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Research Paper

Alternative margin models for mortgage-backed securities

David Li, Roy Cheruvelil and Viktoria Baklanova

US Securities and Exchange Commission, 100 F Street Northeast, Washington, DC 20549, USA;
emails: liyu@sec.gov, baklanovav@sec.gov

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ABSTRACT

Most US mortgages are traded in the form of mortgage-backed securities (MBSs) guaranteed by the US government-sponsored enterprises Fannie Mae and Freddie Mac and the government agency Ginnie Mae. A significant portion of agency MBSs trading occurs in the to-be-announced forward market. Yet, the existing margin models for TBA/MBSs mostly rely on mortgage model suites such as interest rate, prepayment and potentially other macroeconomic models, which makes the modeling process intrinsically complicated from both a model risk perspective and an operational risk perspective. In addition to these complexities, dynamics in the housing market, changes to mortgage regulatory regimes and governmental interventions always make mortgage modeling a challenge (as evidenced historically). In this paper, we conduct a study of margin models for to-be-announced MBSs using common margin frameworks for market risk such as the generalized autoregressive conditional heteroscedasticity (GARCH) t-copula and filtered historical simulation approaches. These are commonly used for other asset classes such as credit default swaps and equity-based markets but have not been widely used in the MBSs market. Such econometric models, which rely solely on market volatility and price

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Corresponding author: V. Baklanova

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return behavior, could potentially be used as a supplemental model framework for to-be-announced MBS margin and stress testing purposes.

Keywords: agency mortgage-backed securities (MBSs); generalized autoregressive conditional heteroscedasticity t-copula (GARCH-t-copula); filtered historical simulation (FHS); fat-tailed distribution; margin model; central clearing counterparties (CCPs).

1 INTRODUCTION

The US mortgage market is characterized by two key features. First, most securitized mortgages carry a credit guarantee (often called "agency mortgage-backed securities (MBSs)") from government housing agencies that protects investors from credit losses in case of defaults on the underlying mortgages.[1] Second, a significant portion of such agency MBSs trading occurs in the to-be-announced (TBA) forward market (see Huh and Kim 2021). In a TBA trade, the seller of the MBS agrees to a sale price but does not specify which particular securities will be delivered to the buyer on settlement day. The precise securities to be delivered are announced only 48 hours prior to settlement, and they are chosen on a "cheapest-to-deliver" basis. The institutional features of the TBA market and their role in supporting the functioning of the US mortgage market are well documented in the growing body of academic literature and industry studies (see, for example, Vickery and Wright 2013). Agency MBSs are considered among the important liquid and safe assets, at par with US Treasury securities, comprising more than US$11 trillion of securities outstanding and nearly US$300 billion in average daily trading volume (see Figures 1 and 2).

Agency MBSs are actively used as collateral in the repo market by a broad range of market participants for various purposes, from financing market-making activity to obtaining leverage and securing investments. For example, in December 2022, market participants provided around US$650 billion of agency MBS collateral in the triparty repo market.[2] Further, agency MBSs receive a low haircut in the liquidity coverage ratio requirement of Basel III and play a role in the implementation of US monetary policy.[3]

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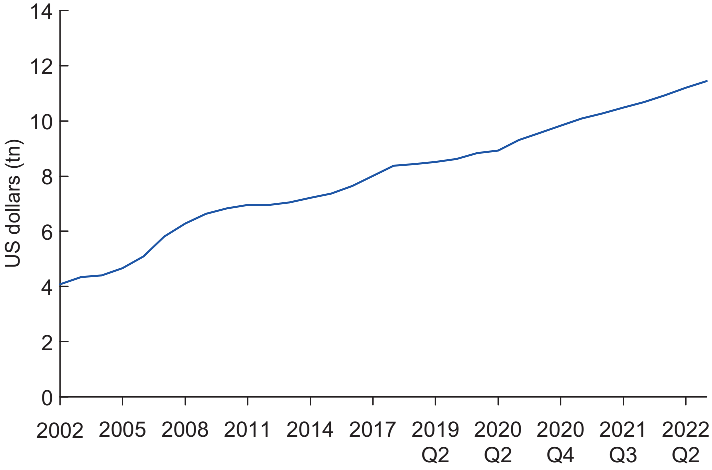
[1] In this paper the term "agency MBSs" refers only to securities issued by Freddie Mac and Fannie Mae or guaranteed by Ginnie Mae and backed by residential properties. Since June 3, 2019, Freddie Mac and Fannie Mae have offered uniform MBSs (UMBSs) to standardize and simplify MBSs issuance.

[2] URL: www.newyorkfed.org/data-and-statistics/data-visualization/tri-party-repo#interactive/volume.

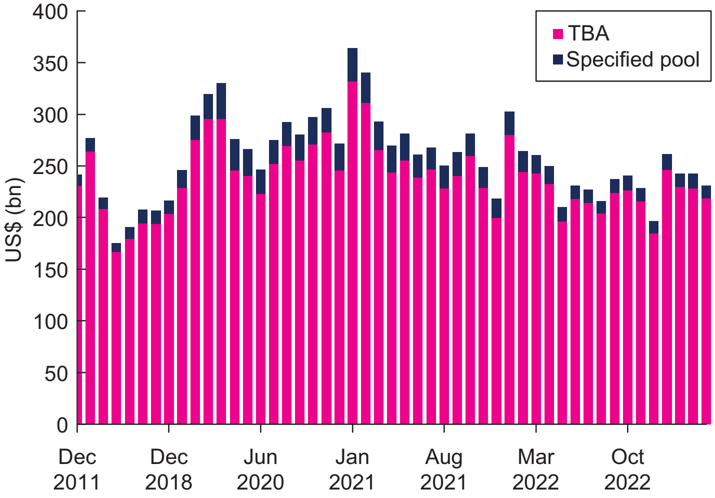
[3] URL: www.newyorkfed.org/markets/domestic-market-operations/monetary-policy-implementation/agency-mortgage-backed-securities.

FIGURE 1 US agency MBSs outstanding.



Source: the Securities Industry and Financial Markets Association (SIFMA), derived from federal agencies (Freddie Mac, Fannie Mae, Ginnie Mae, National Credit Union Administration and Federal Deposit Insurance Corporation), Bloomberg, Dealogic, Thomson Reuters. URL: www.sifma.org/resources/research/us-mortgage-backed-securities-statistics/.

FIGURE 2 Trading volume of US MBSs for TBA and specified pools.



Source: SIFMA, calculated from the Financial Industry Regulatory Authority trade reporting and compliance engine. URL: www.sifma.org/resources/research/us-mortgage-backed-securities-statistics/.

The liquidity of the agency MBSs market is largely attributed to a standardized TBA contract that concentrates trading of heterogeneous MBSs into a smaller number of thickly traded TBA contracts. For example, a TBA contract specifies only that a delivered agency MBS must consist of 30-year fixed-rate mortgages and pay a specific coupon, known as a coupon cohort. Similar cohort trading with delivery flexibility is also used in other markets, such as Treasury futures and commodity futures. Since it was first introduced a few decades ago, the TBA market has grown significantly, with TBA trading volumes substantially surpassing specified pool MBS trading (see Figure 2).

As mentioned above, the credit risk of agency MBSs is limited because they are guaranteed by the US government. However, investing in agency MBSs is still subject to duration, prepayment and liquidity risks. In addition, due to the forward-settling nature of the TBA contract, it exposes both sides of the trade to a meaningful counterparty risk, which is the risk that a counterparty is unable or unwilling to meet its contractual obligations. One way of mitigating the counterparty credit risk is by posting collateral (or margin) to compensate the nondefaulting party for the change in the market value of the securities in case of default. For example, the posting of margin is a common practice in the trading of agency MBSs between members of the Mortgage-Backed Securities Division (MBSD) of the Fixed Income Clearing Corporation (FICC).[4] While the FICC's margining methodology is governed by its rule book, margining practices are less transparent in bilateral trading between dealers and customers that are not MBSD members. To the extent that such trading is insufficiently margined, it can pose significant counterparty risk and, in case of default, potentially transmit losses to a broad array of market participants.[5]

The objective of this paper is to study margin models for TBA/MBSs using some common econometric-based margin models. These models, namely, the generalized autoregressive conditional heteroscedasticity t-copula (GARCH-t-copula) (see, for example, Cont and Kan 2011) and filtered historical simulation (FHS) (see, for example, Gurrola-Perez and Murphy 2015), which largely rely on market volatility and risk factor price return behavior, could potentially be used by a wide range of market participants as one of their model frameworks for TBA/MBSs margin and stress testing purposes. These approaches have been developed and refined for other assets such as credit default swaps, equity options and equities since the global financial crisis of 2007–9. Over the past two decades various volatility estimators have also been widely and comprehensively studied, and sophisticated models, such as varieties of multivariate GARCH or stochastic volatility have been built to account for

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[4] The MBSD clearing rules are available at www.dtcc.com/legal/rules-and-procedures.aspx.

[5] This research is not an attempt to advocate for or promote a specific margin model or methodology for use by any clearing counterparty; rather, it explores an alternative approach to thinking about risks associated with MBSs and other related products.

volatility clustering and heteroscedasticity. At the multivariate level, the GARCH-t-copula approach provides either a dynamic parametric estimator (eg, GARCH-DCC) or a static parametric estimator (GARCH-CCC)[6] for correlation (Li and Cheruvelil 2019; Ivanov 2017), whereas FHS essentially leaves the correlation scheme to the spot historical comovements.

Our data for model fitting and backtesting comprises several data sets (see Section 4 for more details). First, we examine 11 historical time series of UMBSs TBA with different coupon stacks: from 2% to 7% with 0.5% increments. MBSs can be structured with different coupon levels because the mortgages underlying an MBS may have different loan rates due to the timing of loan origination dates or other factors. The benchmark TBA contract is the so-called current coupon, a synthetic 30-year fixed-rate MBS that interpolates to a price of par. Second, we use data series tracking the historical performance of the S&P US Mortgage-Backed Securities Index (S&P US MBS Index) and share price series of the Vanguard Mortgage-Backed Securities Exchange-Traded Fund (VMBS ETF).[7] Lastly, we analyze the Bloomberg (BBG) US MBS Index, which provides unhedged total return values. All these data sets provide daily observations and cover multiyear periods including recent episodes of extreme market volatility such as the onset of the Covid-19 pandemic in March 2020, Fed rate hikes beginning in 2022 and the regional bank crisis of March 2023.

