i), following the same definitions as in Table 1 and column (8)

¹⁴The critical value of the Stock-Yogo weak identification test at 10% maximal IV size is 16.38.

¹⁵Thirteen issuances are the maximum number of issuances within a year by a single issuer.

of Table 3; portfolio-level assets under management ($AUM_{i,j}$), defined as the sum of AUM across all mutual funds holding portfolio j in the month before the current issuance; CRT secondary market trading volume ($CRTTradingVolume_i$); nominal GDP growth ($NominalGDPGrowth_i$), measured in the quarter preceding issuance; and housing and monetary controls comprising the Federal Funds Rate, the 10-year Treasury yield, nominal house price growth, and the change in the 90-day delinquency rate, all measured in the month before the current issuance. Θ_j , Θ_q , and Θ_g denote portfolio, year-quarter, and GSE fixed effects, respectively. Within this framework, identification comes from variation within a given portfolio, quarter, and issuer.

Table 6 reports goodness-of-fit statistics via the pseudo- R^2 from Logit regressions with progressively saturated controls. Unlike the deal-level regression of CRT spreads on mutual fund shares, adding additional controls does not meaningfully improve the fit: the pseudo- R^2 remains approximately 0.3 throughout, indicating that a large share of variation in portfolio-level participation decisions cannot be explained by deal-level characteristics, market-level variables, or the portfolio’s own purchasing history. This evidence is consistent with mutual fund portfolio participation being largely unpredictable within a quarter, conditional on observable characteristics.

Table C4 reports the coefficients from regression (2). The coefficients on the past six issuance dummies are all positive and significant, suggesting that mutual funds exhibit short-term inertia in CRT purchases, that is, recent participation predicts continued participation over a short horizon. These purchasing history variables could be important inputs for underwriters gauging potential demand, which influences initial price guidance and, in turn, the final issuance spread.

A natural concern is that underwriters observe recent mutual fund participation patterns and incorporate them into initial price guidance, creating a channel through which past participation affects current spreads independently of the instrument. To test this, we add the average number of U.S. mutual fund portfolios participating in the past six issuances within each issuer as a control variable in the instrumented regression of specification (1). Table C5 shows that this control is insignificant and leaves the IV estimate unchanged, ruling out the underwriter price guidance channel and further supporting the exclusion restriction.

A further concern is reverse causality. During the book-building process, mutual funds may withdraw their indications of interest entirely, altering their participation indicator. Table C4 shows that an individual mutual fund portfolio is more likely to participate in a new issuance when the recent CRT spread is higher, suggesting that mutual funds are yield-chasing. This behavior would tend to flatten the estimated demand curve between mutual fund participation and spreads. The fact that the estimate of the OLS is less negative than that of the IV in

Table 5 suggests that mutual funds are much less likely to adjust their orders in response to price changes through the extensive margin than the intensive margin, alleviating the concern of reverse causality.

6 Additional Robustness Checks

We perform robustness checks from two perspectives. First, we demonstrate the importance of mutual fund participation in CRT primary market pricing by incorporating the MF factor into the recent structural pricing model of [Capponi et al. \(2026\)](#). Second, we show that the coefficients on MF share in both the OLS and IV regressions are robust to changes in the estimation sample.

6.1 Adding MF Shares to [Capponi et al. \(2026\)](#)

[Capponi et al. \(2026\)](#) develop a structural model of CRT pricing that accounts for a comprehensive set of risk factors, including risks from government bonds, corporate bonds, aggregate labor income, layoffs, and aggregate house prices. They carefully model the cascade of cash flows with respect to tranche seniority and account for prepayment risk. However, their model does not incorporate the role of investors, particularly mutual funds, in CRT pricing. Our paper adds controls for the same risk factors they consider and emphasizes the additional role of mutual funds.

To verify the role of mutual fund participation in CRT spreads, we regress observed CRT issuance spreads on mutual fund purchase shares, controlling for the model-implied spreads from [Capponi et al. \(2026\)](#):

$$\text{Spread}_i = \alpha + \beta_1 \text{Share}_i^{\text{MF}} + \delta \text{Spread}_i^{\text{Model}} + \epsilon_i \quad (3)$$

[Capponi et al. \(2026\)](#) estimate CRT spreads at the tranche level and focus exclusively on STACR securities issued by Freddie Mac. In specification (3), we follow their estimation convention and conduct the regression at the tranche level. We classify tranches into four groups, M1, M2, B1, and B2, where the M1 group includes tranches A1, M1A, M1B, and M1; the M2 group includes M2 and M3; and the B1 group includes B and B1¹⁶. The subscript i

¹⁶Within each tranche group, we compute the average spread weighted by the issuance amount of the constituent tranches.

indexes CRT deals, but the regressions are estimated separately for each tranche group.

As a comparison, we estimate a series of reduced-form regressions at the tranche group level, including mutual fund share and risk factors analogous to those in the deal-level specification (1), which substantially overlap with the risk factors in Capponi et al. (2026). Specifically, we estimate:

$$\text{Spread}_i = \alpha + \beta_1 \text{Share}_i^{\text{MF}} + \boldsymbol{\gamma}'\mathbf{X}_i + \Theta_q + \Theta_g + \epsilon_i \quad (4)$$

We include tranche-level controls for the attachment point, the detachment point, and the total issuance amount of each tranche group. All other control variables follow the deal-level regression (1).

Table C6 reports the results of both specifications (3) and (4). The goal is to assess whether mutual fund participation remains associated with CRT spreads after accounting for structural risk factors comparable to those in Capponi et al. (2026). The coefficient on MF share is negative and statistically significant for mezzanine tranches in both specifications. The magnitudes are similar across the two approaches, suggesting that the role of mutual fund participation in CRT pricing is not an artifact of omitted risk factors.

6.2 Using the Sample of On-the-Run Deals

On-the-run deals are issued periodically and backed by mortgages with original LTV ratios in the ranges of 60%–80% or 81%–97%. Off-the-run deals are issued occasionally and backed by special collateral, such as mortgages under the Home Affordable Refinance Program (HARP) or specific tranches such as B2¹⁷. Since we already control for the risk composition of CRT deals, the results for mutual fund participation should not differ materially between the full sample and the on-the-run subsample.

Table C7 reports investor share coefficients for the on-the-run subsample using the same specification as Table 4. The coefficient on mutual fund share is -1.045 , close to -0.981 in the full sample. Table C8 shows that the ratio of OLS to IV estimates for MF share is similar to that in Table 5, confirming the robustness of the IV results to this sample restriction.

¹⁷There are 11 off-the-run deals in 2013–2025: 2017-HRP1, 2018-HRP1, 2018-HRP2, 2019-FTR1, 2019-FTR2, 2019-FTR3, 2019-FTR4, and 2019-HRP1 issued by Freddie Mac, and 2019-HRP1, 2020-SBT1-1, and 2020-SBT1-2 issued by Fannie Mae.

7 The Implications of Mutual Fund Participation for Credit Risk Pricing

If the GSEs exit conservatorship, they will need to transfer more credit risk to the private sector than they did pre-conservatorship. In a market system, the pricing of CRTs has important implications for mortgage rates because it determines the guarantee fees (g-fees) that compensate for credit risk. Fluctuations in CRT pricing therefore translate directly into fluctuations in g-fees and, consequently, in mortgage rates. Our paper shows that shocks that alter the composition of mortgage credit risk bearers would affect mortgage rates. This has important implications for the design of the housing finance system: the government may wish to maintain some level of market intervention to prevent price spikes if certain classes of buyers withdraw from the market.

CRT spreads are designed to compensate investors for the default risk embedded in the underlying mortgage pool. We examine how mutual fund participation affects this compensation through a two-step procedure. In the first step, we predict the default rate of each mortgage pool using deal characteristics observed at issuance. In the second step, we regress CRT spreads on the predicted default rate and its interaction with mutual fund participation, isolating whether mutual funds compress the pricing of credit risk relative to other investors.

