Rare Disaster Risks and Volatility of the Term-Structure of US Treasury Securities: The Role of El Niño and La Niña Events[#]

Renee van Eyden[*], Rangan Gupta[**], Jacobus Nel[***] and Elie Bouri[****]

Corresponding author: Elie Bouri

Abstract

The purpose of this paper is to determine the impact of rare disaster risks, captured by the El Niño-Southern Oscillation (ENSO) cycle, on the volatility of Treasury securities of the United States (US) involving 1- to 360-month maturities. We use a random coefficients panel-data-based heterogeneous autoregressive-realized variance (HAR-RV) model over the monthly period of 1961:06 to 2019:12, with the RV derived from the sum of squared daily changes in yield over a month. Our results show a positive and statistically significant (at the 1% level) impact of the ENSO cycle on RV, with the results being robust to alternative metrics of the ENSO, consideration of lagged impact, and decomposition of the ENSO cycle into El Niño and La Niña phases, with the former having a relatively stronger effect. With our panel estimation method using heterogeneous slope coefficients, we find that the effect on the entire term structure is positive, with higher impacts observed at the two-ends and the middle-part of the term-structure. Our results have important implications for investors in US Treasury securities.

Keywords: Rare Disaster Risks; ENSO Cycle; Term-Structure Volatility; US Treasury Securities; Panel HAR-RV Model

JEL Codes: C33, E43, Q54

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[*] Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; Email: renee.vaneyden@up.ac.za.

[**] Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; Email: rangan.gupta@up.ac.za.

[***] Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; Email: neljaco380@gmail.com.

[****] School of Business, Lebanese American University, Lebanon. Email: elie.elbouri@lau.edu.lb.

1. Introduction

The El Niño-Southern Oscillation (ENSO) is an irregularly periodic variation in winds and sea surface temperatures over the tropical eastern Pacific Ocean, affecting the climate of much of the tropics and subtropics (Trenberth et al., 2007). The warming phase of the sea temperature is known as El Niño and the cooling phase as La Niña. The two periods last several months each and typically occur every few years with varying intensity per period. The ENSO cycle is known to cause severe natural disasters (such as droughts, floods and hurricanes) that can deeply impact the macroeconomic environment (Cashin et al., 2017), and hence serve as a metric for time-varying rare disaster risks (Bouri et al., 2021; Demirer et al., 2021).

From the perspective of investment, if financial market participants are concerned about an imminent disaster risk, they would move their capital to safer and more liquid assets (as shown theoretically by Brookes and Daoud (2012)), which in turn is likely to push up not only prices (as indicated by Lin et al., 2019), but also volatility because of higher trading (Gupta, et al., 2019), due to the so-called "flight to liquidity" or "flight to quality" phenomenon. In this regard, in terms of traditional "safe-havens", the role of Treasury securities of the United States (US) is well-established because of their strong ability to provide investors with valuable portfolio diversification and hedging benefits during periods of heightened global turmoil (Gupta et al., 2021).

Against this backdrop, the aim of this paper is to test, for the first time, the hypothesis that the ENSO cycle positively impacts the volatility of the entire term-structure of interest rates spanning 1-month to 360-month maturities of US Treasury securities.

Our current study differs from Gupta et al. (2019) who provide evidence of the positive impact of rare disaster risks (captured using the International Crisis Behavior (ICB) database[1]) on volatility of only 10-year US government bonds. Note that, when volatility is interpreted as uncertainty, it becomes a key input for investment decisions and portfolio choices in general. Naturally, if we are able to show that rare disaster risks (i.e., the ENSO cycle in our case) can predict volatility of the entire term structure (rather than just 10-year maturity), then our result is of paramount importance to bond fund managers, as it allows them to decide which horizon of yields to focus on, based on the degree of response.

[1] We do not use this dataset as it ends in 2016.

Methodologically, we analyse the impact of the ENSO cycle on the realized variance (RV) (i.e., the monthly sum of squared daily yield changes) over the monthly period from 1961:06 to 2019:12, using a panel-based model with heterogeneous responses, instead of a time series analysis involving each unit considered separately. This is because the random-coefficients panel data framework allows us to model the underlying interdependence across the 360 yields, while simultaneously capturing the possible heterogeneity in the responses of the volatility of the yields to the ENSO cycle.

The remainder of the paper is organized as follows: Section 2 presents the data and methodology. Section 3 discusses the results. Section 4 concludes.