The remainder of this paper is organized as follows. In Section 2 we discuss the related literature. In Section 3 we describe the general framework for modeling the multivariate distribution for MBSs. In Section 4 we provide details on model fitting and estimation results as applied to various MBS time series, while in Section 5 we describe the modeling approach in greater detail. In Section 6 we describe portfolio margin generation for the backtesting results. In Section 7 we provide the results from the backtesting of the model, including procyclicality analysis. In Section 8 we state our conclusions.

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[6] Here DCC denotes dynamic conditional correlation and CCC denotes constant conditional correlation.

[7] The S&P US MBS Index is a rules-based, market-value-weighted index covering US-dollar-denominated, fixed-rate and adjustable-rate/hybrid mortgage pass-through securities issued by Ginnie Mae, Fannie Mae and Freddie Mac. The VMBS ETF tracks the performance of the Bloomberg US MBS Float Adjusted Index, which covers US MBS pass-through securities issued by Ginnie Mae, Fannie Mae and Freddie Mac. To be included in the index, pool aggregates must have at least US$1 billion currently outstanding and a weighted average maturity of at least one-year market-weighted MBS index (Vanguard 2023).

2 RELATED LITERATURE REVIEW

Our results contribute to the existing literature in several ways. First, we contribute to the literature that examines the structure and institutional features of the MBS TBA market. Vickery and Wright (2013) described the TBA market and the mechanics of a TBA trade and presented evidence suggesting that the liquidity associated with TBA eligibility increases MBS prices and lowers mortgage interest rates. Bessembinder *et al* (2013) analyzed trading costs for various structured products, including MBSs, and found these costs to be lower for TBAs. Gao *et al* (2017) studied parallel trading in a TBA market and a specified pool MBSs market and found that MBS TBA eligibility enhances the trading liquidity of specified pools. Huh and Kim (2022) quantified the impact of the TBA trading structure on mortgage rates and concluded that a liquid TBA market lowers mortgage rates. However, Huh and Kim (2021) also found that despite improved trading liquidity, the adverse selection of mortgage loans can limit the liquidity benefit of the TBA structure. More recently, Fuster *et al* (2022) highlighted the use of the TBA market as a funding vehicle through the execution of "dollar roll" transactions.[8] Liu *et al* (2021) studied a change in the MBSs market design called the Single Security Initiative, which in June 2019 consolidated MBS issuance by the US government housing agencies Fannie Mae and Freddie Mac into a single market. They found that the Single Security Initiative eliminated the liquidity disadvantage of Freddie Mac, a smaller agency, without any noticeable negative effect on the liquidity of Fannie Mae, a larger agency, resulting overall in better liquidity for the MBSs market. We add to this literature by looking at the use of TBA MBS assets in the context of central clearing, in which margining and collateral practices play a major role. This is one of the first papers to consider alternative margin models that rely solely on market volatility and return behavior for this asset class.

Second, we provide an additional contribution to the growing body of studies on financial risk management practices in central clearing counterparties (CCPs). Since the global financial crisis of 2007–9, CCPs have assumed a major role in global financial markets (see Koeppl and Monnet 2010; Norman 2011). In 2012, the CPMI and IOSCO published their "Principles for Financial Market Infrastructures" (Committee on Payment and Settlement Systems–Technical Committee of the International Organization of Securities Commissions 2012) and in 2017, followed up with additional CCP resiliency guidance (Committee on Payments and Market Infrastructures–Board of the International Organization of Securities Commissions

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[8] In a dollar roll, TBAs for a coming delivery month are sold and TBAs for a later month are purchased simultaneously. This provides short-term funding to the seller by postponing the date on which the payment for the long TBA position is due.

2017).[9] Despite significant improvements in CCP resiliency following the publication of the principles, market volatility in the wake of the Covid-19 pandemic highlighted areas of potential weakness, particularly around margin call mechanics and their effects on systemic stability (Financial Stability Board 2020). In 2022, the Basel Committee on Banking Supervision, the CPMI and IOSCO conducted an in-depth analysis of margining practices and proposed further work to better understand the degree and nature of CCP margin models' responsiveness to volatility and other market stresses (Basel Committee on Banking Supervision–Committee on Payments and Market Infrastructures–Board of the International Organization of Securities Commissions 2022). These reports by the international standard-setting bodies provide a high-level view of the existing practices, but more work is needed, particularly regarding the application of margin to specific assets classes.

Regarding the agency MBSs in particular, in 2012 the Treasury Market Practices Group recommended that forward-settling transactions, such as TBAs, be margined in order to prudently manage counterparty exposures (Treasury Market Practices Group 2012). Following this recommendation, in 2016 the Financial Industry Regulatory Authority amendment to Rule 4210 (margin requirements) established margin requirements for TBA transactions (Financial Industry Regulatory Authority 2016). Amid these regulatory developments, market participants and CCPs have used an array of approaches to calculate margin requirements.[10] The current common margin modeling approaches typically involve the direct use of mortgage-related models, such as the interest model, the current coupon model and the prepayment model, or the outputs from such models (eg, sensitivity data such as option-adjusted duration, option-adjusted spread, convexity, etc). Due to the complex nature of these models, the margin models built on top of them generally require significant resources to be developed and maintained on an ongoing basis. This paper offers an alternative or supplemental model framework for to-be-announced MBS (TBA/MBS) margin and stress testing purposes. It is outlined below.

To compute the value-at-risk (VaR) for MBSs or TBA/MBSs, common practice is typically to generate projective scenarios of market conditions. Broadly speaking, there are two ways to derive this set of scenarios:

(1) we can project future market conditions using a Monte Carlo simulation framework;

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[9] The latter report focuses on five key aspects of a CCP's financial risk management framework: governance, stress testing for both credit and liquidity exposures, coverage, margin and a CCP's contribution of its financial resources to losses.

[10] The TBA market is a US market and there is only one CCP clearing the market, FICC; thus, there is limited consensus or best practice around CCP margin models in this area (Fixed Income Clearing Corporation 2023).

(2) we can project future market conditions using historical (actual) changes in market conditions.

The first approach typically involves employing interest rate and prepayment models to simulate various interest paths where prepayment speed along each path can be calculated. In this type of approach, a straightforward full valuation approach is typically computationally intensive. An alternative is to use a delta-normal or delta-gamma sensitivity approach, in which only interest rates are simulated (Han *et al* 2007).[11] The historical simulation approach projects future market conditions by using actual (observed) n-day changes in market conditions over the lookback period.[12] This approach allows the VaR scenarios to account for natural changes in correlation under extreme market moves, such as occur during a flight-to-quality, where risky assets tend to underperform risk-free assets and move in a highly correlated manner. Generally, there are two methods employed to calculate VaR under this framework:

(1) a Taylor approximation of profit and loss (P&L) for each instrument, sometimes called "sensitivity VaR" or "delta-gamma";

(2) a full revaluation of each instrument using its market-accepted technique (ie, pricing model) for valuation.

Both of these methods use the current pricing scheme to reevaluate historical market risk factor (eg, interest rate) moves; the only difference is how the price (or the price change, to be exact) is calculated from an MBS pricing model or estimated via a sensitivity approach. The former uses a sensitivity approach to approximately emulate price, whereas the latter has to rely on a pricing model that typically includes interest rate and prepayment models to reevaluate these historical scenarios. Regardless of whether the pricing scheme uses a sensitivity approach or a full valuation approach, these VaR approaches both need a complete mortgage model suite either directly (full valuation) or indirectly (sensitivity approach).

This paper fills this critical gap by applying a consistent and coherent model framework: specifically, the GARCH-t-copula and FHS approach, which relies solely on TBA/MBSs' market volatility and return behavior and could potentially be used as a supplemental model framework for margin and stress testing purposes.

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[11] The delta-normal and delta-gamma sensitivity approaches, or indeed general sensitivity approaches based on the Taylor expansion, are quite common VaR estimation approaches in the industry.

[12] For TBA/MBSs or general MBSs the liquidation horizon is three days.

3 MODELING THE MULTIVARIATE DISTRIBUTION FOR MORTGAGE-BACKED SECURITIES

3.1 The univariate autoregressive GARCH model framework

The MBS price log return over a time interval Δt is defined as

$$X_{i,t} = \ln \frac{P_{i,t}}{P_{i,t-\Delta t}},$$

where P_t is the MBS price observed at time t.

The autoregressive GARCH (AR-GARCH) framework takes the following general form:

$$\begin{aligned}
X_{i,t} &= \sum_{l=1}^{L} a_{i,l} X_{i,t-l} + \varepsilon_{i,t}, \\
\varepsilon_{i,t} &= \sigma_{i,t} \epsilon_{i,t}, \\
\sigma_{i,t}^2 &= c_i + \sum_{m=1}^{q} a_{i,m} \varepsilon_{i,t-1}^2 + \sum_{n=1}^{p} \gamma_{i,n} \sigma_{i,t-1}^2, \quad i = 1, \dots, k.
\end{aligned}$$

With consideration of model sufficiency and parsimony, our model implementation follows an AR(1)-GARCH(1, 1) model framework for univariate modeling of an MBS price time series. The AR(1) process follows

$$X_{i,t} = a_i X_{i,t-1} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} = \sigma_{i,t} \epsilon_{i,t}, \tag{3.1}$$

where a_i is the autocorrelation coefficient, $\sigma_{i,t}$ is volatility and $\epsilon_{i,t}$ is a standardized residual with unit variance; i stands for any risk factor;

$$\begin{aligned}
E[(\epsilon_{i,t})] &= 0, \\
E[(\epsilon_{i,t}^2)] &= 1;
\end{aligned}$$

and σ_t follows a GARCH(1, 1) process:

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \gamma_i \sigma_{i,t-1}^2, \tag{3.2}$$

where ω is a dummy constant, and where α_i and γ_i are two GARCH model parameters that follow Nelson and Cao (1992) restrictions (ie, $\alpha_i + \gamma_i < 1$). The conditional distribution of the standardized residuals (or innovations) is calculated as

$$\epsilon_{i,t} = \frac{\varepsilon_{i,t}}{\sigma_{i,t}} \,\bigg|\, \Psi_{i,t-1},$$

where ϵ_t is modeled by a symmetric Student t distribution with the degrees of freedom (DoF) estimated by maximum likelihood using a historical time series.

3.2 The Student t and FHS frameworks

For the Student t copula and multivariate Student t distribution, we refer the reader to the online appendix, and for a detailed description of the FHS model framework, we refer the reader to Gurrola-Perez and Murphy (2015).