Step 1:

$$\text{DefaultRate}_i = \alpha + \boldsymbol{\beta}'\mathbf{Z}_i + \gamma \text{Horizon}_i + \Theta_g + \varepsilon_i \quad (5)$$

The regression is estimated at the deal level i , where DefaultRate_i is the cumulative default rate of the mortgage pool of CRT deal i , measured as of October 2025. \mathbf{Z}_i collects deal characteristics and risk composition controls as described in Table 1. Horizon_i is the number of months from deal issuance to October 2025, controlling for the fact that older deals have had more time to accumulate defaults. Θ_g is a GSE fixed effect capturing heterogeneity in mortgage risk across issuers.

Step 2:

$$\text{Spread}_i = \alpha + \beta_1 \widehat{\text{DefaultRate}}_i + \beta_2 \left(\widehat{\text{DefaultRate}}_i \times \text{Share}_i^{\text{MF}} \right) + \boldsymbol{\gamma}'\mathbf{M}_i + \varepsilon_i \quad (6)$$

where $\widehat{\text{DefaultRate}}_i$ is the fitted value from equation (5). The interaction term $\widehat{\text{DefaultRate}}_i \times \text{Share}_i^{\text{MF}}$ captures whether mutual fund participation attenuates the pass-through from predicted default risk to issuance spreads, with $\beta_2 < 0$ indicating compression of credit risk pricing.

The vector \mathbf{M}_i optionally includes bond market controls, potential CRT demand, and housing and economic environment variables as described in Table 1.

Table 7 shows a positive and significant coefficient on the predicted default rate, confirming that investors demand higher spreads for pools expected to experience higher defaults, consistent with rational pricing of credit risk. Quantitatively, a one-standard-deviation increase in the realized default rate (approximately 0.1%) is associated with an increase in CRT spreads of around 70 basis points. However, the negative and significant interaction between predicted default rates and mutual fund share reveals an important economic mechanism: when mutual funds are more involved in a CRT issuance, the sensitivity of spreads to expected defaults is lower. Quantitatively, a one-standard-deviation increase in mutual fund share reduces the pass-through from default rates to CRT spreads by approximately 13 basis points, nearly 20% of the baseline effect of default risk on spreads.

This implies that mutual funds compress the pricing of credit risk: they require smaller risk premiums for riskier pools relative to other investors such as hedge funds or REITs. Economically, this could arise because mutual funds face lower capital constraints, have longer investment horizons, or are evaluated on benchmark-relative rather than absolute returns. Their participation therefore reduces the elasticity of credit risk demand, lowering the cost of transferring mortgage credit risk from the GSEs to the private market.

In equilibrium, greater mutual fund involvement lowers the overall cost of mortgage credit risk transfer, which translates into lower g-fees and, ultimately, lower mortgage rates for borrowers. The investor composition of the CRT market, particularly the share held by mutual funds, thus has direct implications for housing affordability and the stability of housing finance.

We perform a back-of-envelope calculation that maps CRT spreads into g-fees using the cash-flow model of O’Neill (2022), who infers the market-implied g-fee from the difference between scheduled cash flows and CRT market spreads, the latter reflecting the market’s assessment of potential write-downs on the underlying mortgage pools.

Using the implied g-fee series from O’Neill (2022),¹⁸ a univariate regression of the implied g-fee on actual CRT spreads implies that a one-basis-point change in CRT spreads is associated with a change of approximately 0.047 basis points in the credit cost component of the g-fee.¹⁹ Applying this to our estimates, a one-standard-deviation increase in mutual fund par-

¹⁸We use the implied g-fee series from O’Neill (2022).

¹⁹We verify the estimates of O’Neill (2022) against the credit costs implied by CRTs in the Credit Risk Transfer Reports produced by FHFA, which cover the period up to May 2018. A univariate regression of credit costs on actual spreads yields a coefficient of 0.051 using either the FHFA or O’Neill (2022) estimates over the common sample period. Since O’Neill (2022) provides a longer time series of implied g-fees extending to 2022,

ticipation, which implies a 25-basis-point reduction in CRT spreads, would translate into a reduction of approximately 1.2 basis points in the credit cost component of the g-fee. Using the observed average credit risk component of 38.7 basis points (Capponi et al., 2026),²⁰ mutual fund participation alone would account for a difference of approximately 3% in the g-fee.

In 2024, Fannie Mae and Freddie Mac collectively acquired more than \$650 billion of single-family mortgages (FHFA, 2025). If g-fees are linked to CRT issuance spreads, borrowers would save approximately \$78 million annually as a result of mutual fund participation in the CRT market. This saving reflects the impact of mutual funds on the cost of mortgage credit risk transfer—even though, as we showed in Section 4, mutual fund participation is not itself driven by the underlying credit risk of the mortgage pool.

8 Conclusion

This paper studies how investor composition affects the pricing of mortgage credit risk in the Credit Risk Transfer (CRT) market. We show that mutual funds play a central role in this market and that their participation lowers the cost of transferring mortgage credit risk to private investors. In addition, greater mutual fund participation reduces the sensitivity of CRT prices to underlying mortgage default risk, indicating that investor composition influences not only the cost of risk transfer but also how credit risk is reflected in market prices.

These findings have important implications for housing finance policy. Since CRT spreads affect the guarantee fees charged by Fannie Mae and Freddie Mac, changes in investor demand can ultimately influence the mortgage rates paid by households. As a result, the cost of mortgage credit depends not only on the risk characteristics of mortgage borrowers and housing market conditions, but also on the composition of investors participating in the CRT market.

This insight is particularly relevant as policymakers continue to debate the future of the government-sponsored enterprises (GSEs). A central objective of post-crisis housing finance reform has been to increase the role of private capital in bearing mortgage credit risk. Our results suggest that the effectiveness and cost of this risk transfer depend critically on the investor base available to absorb it. If major investor groups reduce their participation because of regulatory changes, shifts in investment mandates, benchmark rebalancing, or fund outflows, the cost of transferring mortgage credit risk could rise even in the absence of changes in underlying mortgage fundamentals.

we use his estimates for the mapping between CRT spreads and g-fees.

²⁰This estimate is consistent with that of Freddie Mac (Freddie Mac, 2017).

More broadly, our findings highlight a channel through which conditions in capital markets can affect housing finance. Efforts to expand private risk sharing may successfully reduce taxpayer exposure, but they also increase the sensitivity of mortgage credit costs to fluctuations in investor demand. Policymakers evaluating the future structure of the housing finance system should therefore consider not only how much risk is transferred to private markets, but also the stability and composition of the investors expected to bear that risk.

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Figures

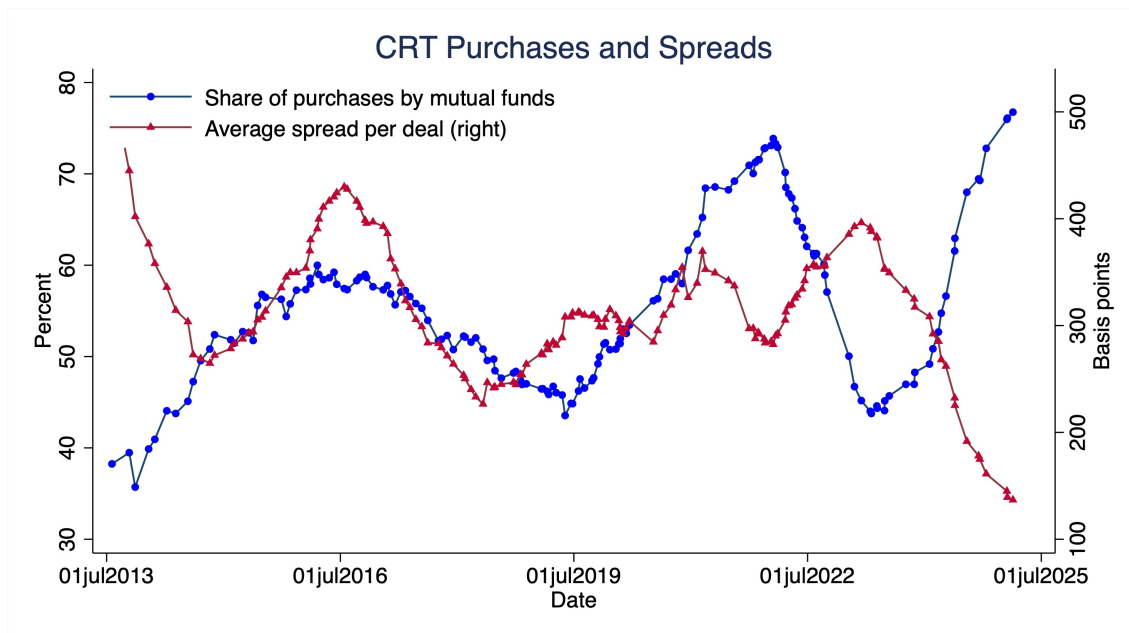


Figure 1. The relationship between CRT spreads and mutual fund shares. This figure displays the time series of CRT spreads and CRT purchasing shares by mutual funds. We take the average of the spreads by closing dates across deals issued on the same date and across issuers, and calculate the purchasing shares by mutual funds relative to the issuance size, both aggregated at closing dates, combining both Fannie Mae and Freddie Mac. To remove short-term volatility, each dot is computed as the moving average of data points across closing dates over the past 364 days and the current closing date.