2. Datasets and Methodology

2.1. Data

We use an unbalanced panel dataset covering the monthly period from 1961:06 to 2019:12, based on availability at the time of writing. Extracted from the recent work of Liu and Wu (2021), the yields on the various US Treasury securities cover maturities of 1 month to 360 months.[2] The filters for selecting the raw data are similar to those of Gurkaynak et al. (2007), but unlike these authors, Treasuries with shorter maturities are included in the sample. While Gurkaynak et al. (2007) use a parametric (Nelson-Siegel-Svensson) approach to smooth the data, Liu and Wu (2021) perform nonparametric kernel smoothing with a local bandwidth selection that adapts to the amount of information at each maturity. This allows for a better fit of the short end of the yield curve and more reliable interpolation in the monthly maturities regression analysis, as in our case. Note that our dependent variable, i.e., realized variance (RV) for a particular maturity i=1, 2,…360, is derived from the sum of squared daily yield changes over a month, following the definition by Andersen and Bollerslev (1998), which in turn yields an observable rather than latent process, and an unconditional metric of volatility.[3] We also use monthly values of the yield changes of each maturity as a control to capture the well-known “leverage effect”, i.e., we expect a negative relationship between changes in yield and volatility. This is because, as bond prices go up and yields go down due to higher demand

[2] The data is downloadable from: https://sites.google.com/view/jingcynthiawu/yield-data?authuser=0.

[3] Conventionally, the time-varying volatility is modelled, and the fit assessed, using various generalized autoregressive conditional heteroscedastic (GARCH) models, under which the conditional variance is a deterministic function of model parameters and past data. Alternatively, some papers consider stochastic volatility (SV) models, where the volatility is a latent variable that follows a stochastic process. Irrespective of whether one uses a GARCH or SV model, the underlying estimate of volatility is not model-free as in the case of RV.

in the event of "bad news", and US Treasury securities are a safe haven, we expect volatility to go up due to higher trading. After the computation of the RV, the coverage of the various maturities are as follows: 1 month to 84 months: 1961:06-2019:12; 85 months to 120 months: 1971:08-2019:12; 121 months to 180 months: 1971:11-2019:12; 181months to 240 months: 1981:07-2019:12, and; 241 months to 360 months: 1985:11-2019:12.

As far as the metric of the ENSO cycle is concerned, we use the Southern Oscillation Index (SOI), obtained from the Bureau of Meteorology, Government of Australia.[4] The SOI, gives an indication of the development and intensity of El Niño or La Niña events in the Pacific Ocean. The SOI is calculated using the pressure difference between Tahiti and Darwin. Sustained negative (positive) values of the SOI below (above) $-7(+7)$ often indicate El Niño (La Niña) episodes. Low atmospheric pressure tends to occur over warm water and high pressure occurs over cold water, in part because of deep convection over warm water. El Niño episodes are defined as sustained warming of the central and eastern tropical Pacific Ocean, and La Niña episodes are defined as sustained cooling of the central and eastern tropical Pacific Ocean, resulting in a decrease and an increase in the strength of the Pacific trade winds, respectively.

The reliability of the SOI, however, is considered limited due to both Darwin and Tahiti being well south of the equator, resulting in the surface air pressure at both locations being less directly related to ENSO. To overcome this issue, a new index called the Equatorial Southern Oscillation Index (EQSOI) has been created.[5] To generate the data for this index, two new regions centred on the equator are delimited, with the western one located over Indonesia and the eastern one located over the equatorial Pacific, close to the South American coast. The EQSOI is obtained from the Climate Prediction Center (National Weather Service) of the National Oceanic and Atmospheric Administration (US Department of Commerce).[6]

In our main analysis, we use the EQSOI as measure of the ENSO, while the SOI is used as a robustness check. Following Cashin et al. (2017), we use (EQ)SOI "anomalies" in our empirical model, defined as a deviation of the (EQ)SOI in any given month from its historical average, normalized (divided) by its historical standard deviation. Given this, sustained negative (EQ)SOI anomaly values below -1 (above +1) indicate El Niño (La Niña) episodes.

[4] http://www.bom.gov.au/climate/current/soihtm1.shtml.

[5] See the discussion of Anthony Barnston of the National Oceanic and Atmospheric Administration here: https://www.climate.gov/news-features/blogs/enso/why-are-there-so-many-enso-indexes-instead-just-one for further details.

[6] https://www.cpc.ncep.noaa.gov/data/indices/.

Focussing on the more reliable EQSOI, to capture the two phases of the ENSO cycle, we create a dummy variable which takes the value of one when EQSOI anomalies are negative (positive) and zero otherwise, and then we multiply the dummy variable by the EQSOI anomalies to obtain a metric for the El Niño (La Niña) episodes. The two resulting EQSOI anomalies, i.e., EQSOI1 and EQSOI2, series are considered together in the model as part of an additional analysis to check if El Niño and La Niña events have a differential impact on RV.