4 MODEL FITTING AND ESTIMATION RESULTS

4.1 MBS price time series

For modeling purposes, we consider daily observations of the various MBS price time series. These include (see Table 1 and Figure 3)

- individual UMBSs TBA with various coupon stacks, from January 2019 to April 2023;[13]
- a TBA current coupon time series obtained from Bloomberg, calculated using Bloomberg's prepayment and pricing models;
- an MBS index or ETF (seasoned MBS as well as TBA), from October 2017 to October 2022 sourced from Yahoo! Finance; and
- the Bloomberg MBS Index (only TBA) data from Bloomberg for January 2008 to October 2022.

Table 1 shows that in all cases the means are very small and effectively close to zero, which indicates a centered mean-reverting process over the long term. UMBSs show various levels of skewness depending on the coupon; the UMBS with the highest coupon (7%) and the Vanguard MBS ETF (VMBS) series appear highly skewed. On the other hand, the iShares MBS ETF (MBB) and Bloomberg US MBS Float Adjusted Indexes (BBG MBS) have relatively small skewness, indicating a more symmetrical distribution. Both the VMBS and the MBB series have relatively large kurtosis, indicating heavy tails and more outliers.

4.2 Univariate model estimates (AR-GARCH-Student t)

Univariate calibration is based on $\mathrm{AR}(1,1)$, $\mathrm{GARCH}(1,1)$ and Student t innovation. The residual after AR component is calibrated simultaneously using the maximum likelihood method.

Tables 2 and 3 show the following results for both the individual TBAs and TBA/MBS indexes or ETFs:

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[13] We use the pricing source "BGR" and the function "LAST_PX", which represents the end-of-day consensus price derived by Bloomberg from pricing quotations provided by various pricing agents and deemed to be reliable. If, on a given day, no reliable quotations are provided, the consensus price is not calculated.

TABLE 1 Summary statistics of various MBS time series.

Name	Mean	Min	Max	SD	Skewness	Kurtosis
UMBS 1.5[a]	–0.000136	–0.027	0.034	0.0046	0.223	5.85
UMBS 2[b]	–0.000110	–0.026	0.029	0.0044	0.084	5.06
UMBS 2.5	–0.000085	–0.026	0.028	0.0041	–0.009	5.94
UMBS 3	–0.000078	–0.024	0.029	0.0036	0.124	8.78
UMBS 3.5	–0.000068	–0.022	0.026	0.0032	0.135	10.19
UMBS 4.5	–0.000053	–0.019	0.023	0.0025	0.489	14.25
UMBS 5.5	–0.000044	–0.013	0.018	0.0018	0.464	15.25
UMBS 6	–0.000049	–0.013	0.014	0.0024	0.169	9.69
UMBS 6.5	–0.000039	–0.014	0.014	0.0024	0.044	13.19
UMBS 7[c]	–0.000036	–0.015	0.030	0.0029	1.180	17.40
SPY MBS Index	–0.000030	–0.018	0.020	0.0032	–0.630	15.38
VMBS ETF	0.000210	–0.009	0.013	0.0018	1.837	20.29
MBB	–0.000018	–0.032	0.031	0.0031	–0.267	23.53
BBG MBS Index I	–0.000080	–0.020	0.019	0.0021	–0.270	11.44
BBG MBS Index II	–0.000090	–0.021	0.013	0.0020	–0.350	11.53

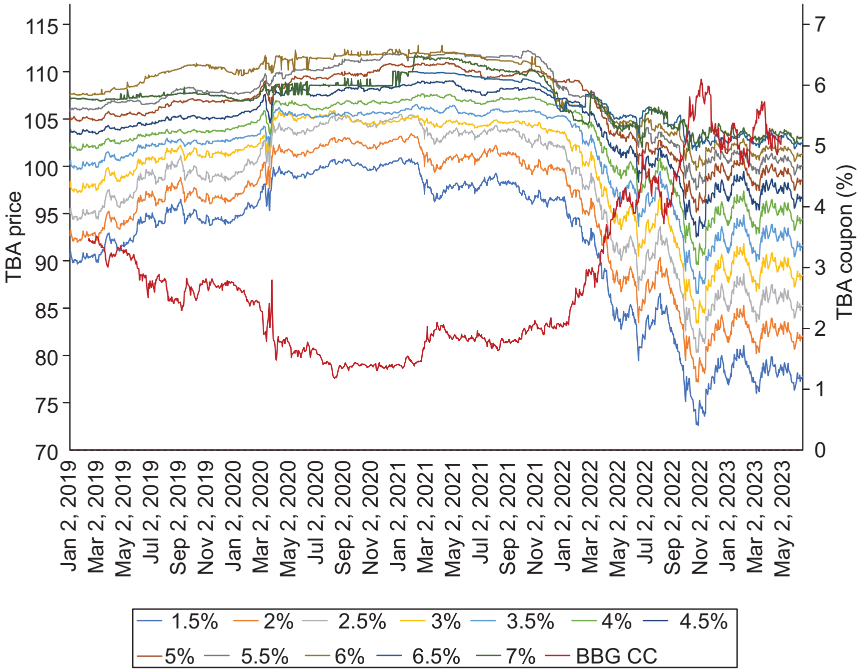
[a] Data started on January 25, 2021. [b] Data started on January 25, 2021. [c] Data started on February 12, 2020. The rest of the time series are imputed. SD, standard deviation. *Source:* data from Bloomberg and Yahoo! Finance (see the text for more details).

- All model parameters are statistically significant.
- Some instruments (eg, TBA high coupon stacks 6%, 6.5% and 7%) exhibit strong autocorrelation (ie, $\alpha > 20\%$).
- Some instruments (such as TBA high coupon stacks (more than 4%) exhibit fat tails; as a reference, VIX's DoF is approximately 4.43 using the same calibration method.
- The TBAs and MBS indexes or ETFs typically exhibit low autocorrelation and slightly fat tails.

It can be seen from Figure 4 that the average DoF of the TBAs and MBS indexes and ETFs (around 6.3) is close to the average of the TBA coupons 2.5%, 3% and 3.5%, indicating that the composition of most of these indexes or ETFs might still be dominated by the low-coupon MBSs originating in the low-interest regimes before 2022.

Low coupons tend to have relatively high DoF, whereas high coupons tend to have low DoF, indicating that these high coupons (in the money (ITM) most of the time during various interest regimes) tend to have fatter tails, which may be related to the more pronounced embedded optionality.

FIGURE 3 TBA price and current coupon time series (January 2, 2019 to May 23, 2023).



Source: data from Bloomberg and Yahoo! Finance (see the text for more details).

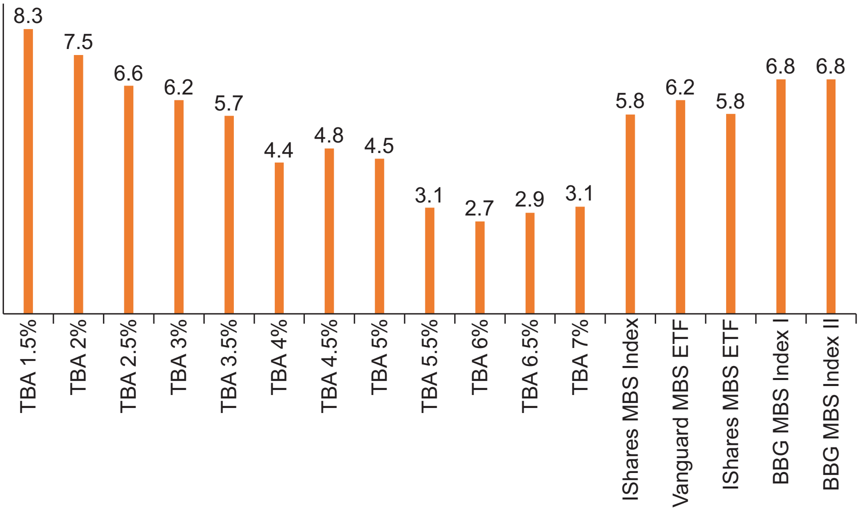
TABLE 2 TBA all coupons univariate model parameters.

Model parameters	α	v	α_0	α_1	γ_1
TBA 1.5%	−0.010	8.3	0.0000000780	0.1276	0.8690
TBA 2%	−0.017	7.5	0.0000000735	0.1262	0.8705
TBA 2.5%	−0.005	6.6	0.0000000765	0.1318	0.8646
TBA 3%	−0.008	6.2	0.0000000273	0.1229	0.8751
TBA 3.5%	0.010	5.7	0.0000000159	0.1294	0.8689
TBA 4%	0.010	4.4	0.0000000114	0.1080	0.8831
TBA 4.5%	−0.006	4.8	0.0000000114	0.1246	0.8735
TBA 5%	−0.008	4.5	0.0000000129	0.1253	0.8622
TBA 5.5%	−0.041	3.1	0.0000000207	0.2445	0.7521
TBA 6%	−0.281	2.7	0.0000000233	0.5480	0.4517
TBA 6.5%	−0.285	2.9	0.0000000221	0.5310	0.4636
TBA 7%	−0.258	3.1	0.0000000532	0.3829	0.6058

TABLE 3 TBA/MBS index or ETF univariate model parameters.

Name	Parameter	Estimate	Standard error	t value	Pr > $\|t\|$
MBB	α	−0.038			
	υ	5.78	0.02	8.36	< 0.0001
	α_1	0.13	0.02	8.08	< 0.0001
	γ_1	0.86	0.02	52.27	< 0.0001
VMBS	α	−0.037			
	υ	6.20	0.02	7.97	< 0.0001
	α_1	0.18	0.03	7.09	< 0.0001
	γ_1	0.80	0.02	32.88	< 0.0001
BBG MBS I	α	0.041			
	υ	6.792	0.0124	11.84	< 0.0001
	α_1	0.098	0.0082	11.86	< 0.0001
	γ_1	0.901	0.0083	108.47	< 0.0001
BBG MBS II	α	0.039			
	υ	6.799	0.0125	11.80	< 0.0001
	α_1	0.097	0.0083	11.81	< 0.0001
	γ_1	0.901	0.0083	108.23	< 0.0001

FIGURE 4 Calibrated DoF from t distribution for both individual TBAs and TBA/MBS indexes and ETFs.



5 MODELING APPROACH

5.1 Individual TBAs

There are generally two approaches to modeling individual TBA time series using historical market prices without relying on complicated mortgage-related model suites such as interest rate, prepayment and other macroeconomic models.

(1) The first approach is to use the price time series with the same coupon consistently through the historical periods regardless of different interest regimes.