Tables

Table 1. Summary Statistics of Deal-level Characteristics

	Unit	Obs	Mean	SD	Min	Median	Max
<u>Dependent variable:</u>							
Average Spread	bps	172	306.77	106.56	106.05	300.9	835
<u>Control variables:</u>							
Deal characteristics:							
Deal size	million USD	172	850.25	328.26	111.22	810.71	1,919
Min. credit enhancement	%	172	4.44	0.96	1	4.50	7
Mortgage pool size	million USD	172	31,037	17,367	5,782	28,040	135,141
Call term	years	172	8.44	2.45	5	10	15
Maturity term	years	172	17.72	6.61	10	20	30
Mortgage pool number of loans	count	172	117,118	63,621	32,465	109,638	575,670
Mortgage pool interest rate	%	172	4.27	0.97	2.81	4.19	7.28
Mortgage pool LTV	%	172	82.69	9.05	73.57	75.94	119.89
Mortgage pool FICO	score	172	749.65	6.93	714.3	749.06	766.3
Mortgage pool DTI	%	172	35.02	6.29	0	35.35	71
Numeric credit rating	score	172	13.8	4.0	7.2	14.0	27.0
Risk composition:							
M1 share	%	172	35.20	19	0	28.98	90.95
M2 share	%	172	45.7	18.7	0	47.63	78.72
B1 share	%	172	12.05	9.13	0	13.06	44.44
B2 share	%	172	7.06	14.84	0	0	100
Bond market controls:							
US Corp. BB Index, last month	bps	172	278.02	70.83	169	258	522
CRT deal spread, last closing date	bps	172	308.61	104.41	106.05	301.76	835.00
Potential CRT demand:							
CRT trading volume, last month	billion USD	172	2.74	1.03	0.33	2.73	5.43
MF AUM	billion USD	172	2,029	328	1,361	2,033	2,652
Housing and economic environment:							
House price monthly growth rate, last month	%	172	0.59	0.43	-0.44	0.48	1.79
Chg. in 90D delinquency rate, last month	%	172	-0.01	0.24	-0.68	0.00	2.62
Fed funds rate, last month	%	172	1.5	1.71	0.06	0.84	5.33
10-yr treasury yield, last month	%	172	2.44	0.89	0.62	2.33	4.80
<u>The instrumental variable:</u>							
Number of MF portfolios in a deal	count	172	73	31	3	70	161
<u>Additional variable(s):</u>							
Deal realized default rate	%	171	0.07	0.10	0.00	0.03	0.64

Note: this table displays the summary statistics of variables used in this paper. The variables are measured at the *deal level*, at the closing date of each deal. For variables with "last month", they are measured in the month immediately before the month of the closing date of a deal. Definitions of all variables can be found in Appendix A.5.

Table 2. Share of Purchases at Issuance by Investor Type (%)

	Obs	Mean	SD	Min	Median	Max
Mutual funds	172	55.74	14.61	4.64	55.61	91.42
Hedge funds	172	30.54	12.31	4.68	29.34	83.93
Insurance companies	172	4.70	5.55	0.00	3.29	44.73
REITs	172	4.17	3.70	0.00	3.26	18.20
Sovereign funds	172	3.37	4.88	0.00	2.06	28.25
Banks and credit unions	172	1.15	4.35	0.00	0.00	38.02
Others	172	0.30	0.53	0.00	0.00	2.37

Note: this table displays the summary statistics of purchasing shares by investor type at CRT issuances. The investor shares are obtained from Fannie Mae and Freddie Mac. The details about investors' definitions can be found in Appendix [A.1](#).

Table 3. Mutual Fund Purchasing Shares and CRT Issuance Spreads

	Dependent variable: Average Spread (bps)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MF share	-2.944*** (0.000)	-2.305*** (0.000)	-2.192*** (0.000)	-1.507*** (0.005)	-1.560*** (0.004)	-1.504*** (0.002)	-1.499*** (0.002)	-0.981** (0.032)
<u>Controls</u>								
Deal characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Risk composition	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	No	No	No	Yes	Yes	Yes	Yes	Yes
GSE FE	No	No	No	No	Yes	Yes	Yes	Yes
Bond market controls	No	No	No	No	No	Yes	Yes	Yes
Potential CRT demand	No	No	No	No	No	No	Yes	Yes
Housing and economic environment	No	No	No	No	No	No	No	Yes
R^2	0.163	0.459	0.499	0.887	0.890	0.908	0.909	0.925
No. of observations	172	172	172	172	172	172	172	172

P-values are reported in parentheses, calculated using heteroscedasticity-robust standard errors.

** $p < 0.05$, *** $p < 0.01$.

Note: this table examines the effects of mutual fund purchasing shares on CRT deal-level average spreads by different levels of control saturation. The mutual fund purchasing share measures the percentage share of a CRT deal purchased by mutual funds over the total issuance size of the deal. Column (1) is the simple univariate regression of CRT deal-level spreads and mutual fund purchasing shares. In each of the columns (2) - (8), one group of control(s) is added relative to the set of controls in the column to its left. Column (8) is the fully saturated version, which is also the specification used in the following analysis. The variables in each control group are classified in the same order as those in Table 1. The coefficients of controls are displayed in Table C1. The constant is included in the regression but not displayed.

Table 4. CRT Purchasing Shares by Investor Type and Deal Spreads

	Dependent variable: Average Spread (bps)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MF share	-0.981** (0.032)						
HF share		0.667 (0.196)					
REITs share			2.099 (0.107)				
Sovereign funds share				1.344 (0.229)			
Insurance company share					0.716 (0.490)		
Banks and credit unions share						-0.404 (0.606)	
Others share							8.394 (0.485)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter, GSE FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.925	0.922	0.922	0.922	0.921	0.920	0.921
No. of observations	172	172	172	172	172	172	172

P-values are reported in parentheses, calculated using heteroscedasticity-robust standard errors.

** $p < 0.05$.

Note: this table shows the estimates of specification (1) for different types of investors. The controls are the same set of variables in Column (8) of Table 3. The constant is included in the regression but not displayed.

Table 5. The Causal Impact of Mutual Funds on CRT Spreads

Dependent variable: Average Spread (bps)		
	(1)	(2)
MF share	-0.981** (0.032)	-1.724* (0.088)
One SD increase in MF share (14.6%)	14.3	25.2
Controls	Yes	Yes
Year-quarter, GSE FEs	Yes	Yes
R^2	0.925	0.797
No. of observations	172	172
Estimation method	OLS	IV
Kleibergen-Paap F-statistic		17.87
Stock–Yogo critical value (10% maximal IV size)		16.38
Underidentification P-value		0.000

P-values are reported in parentheses, calculated using heteroscedasticity-robust standard errors.

* $p < 0.1$, ** $p < 0.05$.

Note: this table compares the regression of CRT deal-level issuance spreads on mutual fund shares using OLS versus instrumental variable (IV) methods. The sample, control variables and fixed effects are the same as those Column (8) of Table 3. The constant is included in the regression but not displayed.