(2) Given the optionality embedded in the TBA/MBS products, the second approach is to construct a synthetic moneyness time series (ie, a current coupon time series and all other ITM and on the money (OTM) moneyness time series) with fixed spread intervals (eg, 50bps).[14]

The first approach is generally acceptable if the interest regimes remain relatively stable over the whole lookback period, and if the future interest environment looks similar to the historical one. As history has shown, this assumption is very restrictive and holds true only for a particular lookback period. In this paper we perform the analysis for both approaches, and our findings are compared in the online appendix. The results show that the first approach generally incurs considerably more breaches than the second, especially for long positions. This is due mainly to the rapid interest regime changes since 2022 Q1, which invalidate the assumption needed for the first approach to be viable. Hence, this paper focuses more on the second approach.

5.1.1 Synthetic moneyness time series

Due to the optionality embedded in MBSs, the same TBAs could be classified as OTM, at the money (ATM) and ITM at different points in time depending on various historical interest regimes, and, subsequently, the price behavior could be vastly different (eg, compare a plain vanilla Treasury bond with an MBS that has negative convexity). Take, for example, a 4% MBS that was ITM throughout the whole Covid period, ATM in summer 2022 and OTM from the summer of 2022 to the present. From a price perspective, an MBS would have experienced a premium price (ie, more than 100), par price and discount price (ie, less than 100). An MBS with an ITM option that is subject to prepayment behaves very differently from one with an OTM option, which behaves more like a plain vanilla bond. To solve this problem, a series of moneyness time series (eg, current coupon, and current coupon +50bps) can

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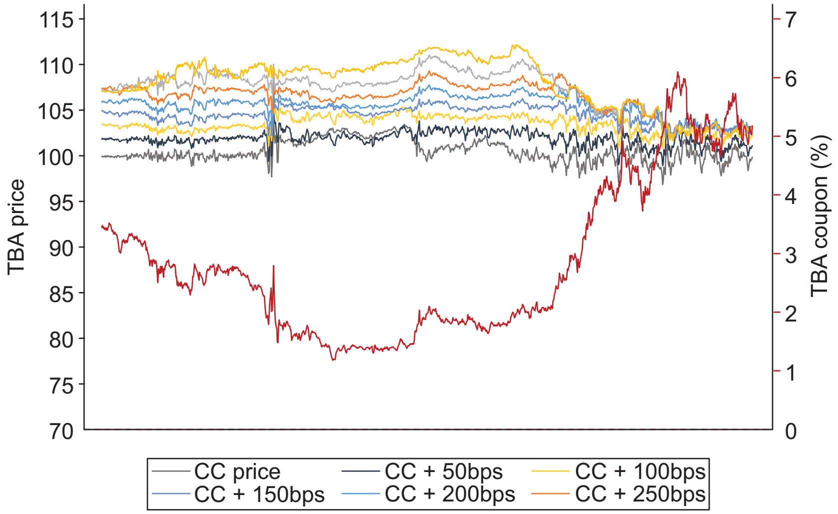
[14] Increments of 50bps are typically used to build separate moneyness buckets for TBA/MBSs in the mortgage industry.

FIGURE 5 TBA synthetic moneyness time series: ITM time series.



The red line shows Bloomberg CC.

be constructed. For a specific moneyness time series, each price data point represents the price from a TBA or MBS that had that same moneyness historically.

The following steps are used to construct a moneyness time series (see also Figures 5 and 6).

STEP 1 Prepare a TBA current coupon time series.[15]

STEP 2 Prepare a TBA price time series with all coupon stacks. For the data points missing from the data source (TBA 1.5% and 2% prior to January 25, 2021 and 7% prior to February 12, 2020) a data imputation method is employed.

STEP 3 On any given day use a weighted approach to derive "par price" based on the two market observable TBA prices whose coupons are the two closest to the current coupon for that day.

STEP 4 The weighted current coupon price p_t^{cc} is given by the following formula:

$$p_t^{\text{cc}} = \frac{((r_{1,t} - \text{cc}_t) p_t^{r_2} + (\text{cc}_t - r_{2,t}) p_t^{r_1})}{50\text{bps}},$$

where $r_{1,t} - r_{2,t} = 50$ bps, $r_{1,t} \geqslant \text{cc}_t \geqslant r_{2,t}$, $p_t^{r_1}$ is the price for $r_{1,t}$ and $p_t^{r_2}$ is the price for $r_{2,t}$.

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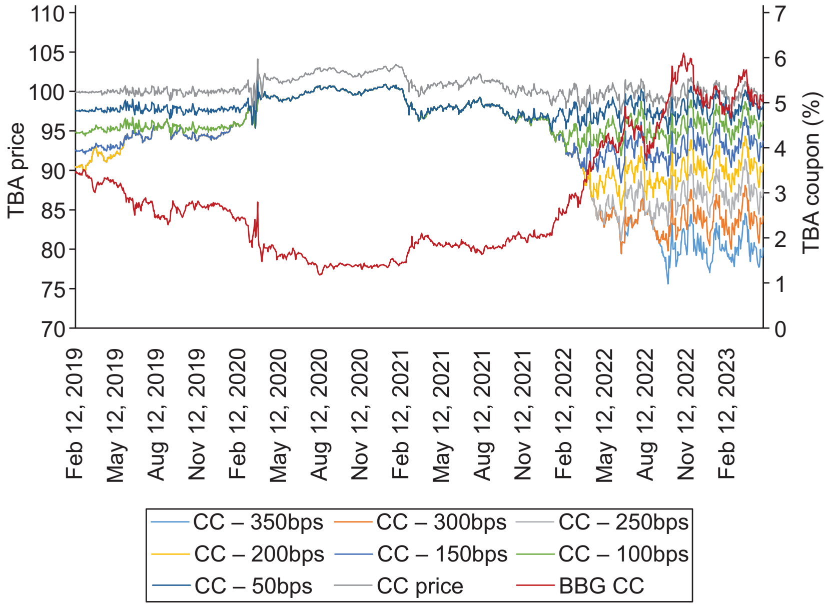
[15] This paper uses the current coupon calculated using Bloomberg's prepayment and pricing model.

FIGURE 6 TBA synthetic moneyness time series: OTM time series.



STEP 5 Once the current coupon synthetic price time series is constructed, all the other moneyness time series can be constructed using the following moneyness structures:

$$p_t^{\text{cc}-350\text{bps}}, p_t^{\text{cc}-300\text{bps}}, \dots, p_t^{\text{cc}-100\text{bps}}, p_t^{\text{cc}-50\text{bps}},$$
$$p_t^{\text{cc}}, p_t^{\text{cc}+50\text{bps}}, p_t^{\text{cc}+100\text{bps}}, \dots, p_t^{\text{cc}+300\text{bps}}, p_t^{\text{cc}+350\text{bps}}.$$

STEP 6 Once all the time series in step 5 are constructed, the model calibration can be performed for each of them. The model parameters are given in Table 4.

STEP 7 Once the model calibration is completed, margin (ie, a margin rate) can be calculated using the selected model methods: t-copula and FHS-EWMA with various decay factors.

Table 4 shows the calibration result for each of these time series. It can be seen that the DoF for the OTM time series are relatively stable and closer to normal distribution, whereas the ITM time series appear to have fatter tails, especially beyond current coupon +150bps. This calibration result seems to align well with the previous univariate calibration result for the individual TBAs with various coupons; that

TABLE 4 Synthetic TBA moneyness time series univariate model parameters.

Model parameters	α	v	α_0	α_1	γ_1
Current coupon +350bps	−0.098	4.02	0.00000017	0.2518	0.7186
Current coupon +300bps	−0.223	3.48	0.00000072	0.4168	0.5103
Current coupon +250bps	−0.099	5.10	0.00000013	0.2192	0.7534
Current coupon +200bps	−0.132	5.19	0.00000009	0.1853	0.7915
Current coupon +150bps	0.011	6.21	0.00000008	0.1813	0.8005
Current coupon +100bps	0.012	6.80	0.00000011	0.1478	0.8309
Current coupon +50bps	0.039	8.01	0.00000016	0.1534	0.8279
Current coupon	0.016	5.71	0.00000009	0.1642	0.8240
Current coupon −50bps	0.001	9.89	0.00000011	0.1735	0.8157
Current coupon −100bps	−0.029	10.06	0.00000009	0.1530	0.8380
Current coupon −150bps	−0.011	8.78	0.00000008	0.1309	0.8610
Current coupon −200bps	−0.015	8.08	0.00000007	0.1271	0.8673
Current coupon −250bps	−0.006	8.70	0.00000007	0.1248	0.8700
Current coupon −300bps	−0.025	7.99	0.00000008	0.1335	0.8608
Current coupon −350bps	−0.057	7.61	0.00000009	0.1401	0.8536

is, the low coupon ones tend to have high DoF, which resemble normal distributions, and the high coupon ones tend to have low DoF, which resemble fat-tailed distributions. As was discussed in Section 4.2, this result basically indicates that the TBAs with higher coupons are more likely to be prepaid in various interest regimes studied in this paper, and hence have more volatile returns in their tails.

5.2 TBA/MBS indexes and ETF

Since the selected indexes and ETFs are already made of MBSs or TBAs with different coupon stacks regardless of the moneyness effect in different historical interest regimes, we use the straightforward first approach (ie, the individual product or index price time series) to model them. The calibration results are shown in Section 4.2.

6 PORTFOLIO MARGIN GENERATION FOR BACKTESTING ANALYSIS

6.1 Margin generation for the TBA synthetic time series

Once the model parameters are calibrated based on the synthetic time series in Section 5, namely,

$$p_t^{\text{cc}-350\text{bps}}, p_t^{\text{cc}-300\text{bps}}, \dots, p_t^{\text{cc}-100\text{bps}}, p_t^{\text{cc}-50\text{bps}}, p_t^{\text{cc}},$$
$$p_t^{\text{cc}+50\text{bps}}, p_t^{\text{cc}+100\text{bps}}, \dots, p_t^{\text{cc}+300\text{bps}}, p_t^{\text{cc}+350\text{bps}},$$

margin can be generated using the selected models for each synthetic TBA,

$$M_t^{\text{cc}-350\text{bps}}, M_t^{\text{cc}-300\text{bps}}, \dots, M_t^{\text{cc}-100\text{bps}}, M_t^{\text{cc}-50\text{bps}}, M_t^{\text{cc}},$$
$$M_t^{\text{cc}+50\text{bps}}, M_t^{\text{cc}+100\text{bps}}, \dots, M_t^{\text{cc}+300\text{bps}}, M_t^{\text{cc}+350\text{bps}},$$

on each day in the lookback period. However, to produce margin for an instrument, for instance, margin for the 4% TBA has to be calculated based on whether the 4% TBA was ITM or OTM, and more specifically which moneyness bucket it belongs to. Hence, at any time during the lookback period, margin for a TBA with a fixed coupon needs to be synthetically constructed. We do this by following the steps below.