Table 6. Decision to purchase a CRT by a mutual fund portfolio

	(1)	(2)	(3)	(4)
Pseudo R^2	0.298	0.312	0.300	0.301
<u>Control variables:</u>				
Dummies of previous CRT purchasing	Yes	Yes	Yes	Yes
Ever purchased CRTs before	Yes	Yes	Yes	Yes
CRT deal spread, last closing date	Yes	Yes	Yes	Yes
BB spread, last month	Yes	Yes	Yes	Yes
Deal characteristics	No	Yes	Yes	Yes
Risk composition	No	Yes	Yes	Yes
AUM	No	No	Yes	Yes
CRT trading volume	No	No	No	Yes
Nominal GDP growth	No	No	No	Yes
Fed funds rate	No	No	No	Yes
10-year treasury yield	No	No	No	Yes
Nominal house price growth	No	No	No	Yes
Chg. in 90D delinquency rate	No	No	No	Yes
Total number of controls	15	29	30	36
Portfolio FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
GSE FE	Yes	Yes	Yes	Yes
No. of observations	136764	135020	119002	119002

Note: this table shows the goodness-of-fit of the Logit regressions of specification (2). The dependent variable is a dummy for whether a mutual fund portfolio has participated in the purchase of a CRT deal from the primary market. For the independent variables, *Dummies of previous CRT purchasing* keep track of whether a portfolio has purchased CRTs in each of the last 13 issuances before the current one, for each issuer. The number 13 is the maximum number of issuances of CRT debt securities that a GSE releases to the market within a year. These dummies are intended to capture the purchasing activities of a mutual fund portfolio in the recent past. *Ever purchased CRTs before* equals 1 if a portfolio has ever purchased a CRT with a particular issuer (Fannie Mae or Freddie Mac) since the debut of CRTs. *CRT deal spread, last closing date* denotes the average CRT spread of a CRT deal by an issuer (Fannie Mae or Freddie Mac) on the most recent closing date. *AUM* denotes the total assets under management held by the mutual funds that own this individual portfolio in the most recent month before the current issuance. *BB spread, last month, Deal characteristics, Risk composition, CRT trading volume, Fed funds rate, 10-year treasury yield, Nominal house price growth, Chg. in 90D delinquency rate* are the same as those in Table 1. *Nominal GDP growth* denotes the annual nominal GDP growth rate in the most recent quarter before a CRT issuance. The number of mutual fund portfolios is 788. The number of year-quarters included in the sample is 47 (2013Q3 - 2025Q1). The number of GSEs is 2: Fannie Mae and Freddie Mac.

Table 7. The Effect of Mutual Funds on CRT Spreads through Default

	Dependent variable: Average Spread (bps)	
	(1)	(2)
Predicted default rate (mortgage pool)	709.65** (0.024)	691.70** (0.042)
Predicted default rate (mortgage pool) ×MF share	-12.60* (0.065)	-12.55* (0.075)
Controls	No	Yes
Year-quarter, GSE FEs	Yes	Yes
R^2	0.658	0.674
No. of observations	171	171

P-values are reported in parentheses, calculated using heteroscedasticity-robust standard errors.

* $p < 0.10$, ** $p < 0.05$.

Note: this table shows the effect of predicted default rates of the mortgage pools of CRT deals, and their interaction with mutual fund participation on the average spread of a CRT deal. The predicted default rates are estimated through an OLS regression on the cumulative default rates of CRT deal mortgage pools, measured by end-of-October, 2025. The regressors in this prediction include deal characteristics at the issuance and risk composition, which are variables in Table 1 under the corresponding categories, and GSE fixed effects. To control for the vintages of loans in different CRT deals, we add a control of the difference of months between the CRT deal closing month and October 2025. The *predicted default rates* are calculated from a linear prediction using coefficients from the OLS regression. The *MF share* in this table is the same as that in Table 2. The controls in column (2) of this table include the U.S. Corporate BB Index, the Federal funds rate, the CRT trading volume, the house price growth, the change in 90-day delinquency rate, and the mutual fund asset under management, all measured at the month before the current issuance of the deal.

Appendix (Not for Publication)

A. Data and Variable Definitions

In this section, we describe our data sources, how we cleaned the data, and the key variables used in our analysis.

A.1 GSE Data

The sample covers all Connecticut Avenue Securities (CAS) and Structured Agency Credit Risk (STACR) securities issued between July 2013 and February 2025, except for four deals. Two of the missing deals are the very first deals issued by each GSE: CAS-2013-C01-G1 by Fannie Mae and STACR-2013-DN1 by Freddie Mac. These are excluded because one variable in regression (1) is the CRT trading volume of each GSE in the previous month, and there was no trading prior to the first issuance by each GSE. The other two missing deals are CAS-2020-SBT1-Group1 and CAS-2020-SBT1-Group2 by Fannie Mae, which lack data on the average interest rates and debt-to-income ratios of the underlying mortgage pools.

Fannie Mae.

(A) For CAS issued by Fannie Mae, the pricing file is called *CAS Pricing*.²¹ The data are listed by deal. For each deal, the data include the deal group (referring to LTV ranges of 60%–80% or 81%–97%), the deal name, the pricing date, the loan acquisition period of the mortgage pool, aggregate principal balance of the mortgage pool, total bond issuance, issuance size by tranche, spreads over benchmark rates (LIBOR, then SOFR since 2021) by tranche, minimum credit enhancement of the deal, credit enhancement by tranche, initial approximate vertical slice retained, and credit ratings for each tranche from up to two rating agencies.

(B) The characteristics of the mortgage pools underlying CAS are from *Fannie Mae Data Dynamics — CAS*. We use the *Deal Relative Profile Comparison* report based on issuance dates from the CAS section. The columns from which we collect data are “Active Loan Count”, “WA FICO”, “WA LTV”, “WA DTI”, and “WA Rate”, which stand for “the total number of active loans at deal issuance”, “the weighted average FICO score, computed as the minimum of the Borrower Credit Score at Origination and the Co-Borrower Credit Score at Origination”, “the

²¹The data are downloadable at: <https://capitalmarkets.fanniemae.com/credit-risk-transfer/single-family-credit-risk-transfer/connecticut-avenue-securities/cas-pricing>.

weighted average loan-to-value ratio at origination, expressed as a percentage”, “the weighted average ratio of total monthly debt expenses to total monthly income of the borrowers at origination or modification”, and “the weighted average original interest rate on the mortgage loans”, respectively.

(C) The investor composition of CAS comes from two sources. The annual tabulation of investors by tranche is obtained from the file *CAS Investor Distribution*. However, it lacks the composition by deal within a year. As a complement, the investor breakdown at the deal level is obtained from the file *CAS Investor Distribution* under “CAS Transactions”. Up to 2020, the deal-level data classifies investors slightly differently from the annual data. For example, the following investor types, money managers, asset managers, mutual funds, endowment foundations, diversified multi-strategy investors, sovereign wealth funds, state or local governments, and pension funds, are all collapsed into a single “asset managers” category. We decompose the deal-level asset managers into money managers, pension/state or local government, and sovereign wealth funds according to their annual shares in the corresponding year from the file *CAS Investor Distribution*.

(D) The 90-day delinquency data for mortgages covered by CAS is obtained from the “Deal Performance Data, Performance Curves” section of *Fannie Mae Data Dynamics -CAS*. Since we measure enterprise-level mortgage market default risk, we obtain the “DLQ90+” measure aggregated across all deals by remittance month.

We also collect the realized default rates of CAS-covered mortgages by deal. We obtain the “Cumulative Default” measure by CAS deal from the “Deal Performance Data, Performance Curves” section. This data covers the cumulative default rate of each deal at monthly frequency from the issuance date to the latest month available.

Freddie Mac.

(A) For STACR issued by Freddie Mac, the pricing file is called *STACR Pricing*.²² The data are listed by deal, with variables including deal closing dates, first payment dates, aggregation periods, call terms, maturity terms, total bond issuance, issuance size by tranche, spreads over benchmark rates (LIBOR, and SOFR since November 2020) by tranche, minimum credit enhancement of the deal, initial credit enhancement by tranche, and credit ratings for each tranche from up to two rating agencies.

(B) The characteristics of the mortgage pools underlying STACR are from *Freddie Mac Clarity - CRT Data Intelligence*. We use the *CRT Origination Characteristics, As of Issuance*

²²The data are downloadable at: <https://capitalmarkets.freddiemac.com/crt/securities/pricing>.

report. The columns from which we collect data are “Loan Count”, “FICO”, “OLTV”, “DTI”, and “Rate”, which stand for “number of loans in the reference pool at deal issuance”, “the average standardized credit score used to evaluate the borrower during loan origination”, “the average ratio of original loan unpaid principal balance to property value”, “the ratio of the borrower’s total monthly debt expense to total gross monthly income at origination”, and “the average mortgage rate of the reference pool”, respectively.

(C) The investor composition of STACR comes from *Freddie Mac Clarity - CRT Data Intelligence*, CRT Investor Participation.

(D) The 90-day delinquency data for mortgages covered by STACR is obtained from the “D90+” series under the “CRT/Charts/ Credit Delinquency” tab in *Freddie Mac Clarity/CRT Data Intelligence*. As with the equivalent CAS measure, we obtain the data aggregated across all deals by remittance month.

The realized default rate of STACR-covered mortgages is obtained from the “Cumulative Default, Basis Points” series under the “CRT/Charts/Credit Event” tab in *Freddie Mac Clarity - CRT Data Intelligence*. As with the equivalent CAS measure, the data cover the cumulative default rate of each deal at a monthly frequency from issuance to the latest month available.

Deal-level data construction. To perform the deal-level analysis, we convert several tranche-level variables to deal-level aggregates, including issuance spreads, investor shares, and credit ratings. The construction of deal-level variables is described in detail in Appendix [A.5](#).

A.2 The CRSP Mutual Fund Database

We identify individual mutual funds that purchased CRTs in the primary market using the Center for Research in Security Prices (CRSP) Survivor-Bias-Free US Mutual Fund Database.

The CRSP Survivor-Bias-Free US Mutual Fund Database records the historical performance of publicly traded open-ended mutual funds. The database was first developed in [Carhart \(1996\)](#) and subsequently inherited by CRSP, which supplemented it with historical data collected from printed sources. From 2007, data back to August 1998 have been provided by Lipper and Thomson Reuters ([CRSP, 2026](#)).

We identify mutual fund portfolio holdings of CRT debt securities by matching the CUSIP of each tranche²³ with those in the *holdings* file of the CRSP Survivor-Bias-Free US Mutual

²³CUSIP codes are obtained from the Bloomberg[®] Terminal.

Fund Database. From this *holdings* dataset, we use the variables “report_dt”, “nbr_shares”, “market_val”, and “crsp_company_key”, which denote “the date of holdings as reported by CRSP’s sources”, “the number of shares of the security held in the portfolio”, “the market value of the security as of the report date”, and “the unique identifier for company information associated with the holdings file”, respectively. The identifier of the *holdings* data is at the mutual fund portfolio level.

To identify primary market purchases by mutual funds from the *holdings* data, we restrict the data to the first record of CRT tranche-level holdings by each portfolio within 90 days²⁴ of a deal issuance. Note that total purchases identified across all portfolios for each tranche cannot exceed its issuance amount. If orders are fulfilled quickly, some holdings recorded close to the 90-day limit may have been acquired in the secondary market. In such cases, we rank all first-time holdings for each tranche by each portfolio by date and retain only the earliest holdings until the aggregate holdings reach the issuance size of the tranche.

The *holdings* data do not explicitly indicate whether a position was acquired in the primary or secondary market. We use the number of shares as the proxy for the value of CRT securities at issuance, rather than the market value in dollars, to avoid potential price deviations between the primary and secondary markets. The two measures are close in scale, implying that in the CRSP mutual fund data the price per share of CRT securities is normalized to \$1.

To connect mutual fund portfolios to fund-level information, we merge the *holdings* data with the *crsp_portno_map* data. Note that one portfolio can be held by several funds, and one fund can hold several portfolios.

Finally, we connect portfolio-level CRT holdings with fund-level total net assets (TNA) using the *monthly_tna* file. Since one portfolio can be held by several funds, we sum the TNA of all funds associated with that portfolio. In cases where multiple portfolios are held by the same set of funds, the TNA associated with each portfolio will be identical. This procedure is intended to capture the total size of the underlying funds supporting each portfolio.

Throughout the paper, we use the term assets under management (AUM) for TNA.

²⁴In CRTcast Episode 5 by Freddie Mac (Freddie Mac, 2022), Mike Reynolds, then Vice President of Credit Risk Transfer, noted that CRTs are generally executed with a one-to-two quarter lag. The 90-day rule used in this paper is therefore conservative. Siani (2022) uses a similar method for corporate bonds.

A.3 TRACE Data

We obtain CRT trading volumes from the Trade Reporting and Compliance Engine (TRACE). We first use CUSIPs to identify CRT transactions. We then replace “1MM+” and “5MM+” in par value trading quantity with 1 million and 5 million, respectively, where the precise volume is not reported. Finally, we sum trading quantities across all tranches and all deals for each GSE per month.

A.4 Other Economic and Financial Data

Federal Reserve Economic Data (FRED). We obtain the monthly average US corporate index option-adjusted spreads at BBB, BB, and C ratings using the series codes BAMLC0A4CBBB, BAMLH0A1HYBB, and BAMLH0A3HYC, respectively. We obtain the monthly Federal Funds Effective Rate using the code FEDFUNDS, and the monthly average market yield on US Treasury securities at 10-year constant maturity using the code DGS10. We obtain quarterly real gross domestic product (GDP) using the code GDPC1 and compute the annual real GDP growth rate as the percentage change over the preceding four quarters.

Federal Housing Finance Agency (FHFA). We obtain the US national-level house price index (HPI) from the *Monthly Purchase-Only Indexes* published by FHFA. We compute the monthly house price growth rate using the seasonally adjusted HPI.

A.5 Variable Definitions

Deal average spread (bps): the average spread of each CRT deal, weighted by the issuance size of tranches within the deal.

Deal size (mil. USD): the total issuance size of a CRT deal, covering all tranches sold to investors, in millions of US dollars.

Min. credit enhancement (%): the share of credit protection over the reference pool provided by the CRT deal.

Mortgage pool size (mil. USD): the unpaid principal balance of the reference pool at the issuance of a CRT deal.

Call term (years): the number of years until the GSE may exercise the call option on the deal.

Maturity term (years): the number of years until the CRT deal matures.

Mortgage pool # loans: the number of loans in the reference pool of a CRT deal.

Mortgage pool interest rate (%): the average mortgage rate of the reference pool, weighted by loan amount.

Mortgage pool LTV: the average loan-to-value ratio of the reference pool, weighted by loan amount.

Mortgage pool FICO: the average credit score of the reference pool, weighted by loan amount.

Mortgage pool DTI (%): the average debt-to-income ratio of the reference pool, weighted by loan amount.

Numeric credit rating: each tranche in a CRT deal is rated by at most two rating agencies: Dominion Bond Rating Service (DBRS),²⁵ Fitch, Kroll Bond Rating Agency (Kroll), Moody's, Morningstar, and S&P. We assign numeric values to ratings across agencies according to the Generic Rating Symbol Mapping by the National Association of Insurance Commissioners (NAIC) 2020, with lower values assigned to better ratings. The numeric assignment is shown in Table C9. For each tranche, we take the simple average of the numeric ratings from the two agencies. The deal-level rating is then computed as the issuance-amount-weighted average of tranche-level numeric ratings.

M1 share (%): the percentage share obtained by summing the issuance sizes of tranches A1, M1A, M1B, and M1 relative to the total issuance size of a CRT deal. Tranche A1 was introduced by Freddie Mac starting with STACR 2023-HQA3. Tranches M1A and M1B were introduced by Freddie Mac from 2022 through STACR 2023-HQA2. In specification (1), the M1 share is omitted to avoid collinearity with the M2, B1, and B2 shares.