STEP 1 Produce margins for each moneyness bucket $M_t^{\text{cc}-i}$, including the current coupon one. Here i represents different moneyness buckets ranging from -350bps below the current coupon (ie, cc $-$ 350bps) to above the current coupon (ie, cc $+$ 350bps) on any day t.

STEP 2 Margin (ie, margin rate) is calculated using the selected model methods in this paper: namely, t-copula and FHS-EWMA with various decay factors (ie, 0.95, 0.97 and 0.99).

STEP 3 For a fixed TBA coupon c, calculate the difference between the coupon and the current coupon on any day:

$$d_t^c = c - \text{cc}_t.$$

STEP 4 On any given day t, use a weighted approach to derive a "weighted margin" based on the two closest moneyness buckets where d_t^c lies in between.

STEP 5 The weighted margin M_t^c is given by the following formula:

$$M_t^c = \frac{((d_1 - d_t^c)M_t^{d_2} + (d_t^c - d_2)M_t^{d_1})}{50\text{bps}},$$

where $d_1 - d_2 = 50$bps, $d_1 \geqslant d_t^c \geqslant d_2$, $M_t^{d_1}$ denotes the margin for d_1 at t, $M_t^{d_2}$ denotes the margin for d_2 at t and

$$d_1, d_2 \in [-350\text{bps}, -300\text{bps}, \dots 0, \dots 300\text{bps}, 350\text{bps}].$$

STEP 6 Once the margin M_t^c is calculated, the portfolio's P&L PL_t^c can be calculated for backtesting analysis.

7 MODEL RESULTS

7.1 Backtesting and procyclicality analysis results

In this section, individual TBAs with various coupons are backtested using the selected margin models, namely, the GARCH-t-copula and FHS-EWMA. Procyclicality metrics using one-day and three-day max as well as peak-to-trough are also

TABLE 5 VaR backtesting for long TBA 2% (February 4, 2020 to January 3, 2023).

Model	Exceedance	Kupiec statistic	p-value
Multivariate t-copula CCC	12	2.6252	0.1052
FHS VaR ($\lambda = 0.95$)	7	0.0088	0.9252
FHS VaR ($\lambda = 0.97$)	6	0.2313	0.6306
FHS VaR ($\lambda = 0.99$)	5	0.7914	0.3737

TABLE 6 Procyclicality analysis for long TBA 2% (February 4, 2020 to January 3, 2023).

Model	One-day max margin rate change (%)	Three-day max margin rate change (%)	Peak-to-trough (%)
Multivariate t-copula CCC	48	115	7.61
FHS VaR ($\lambda = 0.95$)	62	94	6.53
FHS VaR ($\lambda = 0.97$)	60	90	6.03
FHS VaR ($\lambda = 0.99$)	56	60	4.81

TABLE 7 VaR backtesting for long TBA 3% (February 4, 2020 to January 3, 2023).

Model	Exceedance	Kupiec statistic	p-value
Multivariate t-copula CCC	8	0.0758	0.7830
FHS VaR ($\lambda = 0.95$)	7	0.0088	0.9252
FHS VaR ($\lambda = 0.97$)	5	0.7914	0.3737
FHS VaR ($\lambda = 0.99$)	4	1.7570	0.1850

calculated in order to give a more holistic view of these models' performance. Note that the historical period used in the analysis contains multiple market stress events including those associated with the Covid-19 pandemic.

7.1.1 TBA (long) with various coupon stacks

First, we show the results of backtesting and procyclicality analysis for a long TBA portfolio with various coupon stacks covering a time period from February 4, 2020 to January 3, 2023 (see Tables 5–14). We also illustrate backtesting using a t-copula and EWMA with various decays for TBAs with a 3% coupon (see Figure 7).

TABLE 8 Procyclicality analysis for long TBA 3% (February 4, 2020 to January 3, 2023).

Model	One-day max margin rate change (%)	Three-day max margin rate change (%)	Peak-to-trough (%)
Multivariate t-copula CCC	62	134	6.28
FHS VaR ($\lambda = 0.95$)	59	237	5.87
FHS VaR ($\lambda = 0.97$)	56	210	5.30
FHS VaR ($\lambda = 0.99$)	40	146	4.82

TABLE 9 VaR backtesting for long TBA 4% (February 4, 2020 to January 3, 2023).

Model	Exceedance	Kupiec statistic	p-value
Multivariate t-copula CCC	5	0.7914	0.3737
FHS VaR ($\lambda = 0.95$)	5	0.7914	0.3737
FHS VaR ($\lambda = 0.97$)	5	0.7914	0.3737
FHS VaR ($\lambda = 0.99$)	4	1.7570	0.1850

TABLE 10 Procyclicality analysis for long TBA 4% (February 4, 2020 to January 3, 2023).

Model	One-day max margin rate change (%)	Three-day max margin rate change (%)	Peak-to-trough (%)
Multivariate t-copula CCC	73	153	5.39
FHS VaR ($\lambda = 0.95$)	68	125	5.11
FHS VaR ($\lambda = 0.97$)	56	104	4.89
FHS VaR ($\lambda = 0.99$)	35	85	4.58

TABLE 11 VaR backtesting for long TBA 5% (February 4, 2020 to January 3, 2023).

Model	Exceedance	Kupiec statistic	p-value
Multivariate t-copula CCC	6	0.2313	0.6306
FHS VaR ($\lambda = 0.95$)	6	0.2313	0.6306
FHS VaR ($\lambda = 0.97$)	7	0.0088	0.9252
FHS VaR ($\lambda = 0.99$)	6	0.2313	0.6306

TABLE 12 Procyclicality analysis for long TBA 5% (February 4, 2020 to January 3, 2023).

Model	One-day max margin rate change (%)	Three-day max margin rate change (%)	Peak-to-trough (%)
Multivariate t-copula CCC	114	147	5.36
FHS VaR ($\lambda = 0.95$)	65	136	4.30
FHS VaR ($\lambda = 0.97$)	47	87	4.19
FHS VaR ($\lambda = 0.99$)	40	47	4.02

TABLE 13 VaR backtesting for long TBA 6% (February 4, 2020 to January 3, 2023).

Model	Exceedance	Kupiec statistic	p-value
Multivariate t-copula CCC	19	13.3040	0.0003
FHS VaR ($\lambda = 0.95$)	15	6.3954	0.0114
FHS VaR ($\lambda = 0.97$)	15	6.3954	0.0114
FHS VaR ($\lambda = 0.99$)	16	7.9379	0.0048

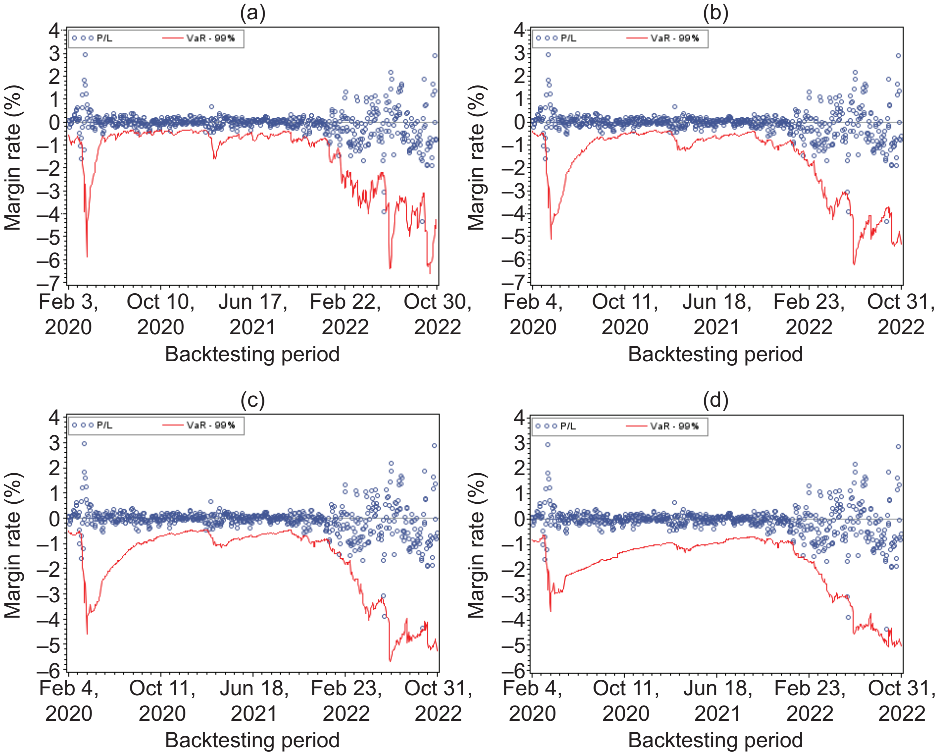
TABLE 14 Procyclicality analysis for long TBA 6% (February 4, 2020 to January 3, 2023).

Model	One-day max margin rate change (%)	Three-day max margin rate change (%)	Peak-to-trough (%)
Multivariate t-copula CCC	127	188	3.67
FHS VaR ($\lambda = 0.95$)	50	91	3.07
FHS VaR ($\lambda = 0.97$)	29	48	2.81
FHS VaR ($\lambda = 0.99$)	21	42	2.69

7.1.2 TBA (short) with various coupon stacks

In this section we show the results of backtesting and procyclicality analysis for a short TBA portfolio with various coupon stacks covering a time period from February 4, 2020 to January 3, 2023 (see Tables 15–24). We also provide an illustration of backtesting using the t-copula and EWMA with various decays for TBA with a 4% coupon (see Figure 8).

FIGURE 7 Backtesting using the t-copula and EWMA with various decays TBA 3% long.



(a) t-copula, backtesting multivariate GARCH copula VaR 99%. (b) EWMA 95, backtesting TBAEWMAL95 VaR 99%. (c) EWMA 97, backtesting TBAEWMAL97 VaR 99%. (d) EWMA 99, backtesting TBAEWMAL99 VaR 99%.

TABLE 15 VaR backtesting for short TBA 2% (February 4, 2020 to January 3, 2023).

Model	Exceedance	Kupiec statistic	p-value
Multivariate t-copula CCC	2	5.3869	0.0203
FHS VaR ($\lambda = 0.95$)	10	0.9422	0.3317
FHS VaR ($\lambda = 0.97$)	5	0.7914	0.3737
FHS VaR ($\lambda = 0.99$)	5	0.7914	0.3737

7.1.3 Key observations for backtesting and procyclicality analysis of individual TBAs

From the analysis performed for long and short TBA positions in Sections 7.1.1 and 7.1.2, we derive the following key takeaways.

TABLE 16 Procyclicality analysis for short TBA 2% (February 4, 2020 to January 3, 2023).

Model	One-day max margin rate change (%)	Three-day max margin rate change (%)	Peak-to-trough (%)
Multivariate t-copula CCC	51	112	8.31
FHS VaR ($\lambda = 0.95$)	76	78	5.80
FHS VaR ($\lambda = 0.97$)	68	72	5.32
FHS VaR ($\lambda = 0.99$)	69	71	4.34

TABLE 17 VaR backtesting for short TBA 3% (February 4, 2020 to January 3, 2023).

Model	Exceedance	Kupiec statistic	p-value
Multivariate t-copula CCC	2	5.3869	0.0203
FHS VaR ($\lambda = 0.95$)	12	2.6252	0.1052
FHS VaR ($\lambda = 0.97$)	5	0.7914	0.3737
FHS VaR ($\lambda = 0.99$)	5	0.7914	0.3737

TABLE 18 Procyclicality analysis for short TBA 3% (February 4, 2020 to January 3, 2023).

Model	One-day max margin rate change (%)	Three-day max margin rate change (%)	Peak-to-trough (%)
Multivariate t-copula CCC	64	135	6.57
FHS VaR ($\lambda = 0.95$)	50	150	5.85
FHS VaR ($\lambda = 0.97$)	61	144	5.60
FHS VaR ($\lambda = 0.99$)	58	175	4.89

TABLE 19 VaR backtesting for short TBA 4% (February 4, 2020 to January 3, 2023).

Model	Exceedance	Kupiec statistic	p-value
Multivariate t-copula CCC	4	1.7570	0.1850
FHS VaR ($\lambda = 0.95$)	8	0.0758	0.7830
FHS VaR ($\lambda = 0.97$)	4	1.7570	0.1850
FHS VaR ($\lambda = 0.99$)	3	3.2308	0.0723

TABLE 20 Procyclicality analysis for short TBA 4% (February 4, 2020 to January 3, 2023).

Model	One-day max margin rate change (%)	Three-day max margin rate change (%)	Peak-to-trough (%)
Multivariate t-copula CCC	76	153	5.80
FHS VaR ($\lambda = 0.95$)	58	90	5.02
FHS VaR ($\lambda = 0.97$)	50	81	5.14
FHS VaR ($\lambda = 0.99$)	41	79	4.75

TABLE 21 VaR backtesting for short TBA 5% (February 4, 2020 to January 3, 2023).

Model	Exceedance	Kupiec statistic	p-value
Multivariate t-copula CCC	3	3.2308	0.0723
FHS VaR ($\lambda = 0.95$)	9	0.3963	0.5290
FHS VaR ($\lambda = 0.97$)	2	5.3869	0.0203
FHS VaR ($\lambda = 0.99$)	2	5.3869	0.0203

TABLE 22 Procyclicality analysis for short TBA 5% (February 4, 2020 to January 3, 2023).

Model	One-day max margin rate change (%)	Three-day max margin rate change (%)	Peak-to-trough (%)
Multivariate t-copula CCC	122	144	5.60
FHS VaR ($\lambda = 0.95$)	53	84	3.76
FHS VaR ($\lambda = 0.97$)	42	90	3.77
FHS VaR ($\lambda = 0.99$)	39	98	3.69

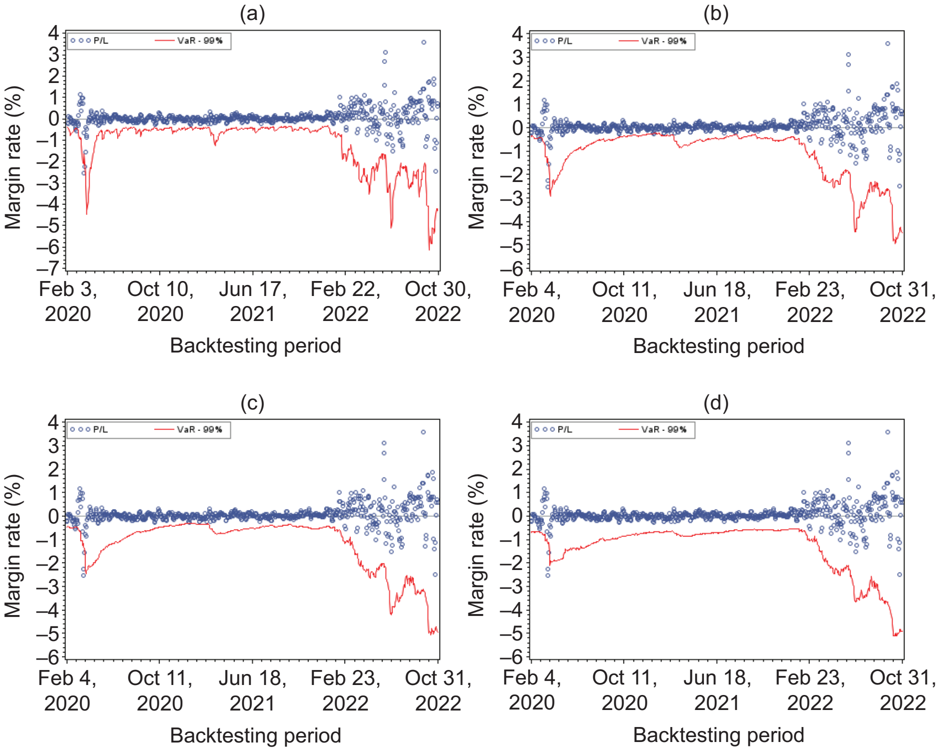
TABLE 23 VaR backtesting for short TBA 6% (February 4, 2020 to January 3, 2023).

Model	Exceedance	Kupiec statistic	p-value
Multivariate t-copula CCC	14	4.9892	0.0255
FHS VaR ($\lambda = 0.95$)	13	3.7288	0.0535
FHS VaR ($\lambda = 0.97$)	11	1.6913	0.1934
FHS VaR ($\lambda = 0.99$)	15	6.3954	0.0114

TABLE 24 Procyclicality analysis for short TBA 6% (February 4, 2020 to January 3, 2023).

Model	One-day max margin rate change (%)	Three-day max margin rate change (%)	Peak-to-trough (%)
Multivariate t-copula CCC	132	185	3.92
FHS VaR ($\lambda = 0.95$)	43	84	2.68
FHS VaR ($\lambda = 0.97$)	30	74	2.58
FHS VaR ($\lambda = 0.99$)	33	58	2.60

FIGURE 8 Backtesting using the t-copula and EWMA with various decays TBA 4% short.



(a) t-copula, backtesting multivariate GARCH copula VaR 99%. (b) EWMA 95, backtesting TBAEWMAS95 VaR 99%. (c) EWMA 97, backtesting TBAEWMAS97 VaR 99%. (d) EWMA 99, backtesting TBAEWMAS99 VaR 99%.

(1) Both the econometric-based margin models (t-copula and FHS-EWMA) are mostly sufficient in terms of coverage ratio except for very high coupons such as 6%, where both types of models failed the Kupiec test with a 99% confidence level. This might be due to the fact that these high-coupon TBAs tend to have more unpredictable and volatile tail behaviors caused by the pronounced embedded optionality.

(2) Both models have better performance in terms of coverage for short positions than for long positions. This is mainly because both models have relatively poor performance during the rate-hike period that started around 2022, and long positions suffered more loss during this period. Comparatively, short positions suffered more loss during the Covid period.

(3) For long positions, the t-copula model has similar results to the FHS-EWMA models in term of coverage, whereas for short positions, the t-copula model tends to have better performance. This is mainly because the t-copula model tends to have better reactivity than the FHS-EWMA models, and loss is more pronounced for short positions during the Covid period.

(4) From the model procyclicality perspective, both models exhibit comparable procyclicality measured by one-day and three-day max margin rate change and by the peak-to-trough rate for the whole backtesting period.

(5) As expected, the t-copula model tends to be more procyclical than the FHS-EWMA model, and the smaller the decay factor value, the more procyclical the FHS-EWMA model.

(6) Out of the three choices of FHS-EWMA model, 0.97 tends to strike a better balance between coverage and procyclicality.

7.1.4 Additional analysis on the rate-hike period

The historical rate-hike period offers an interesting experiment in seeing how the model calibrated to one regime (low and relatively stable rates; eg, prior to 2022) reacts when the regime transitions into a high-rate environment. The results show that tmost of the major margin jumps and breaches for long positions (see Figure 11 in the online appendix) occurred during the rate-hike period. We performed tests to see the difference in performance when the model is calibrated using only the pre-2022 time series where rates were more stable and low. For example, the performance for 5% TBA (shown in Table 41 in the online appendix) is worse. This may partly explain the continued resistance to using the fixed coupon time series (ie, approach 1) to model optionality in the rate regime changing environment.

TABLE 25 VaR backtesting for long MBS ETF (February 3, 2020 to January 6, 2023).

Model	Exceedance	Kupiec statistics	p-value
Multivariate t-copula CCC	**17**	**9.3380**	**0.0022**
FHS VaR ($\lambda = 0.95$)	18	11.1008	0.0009
FHS VaR ($\lambda = 0.97$)	19	12.9776	0.0003
FHS VaR ($\lambda = 0.99$)	21	17.0502	0.0000

TABLE 26 VaR backtesting for short MBS ETF (February 3, 2020 to January 6, 2023).

Model	Exceedance	Kupiec statistic	p-value
Multivariate t-copula CCC	8	0.3492	0.5546
FHS VaR ($\lambda = 0.95$)	7	0.0171	0.8959
FHS VaR ($\lambda = 0.97$)	8	0.3492	0.5546
FHS VaR ($\lambda = 0.99$)	16	7.6957	0.0055

TABLE 27 Procyclicality analysis for long MBS ETF (February 3, 2020 to January 6, 2023).

Model	One-day max margin rate change (%)	Three-day max margin rate change (%)	Peak-to-trough (%)
Multivariate t-copula CCC	158	557	6.22
FHS VaR ($\lambda = 0.95$)	185	358	4.01
FHS VaR ($\lambda = 0.97$)	171	295	3.29
FHS VaR ($\lambda = 0.99$)	106	**167**	**2.71**

7.1.5 ETF portfolio (VMBS, MBB)

In this section, we show the results of backtesting and procyclicality analysis for long and short portfolios of VMBS and MBB ETFs for the period from February 3, 2020 through January 6, 2023 (see Tables 25–28). We also illustrate backtesting using the t-copula and EWMA with various decays for MBS ETFs (see Figure 9). The multivariate t-copula CCC model showed fewer exceedances of the long MBS ETF portfolio (illustrated by the boldface values in Table 25), while the FHS VaR ($\lambda = 0.99$) appeared to be the least procyclical in terms of margin rate change (Table 27).