M2 share (%): the percentage share obtained by summing the issuance sizes of tranches M2 and M3 relative to the total issuance size of a CRT deal. Tranche M3 appeared in Freddie Mac STACR deals from 2014 to 2016, and in deals STACR 2018-HRP2 and STACR 2019-HRP1.

B1 share (%): the percentage share obtained by summing the issuance sizes of tranches B and B1 relative to the total issuance size of a CRT deal. Tranche B was introduced in Freddie Mac STACR deals from 2015 to 2016, and in Fannie Mae deals from 2016.

B2 share (%): the percentage share of tranche B2 relative to the total issuance size of a CRT deal.

²⁵DBRS was acquired by Morningstar in 2019.

US Corp. BB Index, last month (bps): the option-adjusted spread (OAS) of the ICE BofA US Corporate BB Index, a subset of the ICE BofA US High Yield Master II Index tracking US dollar-denominated below-investment-grade corporate debt publicly issued in the US domestic market. This subset includes all securities rated BB. The ICE BofA OAS is computed as the spread between an OAS index of all bonds in a given rating category and a spot Treasury curve (FRED). In our empirical analysis, this spread is measured in the month before the closing date of a CRT deal.

CRT deal spread, last closing date: for each CRT deal, this variable records the deal-level average spread from the closing date immediately preceding the current one within the same issuer (Fannie Mae or Freddie Mac).

CRT trading volume, last month (bil. USD): CRT trading volume combining all tranches and all deals by issuer in the secondary market, measured in the month before the closing date of the current CRT deal.

MF AUM, last issuance (bil. USD): the aggregate assets under management of all mutual funds that purchased CRTs in the previous issuance relative to the current CRT issuance. There is no double-counting: we count the total net assets (TNA) of each fund only once if any of its associated portfolios participated in a CRT issuance. We then sum TNA across all such funds for each CRT deal issuance.

House price growth, last month (%): the monthly growth rate of the seasonally adjusted house price index published by FHFA, measured in the month before the closing date of a CRT deal.

Chg. in 90D delinquency rate, last month (%): the month-to-month change in the 90-day delinquency rate of the mortgage pool underlying CAS or STACR, measured in the month before the closing date of the current CRT deal.

Fed funds rate, last month (%): the interest rate at which depository institutions trade federal funds (balances held at Federal Reserve Banks) with each other overnight (FRED). In our empirical analysis, this rate is measured in the month before the closing date of a CRT deal.

10-yr Treasury yield, last month (%): the market yield on US Treasury securities at 10-year constant maturity, quoted on an investment basis (FRED). In our empirical analysis, this yield is measured in the month before the closing date of a CRT deal.

Number of MF portfolios in a deal: the number of mutual fund portfolios that participated in a CRT deal issuance, identified from the CRSP mutual fund database as described in Section [A.2](#). A mutual fund portfolio is counted as a participant if it holds a positive number of shares at

issuance for any tranche within the deal.

Annual GDP growth, last quarter (%): the annual growth rate of nominal GDP at quarterly frequency (FRED), measured in the quarter before the closing date of a CRT deal.

Deal realized default rate (%): the realized default rate of each CRT deal, defined as the cumulative default rate as of end-of-October 2025.

B. Additional Figures

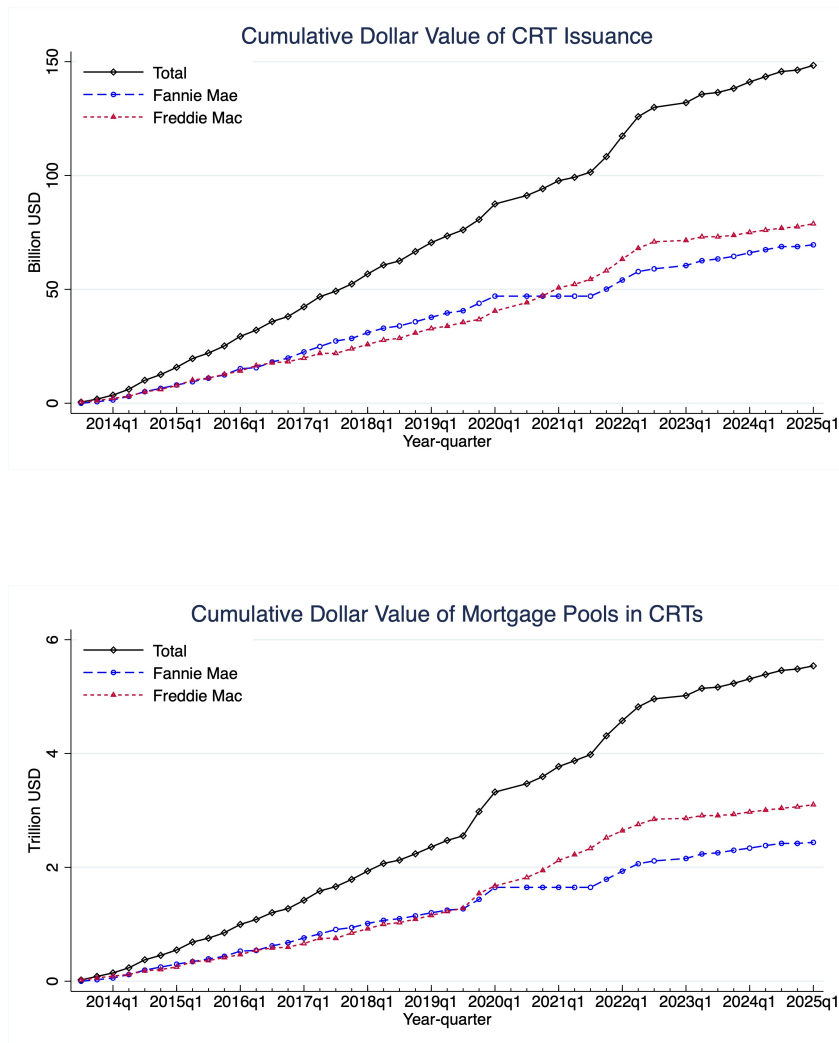


Figure B1. The CRT issuance size and principal balance in mortgage pools covered by CRTs. This figure plots the *cumulative* dollar value of (1) the issuance of CRT bond securities, by Fannie Mae and Freddie Mac, and the total amount of the two GSEs; (2) the principal balance of all mortgages in pools linked to CRTs issued by Fannie Mae and by Freddie Mac, as well as the sum of both. The figure includes all deals issued between July 2013 and February 2025. Data sources are described in Appendix A.1.