TABLE 28 Procyclicality analysis for short MBS ETF (February 3, 2020 to January 6, 2023).

Model	One-day max margin rate change (%)	Three-day max margin rate change (%)	Peak-to-trough (%)
Multivariate t-copula CCC	104	162	4.54
FHS VaR ($\lambda = 0.95$)	194	315	3.54
FHS VaR ($\lambda = 0.97$)	171	269	3.00
FHS VaR ($\lambda = 0.99$)	107	**148**	**2.26**

7.1.6 Index portfolio (BBG MBS)

Lastly, we show the results of backtesting and procyclicality analysis for a long and short BBG MBS Index for the period from February 3, 2020 to January 6, 2023 (see Tables 29–32). We also provide an illustration of backtesting using the t-copula and EWMA with various decays for the index portfolio (see Figure 10).

7.1.7 Key observations for TBA/MBS index or ETF backtesting and procyclicality analysis

From the analysis performed for long and short indexes or ETF positions in Sections 7.1.4 and 7.1.5, the following are the key takeaways.

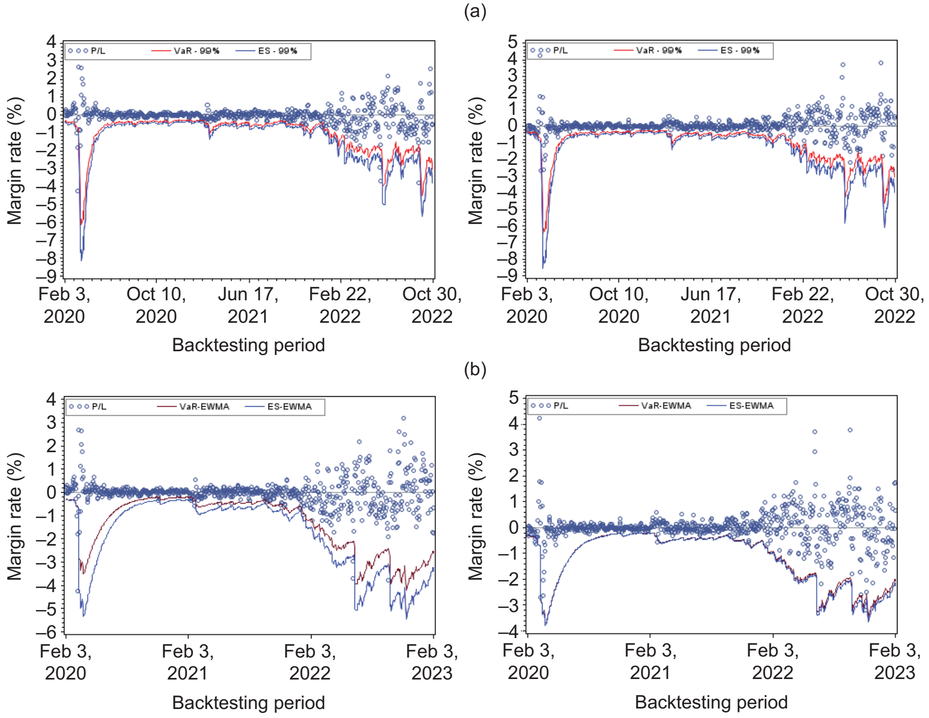
(1) Both econometric-based margin models, t-copula and FHS-EWMA, perform better for short positions than long positions. Both are mostly sufficient in terms of coverage ratio for short positions, whereas for long positions both failed the Kupiec test at 99%.

(2) For both long and short positions, the t-copula model has the best performance in terms of coverage ratio. For the FHS-EWMA models, generally speaking, the one with a 0.97 decay factor has the best performance.

(3) Better performance for short positions than long positions is mainly attributed to the fact that both models have relatively poor performance during the rate-hike period that started around 2022, and long positions suffered more loss during this period. Comparatively short positions suffered more loss during the Covid period. This is similar to the observation for the individual TBA performance.

(4) From the model procyclicality perspective, both models exhibit comparable procyclicality measured by one-day and three-day max margin rate change as well as by peak-to-trough for the whole backtesting period.

FIGURE 9 Backtesting using the t-copula and EWMA with various decays for MBS ETFs. [Figure continues on next page.]



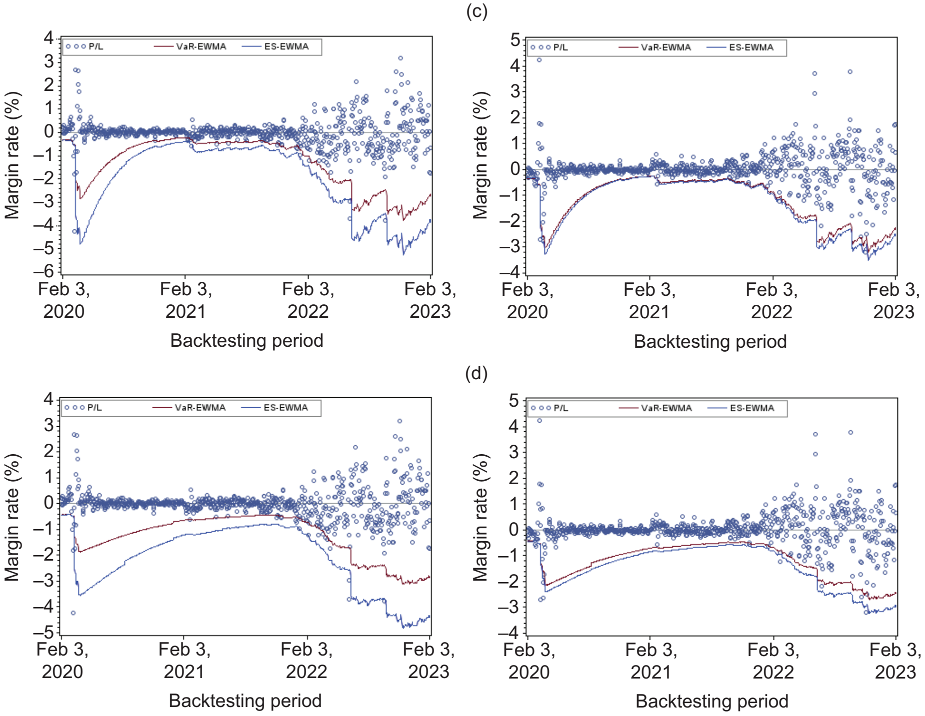
(a) Multivariate t-copula CCC, backtesting GARCH CCC (MBSETF – 20p1 margin or ES quantile: 0.01). (b) FHS VaR ($\lambda = 0.95$), backtesting EWMA FHS (MBSETF – EWMA margin or ES quantile: 0.01).

(5) Compared with the individual TBAs, the model procyclicality appears to be greater for the TBA/MBS index and ETF for long positions, whereas it is comparable for the short positions.

8 CONCLUSION

This paper explored alternative margin models for the TBA/MBS asset class in the context of the CCP market and general market risk management. These alternative margin models, which rely solely on market volatility and return behavior, could potentially be used as a supplemental/alternative model framework for margin and stress testing purposes. The models considered (the GARCH-t-copula and the FHS) are relatively common in some other CCPs for their corresponding products (eg, credit default swaps). Based on our results, TBA/MBS price returns show

FIGURE 9 Continued.



(c) FHS VaR ($\lambda = 0.97$), backtesting EWMA FHS (MBSETF – EWMA margin or ES quantile: 0.01). (d) FHS VaR ($\lambda = 0.99$), backtesting EWMA FHS (MBSETF – EWMA margin or ES quantile: 0.01). Left-hand columns show portfolio (+VMBS, +MBB), right-hand columns show portfolio (−VMBS, −MBB).

TABLE 29 VaR backtesting for long BBG MBS Index (February 3, 2020 to January 6, 2023).

Model	Exceedance	Kupiec statistic	p-value
Multivariate t-copula CCC	**15**	**6.1812**	**0.0129**
FHS VaR ($\lambda = 0.95$)	23	21.5156	0.0000
FHS VaR ($\lambda = 0.97$)	20	14.9625	0.0001
FHS VaR ($\lambda = 0.99$)	24	23.8849	0.0000

mixed behaviors with high kurtosis (eg, compared with VIX) and fat tails with ITM coupons (typically high coupons) and mild tail behavior with OTM coupons. TBAs with high coupons tend to show strong autocorrelation and high skewness.

TABLE 30 VaR backtesting for short BBG MBS Index (February 3, 2020 to January 6, 2023).

Model	Exceedance	Kupiec statistic	p-value
Multivariate t-copula CCC	8	0.3492	0.5546
FHS VaR ($\lambda = 0.95$)	13	3.5705	0.0588
FHS VaR ($\lambda = 0.97$)	13	3.5705	0.0588
FHS VaR ($\lambda = 0.99$)	15	6.1812	0.0129

TABLE 31 Procyclicality analysis for long BBG MBS Index (February 3, 2020 to January 6, 2023).

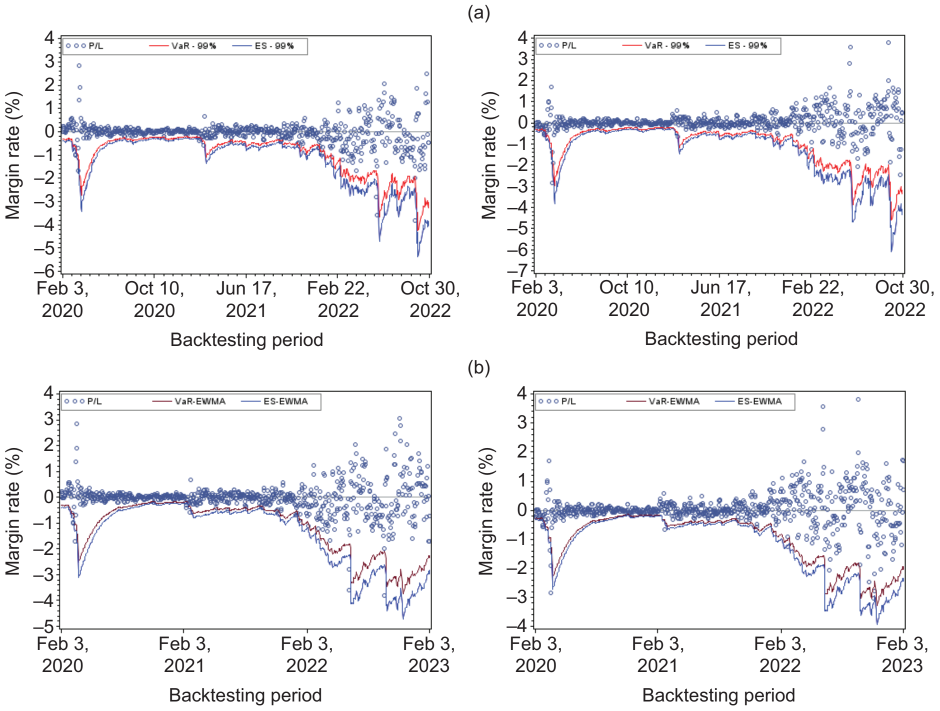
Model	One-day max margin rate change (%)	Three-day max margin rate change (%)	Peak-to-trough (%)
Multivariate t-copula CCC	98	146	4.27
FHS VaR ($\lambda = 0.95$)	52	110	3.58
FHS VaR ($\lambda = 0.97$)	39	71	3.29
FHS VaR ($\lambda = 0.99$)	31	**56**	**2.48**

TABLE 32 Procyclicality analysis for short BBG MBS Index (February 3, 2020 to January 6, 2023).