C. Additional Tables

Table C1. Coefficients of Controls of Table 3

	Dependent variable: Average Spread (bps)						
	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deal size (mil. USD)	-0.049*	0.004	0.055**	0.055**	0.067***	0.066***	0.072***
	(0.060)	(0.894)	(0.031)	(0.028)	(0.004)	(0.005)	(0.001)
Min. credit enhancement (%)	42.464***	36.341***	-9.004	-15.327	-19.620**	-19.454**	-14.017
	(0.000)	(0.000)	(0.356)	(0.124)	(0.027)	(0.030)	(0.104)
Mortgage pool size (mil. USD)	0.004***	0.004***	0.003***	0.002***	0.002**	0.002**	0.002**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.024)	(0.032)	(0.015)
Call term (years)	-4.932	-0.980	-5.841	-7.910	-7.081	-7.638	-7.564
	(0.150)	(0.808)	(0.325)	(0.184)	(0.201)	(0.179)	(0.152)
Maturity term (years)	2.480**	0.726	2.729**	1.824	0.784	0.782	0.933
	(0.032)	(0.600)	(0.038)	(0.185)	(0.554)	(0.557)	(0.417)
Mortgage pool # loans	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mortgage pool interest rate (%)	-46.528***	-41.577***	6.737	4.185	2.661	2.862	-10.282
	(0.000)	(0.000)	(0.658)	(0.760)	(0.833)	(0.821)	(0.428)
Mortgage pool LTV (%)	-0.643	-0.590	0.696	0.567	0.533	0.513	0.683
	(0.485)	(0.510)	(0.267)	(0.354)	(0.391)	(0.412)	(0.264)
Mortgage pool FICO	0.628	-0.020	-0.709	-1.250	-1.883	-1.614	-0.775
	(0.636)	(0.988)	(0.576)	(0.313)	(0.129)	(0.227)	(0.544)
Mortgage pool DTI (%)	-1.950	-1.626	-0.232	0.177	1.180	1.124	1.127
	(0.267)	(0.316)	(0.845)	(0.879)	(0.396)	(0.426)	(0.409)
Numeric credit rating	6.293**	3.343	0.866	1.574	2.190	2.298	5.569**
	(0.030)	(0.242)	(0.737)	(0.557)	(0.410)	(0.390)	(0.043)
M2 share (%)		0.344	-0.833	-0.741	-0.543	-0.506	-0.408
		(0.597)	(0.202)	(0.259)	(0.346)	(0.385)	(0.477)
B1 share (%)		-1.324*	1.446**	2.206***	2.620***	2.652***	2.585***
		(0.095)	(0.042)	(0.008)	(0.002)	(0.002)	(0.001)
B2 share (%)		2.887**	4.745***	4.817***	5.431***	5.444***	5.390***
		(0.013)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
US Corp. BB Index, last month (bps)					0.872***	0.877***	0.939***
					(0.002)	(0.002)	(0.001)
CRT deal spread, last issuance					0.081	0.093	0.115*
					(0.155)	(0.135)	(0.055)
CRT trading volume, last month (bil. USD)						4.649	5.576
						(0.490)	(0.429)
MF AUM (bil. USD)						0.014	0.027
						(0.824)	(0.598)
Fed funds rate, last month (%)							81.273**
							(0.034)
10-yr treasury yield, last month (%)							71.225**
							(0.017)
House price monthly growth rate, last month (%)							4.314
							(0.851)
Chg. in 90D delinquency rate, last month (%)							40.874***
							(0.007)
Year-quarter FE	No	No	Yes	Yes	Yes	Yes	Yes
GSE FE	No	No	No	Yes	Yes	Yes	Yes
R^2	0.459	0.499	0.887	0.890	0.908	0.909	0.925
No. of observations	172	172	172	172	172	172	172

P-values are reported in parentheses, calculated using heteroscedasticity-robust standard errors.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Note: this table reports the coefficients of control variables from Table 3. The column order matches that of Table 3, omitting column (1). Constants are included in the regressions but not shown.

Table C3. Mutual Fund Types Among CRT Buyers

Fund Type	Share of CRT Purchases (%)
Fixed-Income (FI)	78.19
Equity	2.13
Mixed FI & Equity	8.71
Other	10.97
Total	100

Note: This table shows the investment style breakdown of mutual funds in the CRSP Survivor-bias-free US Mutual Fund Database identified as CRT buyers in the primary market. Each row reports the share of CRT issuance (%) purchased by a given fund type relative to the total purchases by mutual funds in the CRSP database.

Table C4. First Stage: Mutual Fund Share and the Instrumental Variable

	Mutual fund purchase share (%) in each CRT deal
Number of participating portfolios	0.226*** (0.000)
Controls	Yes
Year-quarter FE	Yes
GSE FE	Yes
No. of observations	172
R^2	0.562

P-values are reported in parentheses, calculated using heteroscedasticity-robust standard errors.

*** $p < 0.01$.

Note: the sample, control variables, and fixed effects are the same as those in column (2) of Table 5.

Table C4 . The Coefficients of Variables in Table 6

	Dependent variable: Dummy of purchasing a CRT by a mutual fund portfolio			
	(1)	(2)	(3)	(4)
Ever purchased CRTs before	1.893*** (0.000)	1.907*** (0.000)	1.734*** (0.000)	1.735*** (0.000)
Purchased CRT in issuance $i - 1$	1.103*** (0.000)	1.171*** (0.000)	1.129*** (0.000)	1.127*** (0.000)
Purchased CRT in issuance $i - 2$	0.552*** (0.000)	0.533*** (0.000)	0.510*** (0.000)	0.515*** (0.000)
Purchased CRT in issuance $i - 3$	0.347*** (0.000)	0.347*** (0.000)	0.332*** (0.000)	0.329*** (0.000)
Purchased CRT in issuance $i - 4$	0.266*** (0.000)	0.266*** (0.000)	0.256*** (0.000)	0.269*** (0.000)
Purchased CRT in issuance $i - 5$	0.115*** (0.000)	0.144*** (0.000)	0.139*** (0.000)	0.138*** (0.000)
Purchased CRT in issuance $i - 6$	0.126*** (0.000)	0.103*** (0.001)	0.0999*** (0.002)	0.102*** (0.001)
Purchased CRT in issuance $i - 7$	0.00498 (0.876)	0.00573 (0.860)	0.00784 (0.808)	0.0124 (0.702)
Purchased CRT in issuance $i - 8$	0.00261 (0.935)	-0.0202 (0.537)	-0.0185 (0.568)	-0.0228 (0.483)
Purchased CRT in issuance $i - 9$	-0.00165 (0.960)	0.0164 (0.618)	0.0200 (0.543)	0.0214 (0.516)
Purchased CRT in issuance $i - 10$	0.0174 (0.595)	-0.00804 (0.809)	-0.00267 (0.936)	-0.00140 (0.966)
Purchased CRT in issuance $i - 11$	-0.109*** (0.001)	-0.105*** (0.002)	-0.0981*** (0.004)	-0.0973*** (0.004)
Purchased CRT in issuance $i - 12$	0.0133 (0.691)	-0.00330 (0.923)	0.00659 (0.846)	0.00417 (0.902)
Purchased CRT in issuance $i - 13$	-0.0361 (0.271)	-0.0348 (0.296)	-0.0192 (0.563)	-0.0169 (0.611)
CRT deal spread, last closing date	0.00105*** (0.000)	0.000617*** (0.002)	0.000646*** (0.001)	0.000795*** (0.000)
US Corp. BB Index, last month (bps)	0.231*** (0.001)	0.196** (0.012)	0.201*** (0.010)	0.176** (0.032)
Deal size (mil. USD)		0.000956*** (0.000)	0.000982*** (0.000)	0.000964*** (0.000)
Min. credit enhancement (%)		0.00107 (0.970)	-0.00261 (0.927)	-0.0270 (0.354)
Mortgage pool size (mil. USD)		0.00000133 (0.708)	0.00000109 (0.759)	-0.000000531 (0.881)
Call term (years)		0.0373** (0.031)	0.0355** (0.040)	0.0397** (0.027)
Maturity term (years)		0.000426 (0.929)	0.000200 (0.967)	-0.00226 (0.647)
Mortgage pool # loans		0.000000263 (0.777)	0.000000201 (0.829)	0.000000543 (0.564)
Mortgage pool interest rate (%)		0.151*** (0.001)	0.141*** (0.002)	0.231*** (0.000)
Mortgage pool LTV (%)		-0.00568*** (0.002)	-0.00554*** (0.003)	-0.00554*** (0.006)
Mortgage pool FICO		0.0341*** (0.000)	0.0356*** (0.000)	0.0345*** (0.000)
Mortgage pool DTI (%)		-0.0198*** (0.000)	-0.0202*** (0.000)	-0.0202*** (0.000)

Continued on next page

Table C4 – continued from previous page

	Dependent variable: Dummy of purchasing a CRT by a mutual fund portfolio			
	(1)	(2)	(3)	(4)
Numeric credit rating		-0.0626***	-0.0633***	-0.0742***
		(0.000)	(0.000)	(0.000)
M2 share (%)		0.405**	0.382*	0.345*
		(0.043)	(0.059)	(0.097)
B1 share (%)		0.446	0.499*	0.510*
		(0.108)	(0.075)	(0.070)
B2 share (%)		-0.501*	-0.471*	-0.389
		(0.076)	(0.097)	(0.181)
AUM of the portfolio before this issuance			0.0104***	0.0103***
			(0.000)	(0.000)
CRT trading volume, last month (bil. USD)				0.0000649**
				(0.013)
Annual nominal GDP growth, last quarter (%)				-4.017**
				(0.029)
Fed funds rate, last month (%)				-0.325***
				(0.005)
10-yr Treasury yield, last month (%)				-0.426***
				(0.000)
House price monthly growth rate, last month (%)				-0.164**
				(0.037)
Chg. in 90D delinquency rate, last month (%)				-0.157**
				(0.013)
Portfolio FE	Yes	Yes	Yes	Yes
Year-quarter, GSE FEs	Yes	Yes	Yes	Yes
Pseudo R^2	0.298	0.312	0.300	0.301
Observations	136,764	135,020	119,002	119,002

P-values are reported in parentheses, calculated using heteroscedasticity-robust standard errors.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Note: this table reports the coefficients from the Logit regression of the decision to participate in CRT issuance by a mutual fund (MF) portfolio, as shown in Table 6. The variable *Ever purchased CRTs before* equals 1 if a MF portfolio has ever purchased a CRT deal from a given issuer (Fannie Mae or Freddie Mac), and 0 otherwise. The variables *Purchased CRT in issuance $i-k$* , where $k \in [1, 13]$, indicate whether a MF portfolio purchased shares in issuance $i-k$ relative to the current issuance i , within a given issuer. Definitions of other variables can be found in Appendix A.5. The constant is included but not displayed.

Table C5. Robustness Check: Adding a Control to the IV Regression

Dependent variable: Average Spread (bps)		
	(1)	(2)
MF share	-1.724*	-1.724*
	(0.090)	(0.088)
Ave. # of MF portfolios in past 6 issuances	-0.0156	
	(0.968)	
Estimation method		IV
Kleibergen–Paap F -statistic	17.69	17.87
Underidentification p -value	0.00000550	0.00000555
Controls	Yes	Yes
Year-quarter, GSE FEs	Yes	Yes
R^2	0.797	0.797
No. of observations	172	172

P-values are reported in parentheses, calculated using heteroscedasticity-robust standard errors.

* $p < 0.10$.

Note: this table examines the robustness of the IV regression of CRT deal-level issuance spreads on mutual fund share. The sample, control variables, and fixed effects are the same as those in column (8) of Table 3. Stock-Yogo critical value (10% maximal IV size) equals 16.38. Column (1) adds the average number of U.S. mutual fund portfolios purchasing CRTs in the past six issuances relative to the current one as an additional control. Column (2) replicates column (2) of Table 5. The constant is included but not displayed.

Table C6. CRT spreads at the tranche level

	(1)	(2)	(3)	(4)
Adding MF shares to the model by Capponi et al. (2026)				
MF share	-1.240*** (0.008)	-1.957** (0.013)	-1.167 (0.248)	-5.159 (0.290)
Model spread	36.613** (0.034)	0.304 (0.948)	-1.842 (0.816)	-3.648 (0.882)
Tranche	M1	M2	B1	B2
Year-quarter FE	Yes	Yes	Yes	Yes
R^2	0.960	0.931	0.961	0.839
No. of observations	87	87	64	40
Reduced form regression of CRT spreads on MF shares				
MF share	-0.372* (0.086)	-1.089*** (0.005)	-0.348 (0.360)	-2.750 (0.205)
Tranche	M1	M2	B1	B2
Controls	Yes	Yes	Yes	Yes
Year-quarter, GSE FEs	Yes	Yes	Yes	Yes
R^2	0.950	0.929	0.975	0.944
No. of observations	165	168	129	63

P-values are reported in parentheses, calculated using heteroscedasticity-robust standard errors.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Note: this table shows the impact of mutual funds on CRT spreads at the tranche level. The tranches are classified into four categories: M1 including A1, M1, M1A, M1B; M2 including M2 and M3; B1 including B and B1; and B2. Within each category, the CRT spreads are calculated as the average of sub-tranches weighted by tranche amount; while the mutual fund (MF) share is calculated as the total MF purchases over the issuance size within a certain tranche category. In the upper table, the MF shares are added to the actual STACR spreads by Freddie Mac and model spreads in Table A.3. in the study of Capponi et al. (2026), together with the year-quarter fixed effects. There were no other controls in the upper table. In the lower table, the controls include the attachment points and the detachment points of the tranche categories; the issuance size of the tranche category; the average credit ratings of the tranche category; other *Deal characteristics* as listed in Table 1. We also added the *Potential CRT demand* variables and *Housing and economic environment* variables as listed in Table 1. In terms of the corporate bond selection with similar risk of a particular tranche group, we add BBB US corporate spreads in the regression of M1 tranche; BB spreads in the regression of M2 tranche; and C spreads in the regressions of the B1 and B2 tranches. All corporate spreads are measured in the month before the current issuance.

Table C7. Robustness Check for Only On-the-Run Deals: Average Spread per Deal

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MF share	-1.045** (0.023)						
HF share		0.712 (0.126)					
REITs share			1.666 (0.249)				
Sovereign wealth funds share				1.559 (0.145)			
Insurance company share					0.465 (0.650)		
Banks/credit unions share						-0.399 (0.598)	
Others share							16.557* (0.081)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter, GSE FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.929	0.925	0.925	0.926	0.924	0.924	0.926
No. of observations	163	163	163	163	163	163	163

P-values are reported in parentheses, calculated using heteroscedasticity-robust standard errors.

* $p < 0.10$, ** $p < 0.05$.

Note: this table displays OLS regression results for specification (1) using only on-the-run deals issued from July 2013 to February 2025.

Table C8. Robustness of On-the-Run Deals: OLS and IV Estimations

Dependent variable: average spread per deal		
	(1)	(2)
MF share	-1.045** (0.023)	-2.101* (0.069)
Estimation	OLS	IV
Kleibergen-Paap F -statistic		13.82
Underidentification p -value		0.000
Controls	Yes	Yes
Year-quarter, GSE FEs	Yes	Yes
No. of observations	163	163
R^2	0.929	0.578

P-values are reported in parentheses, calculated using heteroscedasticity-robust standard errors.

* $p < 0.10$, ** $p < 0.05$.

Note: the sample, control variables, and fixed effects are the same as those in Table C7.

Table C9. Credit Rating Crosswalk

Numeric rating	Moody's	S&P	Fitch	DBRS	MorningStar	Kroll
1	Aaa	AAA	AAApre, AAA	AAA, Pfd-1 (high)	AAA	AAA
2	Aa1	AA+	AA+	AA (high), Pfd-1	AA+	AA+
3	Aa2	AA	AA	AA, Pfd-1 (low)	AA	AA
4	Aa3	AA-	AA-	AA (low), Pfd-1	AA-	AA-
5	A1	A+	A+	A (high)	A+	A+
6	A2	A	A	A	A	A
7	A3	A-	A-	A (low)	A-	A-
8	Baa1	BBB+	BBB+	BBB (high), Pfd-2 (high)	BBB+	BBB+
9	Baa2	BBB	BBB	BBB, Pfd-2	BBB	BBB
10	Baa3	BBB-	BBB-	BBB (low), Pfd-2 (low)	BBB-	BBB-
11	Ba1	BB+	BB+	BB (high), Pfd-3 (high)	BB+	BB+
12	Ba2	BB	BB	BB, Pfd-3	BB	BB
13	Ba3	BB-	BB-	BB (low), Pfd-3 (low)	BB-	BB-
14	B1	B+	B+	B (high), Pfd-4 (high)	B+	B+
15	B2	B	B	B, Pfd-4	B	B
16	B3	B-	B-	B (low), Pfd-4 (low)	B-	B-
17	Caa1	CCC+	CCC+	CCC (high), Pfd-5 (high)	CCC+	CCC+
18	Caa2	CCC	CCC	CCC, Pfd-5	CCC	CCC
19	Caa3	CCC-	CCC-	CCC (low), Pfd-5 (low)	CCC-	CCC-
20	Ca	CC	CC	CC (high)	CC	CC
21	C	C	C	CC	C	C
22		D	DDD	CC (low)	D	D
23			DD	C (high)		
24			D	C		
25				C (low)		
26				D		
27	Unrated	Unrated	Unrated	Unrated	Unrated	Unrated

Note: this table reports the numeric value assigned to credit ratings from different rating agencies used in this paper.