Model	One-day max margin rate change (%)	Three-day max margin rate change (%)	Peak-to-trough (%)
Multivariate t-copula CCC	104	162	4.54
FHS VaR ($\lambda = 0.95$)	52	110	3.14
FHS VaR ($\lambda = 0.97$)	40	75	2.81
FHS VaR ($\lambda = 0.99$)	33	**59**	**2.06**

Both GARCH and EWMA volatility estimators can be used carefully to describe TBA/MBSs' price return volatility. Fat-tailed distribution (t with three to six DoF) can be used for describing price return residual distribution. Synthetic moneyness time series were constructed and used to calibrate econometric models in consideration of TBA/MBSs' embedded optionality. Backtesting shows reasonable model performance during the Covid-19 and rate-hike periods. Therefore, both the GARCH-t-copula and EWMA approaches appear to be viable without dependency on typically used mortgage risk factor models.

FIGURE 10 Backtesting using the t-copula and EWMA with various decays for long and short BBG MBS portfolios. [Figure continues on next page.]

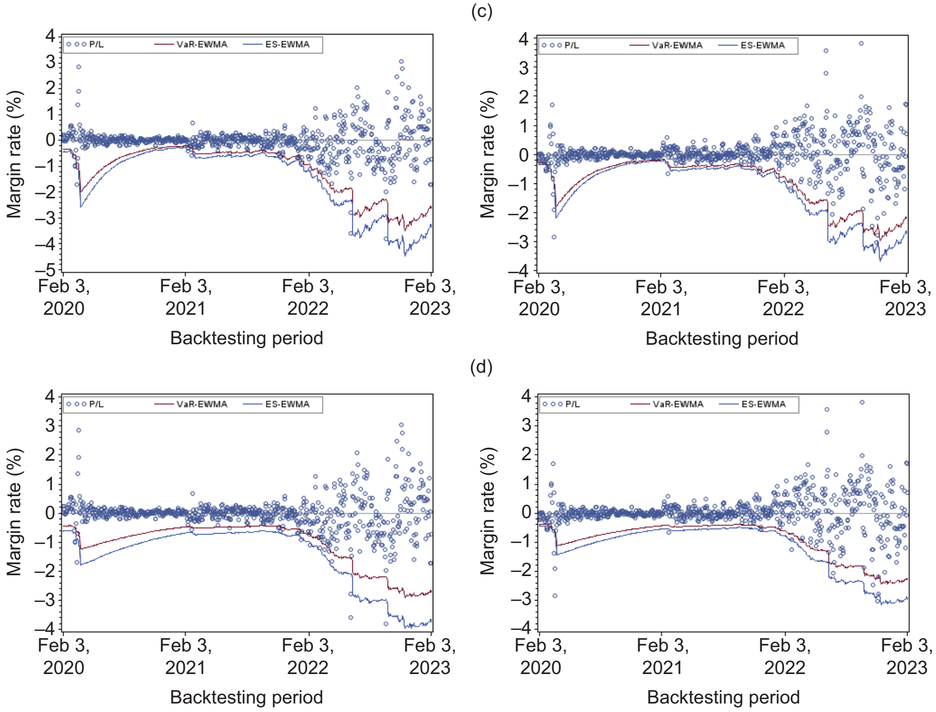


(a) Multivariate t-copula CCC, backtesting GARCH CCC (BBGTBA – 20p1 margin or ES quantile: 0.01). (b) FHS VaR ($\lambda = 0.95$), backtesting EWMA FHS (BBGTBA – EWMA margin or ES quantile: 0.01).

DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper. The US Securities and Exchange Commission (SEC) disclaims responsibility for any private publication or statement of any SEC employee or commissioner. This paper expresses the authors' views and does not necessarily reflect those of the commission, the commissioners or the members of staff. David Li and Viktoria Baklanova are at the SEC. Roy Cheruvelil was at the SEC at the time of writing this paper.

FIGURE 10 Continued.



(c) FHS VaR ($\lambda = 0.97$), backtesting EWMA FHS (BBGTBA – EWMA margin or ES quantile: 0.01). (d) FHS VaR ($\lambda = 0.99$), backtesting EWMA FHS (BBGTBA – EWMA margin or ES quantile: 0.01). Left-hand columns show portfolio (+BBG MBS), right-hand columns show portfolio (−BBG MBS).

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REFERENCES

Basel Committee on Banking Supervision–Committee on Payments and Market Infrastructures–Board of the International Organization of Securities Commissions (2022). Review of margining practices. Report, September, Bank for International Settlements, Basel. URL: www.bis.org/bcbs/publ/d537.pdf.

Bessembinder, H., Maxwell, W. F., and Venkataraman, K. (2013). Trading activity and transaction costs in structured credit products. *Financial Analysts Journal* **69**(6), 55–67 (https://doi.org/10.2469/faj.v69.n6.2).

Committee on Payment and Settlement Systems–Technical Committee of the International Organization of Securities Commissions (2012). Principles for financial market infrastructures. CPMI Paper 101, April, Bank for International Settlements. URL: www.bis.org/cpmi/publ/d101a.pdf.

Committee on Payments and Market Infrastructures–Board of the International Organization of Securities Commissions (2017). Resilience and recovery of central parties (CCPs): further guidance on the PFMI. Final Report, Bank for International Settlements. URL: http://bit.ly/2xKPGlr.

Cont, R. and Kan, Y. H. (2011). Statistical modeling of credit default swap portfolios. Working Paper, Social Science Research Network (https://doi.org/10.2139/ssrn.1771862).

Financial Industry Regulatory Authority (2016). (Margin requirements) to establish margin requirements for covered agency transactions. Regulatory Notice 16-31, FINRA. URL: www.finra.org/rules-guidance/notices/16-31.

Financial Stability Board (2020). Holistic review of the March market turmoil. Report, November 17, FSB, Basel. URL: www.fsb.org/wp-content/uploads/P171120-2.pdf.

Fixed Income Clearing Corporation (2023). Disclosure framework for covered clearing agencies and financial market infrastructures, White Paper, March, FICC, Jersey City, NJ. URL: www.dtcc.com/-/media/Files/Downloads/legal/policy-and-compliance/FICC_Disclosure_Framework.pdf.

Fuster, A., Lucca, D., and Vickery, J. (2022). Mortgage-backed securities. Staff Report 1001, Federal Reserve Bank of New York. URL: www.newyorkfed.org/medialibrary/media/research/staff_reports/sr1001.pdf.

Gao, P., Schultz, P., and Song, Z. (2017). Liquidity in a market for unique assets: specified pool and to-be-announced trading in the mortgage-backed securities market. *Journal of Finance* **72**(3), 1119–1170 (https://doi.org/10.1111/jofi.12496).

Gurrola-Perez, P., and Murphy, D. (2015). Filtered historical simulation value-at-risk models and their competitors. Working Paper 525, Bank of England (https://doi.org/10.2139/ssrn.2574769).

Han, C., Park, F. C., and Kang, J. (2007). Efficient value-at-risk estimation for mortgage-backed securities. *The Journal of Risk* **9**(3), 37–61 (https://doi.org/10.21314/JOR.2007.168).

Huh, Y., and Kim, Y. S. (2021). Cheapest-to-deliver pricing, optimal MBS securitization, and market quality. Finance and Economics Discussion Series 2021-031, Board of Governors of the Federal Reserve System, Washington, DC (https://doi.org/10.17016/FEDS.2021.031).

Huh, Y., and Kim, Y. S. (2022). The real effects of secondary market trading structure: evidence from the mortgage market. *Review of Financial Studies* **35**(8), 3574–3616 (https://doi.org/10.1093/rfs/hhab116).

Ivanov, S. (2017). Initial margin estimations for credit default swap portfolios. *The Journal of Financial Market Infrastructures* **5**(4), 23–49 (https://doi.org/10.21314/JFMI.2017.079).

Koeppl, T. V., and Monnet, C. (2010). The emergence and future of central counterparties. Working Paper 10-30, Federal Reserve Bank of Philadelphia (https://doi.org/10.21799/frbp.wp.2010.30).

Li, D., and Cheruvelil, R. (2019). Study of correlation impact on credit default swap margin using a GARCH–DCC-copula framework. *The Journal of Financial Market Infrastructures* **8**(1), 51–92 (https://doi.org/10.21314/JFMI.2018.113).

Liu, H., Song, Z., and Vickery, J. (2021). Defragmenting markets: evidence from agency MBS. Staff Report 965, Federal Reserve Bank of New York. URL: www.newyorkfed.org/medialibrary/media/research/staff_reports/sr965.pdf?sc_lang=en.

Nelson, D. B., and Cao, C. (1992). Inequality constraints in the univariate GARCH model. *Journal of Business and Economic Statistics* **10**, 229–235 (https://doi.org/10.1080/07350015.1992.10509902).

Norman, P. (2011). *The Risk Controllers: Central Counterparty Clearing in Globalised Financial Markets*. Wiley (https://doi.org/10.1002/9781119205913).

Treasury Market Practices Group (2012). Margining in agency MBS trading. Report, November, Treasury Market Practices Group. URL: www.newyorkfed.org/medialibrary/microsites/tmpg/files/margining_tmpg_11142012.pdf.

Vanguard (2023). Sector bond ETFs prospectus. Report, December 22, Vanguard Corporation, Malvern, PA. URL: https://fund-docs.vanguard.com/p3142.pdf.

Vickery, J., and Wright, J. (2013). TBA trading and liquidity in the agency MBS market. *Economic Policy Review* **19**(1), 1–18 (https://doi.org/10.2139/ssrn.2324222).