2.2. Model and Estimation

The model that we estimate is an extended version of the heterogeneous autoregressive-realized volatility (HAR-RV) model of Corsi (2009), which can capture well-established long-memory and multi-scaling properties of asset markets, despite having a simplistic structure. In this regard, the key feature of the HAR-RV model is that it uses volatilities with different time resolutions to forecast the realized variance of bond yield changes. The model, thereby, captures the main idea motivating the heterogeneous market hypothesis (Müller et al., 1997), which states that different classes of market participants populate the bond market and differ in their sensitivity to information flows at different time horizons. Formally, the econometric model in a panel set-up for i=1, 2, …, 360 is given by:

$$RV_{i,t} = \beta_{0i} + \beta_{1i}RV_{i,t-1} + \beta_{2i}RV_{qi,t-1} + \beta_{3i}RV_{yi,t-1} + \beta_{4i}\Delta Yield_{i,t} + \beta_{5i}ENSO_t + \varepsilon_{i,t} \quad (1)$$

where RV is the realized variance, and RVq and RVy are the corresponding quarterly and yearly RVs respectively, $\Delta Yield$ depicts the change in yields, and *ENSO* is captured by EQSOI and SOI, as well as EQSOI1 and EQSOI2 for El Niño and La Niña events. The β's capture the cross-section-specific parameters, and the error term ($\varepsilon_{i,t}$) is distributed with mean zero and variance $\sigma_{ii,t}I$.

Fixed- and random-effects models incorporate panel-specific heterogeneity by including a set of nuisance parameters that essentially provide each panel with its own constant term. However, all panels share common slope parameters, which is undesirable in the current context. Random-coefficients (RC) models (Swamy, 1970) are more general in that they allow each panel to have its own vector of slopes randomly drawn from a distribution common to all panels. Implementation of the estimator ensures best linear unbiased predictors of the panel-specific draws from said distribution (Poi, 2003).

Consider a general random-coefficients model, with *y* being the dependent variable and *X* being the predictor, of the form:

$$y_i = X_i\beta_i + \varepsilon_i \tag{2}$$

In the case of RC, each panel specific β_i is related to an underlying common parameter vector β:

$$\beta_i = \beta + v_i \tag{3}$$

where $E\{v_i\} = 0, E\{v_i v_i'\} = \Sigma, E\{v_i v_j'\} = 0$ for $j \neq i$, and $E\{v_i \epsilon_j'\} = 0$ for all i and j. We may combine equations (2) and (3) to get:

$$\begin{aligned} y_i &= X_i(\beta + v_i) + \varepsilon_i \\ &= X_i\beta + u_i \end{aligned}$$

with $u_i \equiv X_i v_i + \varepsilon_i$. Furthermore:

$$\begin{aligned} E\{u_i u_i'\} &= E\{(X_i v_i + \varepsilon_i)(X_i v_i + \varepsilon_i)'\} \\ &= X_i \Sigma X_i' + \sigma_{ii} I \\ &\equiv \Pi_i \end{aligned}$$

We can stack the P panels:

$$y = X\beta + u \tag{4}$$

where:

$$\Pi \equiv E\{u_i u_i'\} = \begin{bmatrix} \Pi_1 & 0 & \cdots & 0 \\ 0 & \Pi_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Pi_P \end{bmatrix}$$

Estimating the parameters in equation (3) is a standard problem, which can be solved with generalized least squares (GLS):

$$\hat{\beta} = (X'\Pi^{-1}X)^{-1}X'\Pi^{-1}y$$

$$= \left(\sum_i X_i'\Pi_i^{-1}X_i\right)^{-1} \sum_i X_i'\Pi_i^{-1}y_i$$

$$= \sum_i W_i b_i \tag{5}$$

with W_i the GLS weight and $b_i = (X_i'X_i)^{-1}X_i'y$. The resulting $\hat{\beta}$ for the overall (national) result is therefore a weighted average of the state-specific OLS estimates. For more details of GLS weight and $\hat{\beta}$ variance specification, the reader can refer to Poi (2003).

In order to obtain the state-specific $\widehat{\beta_i}$ vectors, Judge et al. (1985) suggest that if attention is restricted to the class of estimators $\{\beta_i^*\}$ for which $E\{\beta_i^*|\beta_i\} = \beta_i$, then the state-specific OLS estimator b_i is appropriate. Following Green's (1997) suggested method of obtaining the variance of $\widehat{\beta_i}$, it follows that $\hat{\beta}$ is both consistent and efficient; and although inefficient, b_i is also a consistent estimator of β.

Poi (2003) also suggests a test to determine whether the panel-specific β_is are significantly different from one another. The null hypothesis is stated as:

$$H_0: \beta_1 = \beta_2 = \cdots = \beta_P \tag{6}$$

and the test statistic is defined as:

$$T \equiv \sum_{t=1}^{P} (b_i - \beta^\dagger)' \{\hat{\sigma}_{ii}^{-1}(X_i X_i)\} (b_i - \beta^\dagger) \tag{7}$$

where

$$\beta^\dagger = \{\textstyle\sum_{t=1}^{P} \hat{\sigma}_{ii}^{-1}(X_i X_i)\}^{-1} \sum_{t=1}^{P} \hat{\sigma}_{ii}^{-1}(X_i X_i) b_i.$$

The test statistic T is distributed as χ^2 with $k(P-1)$ degrees of freedom.

In the next section, we present the empirical results for equation (1).

3. Empirical Findings

Table 1 presents the findings of our analyses based on various model specifications. As can be seen, there is strong evidence of long-memory, i.e., persistence and multi-scaling behaviour in a consistent manner, as depicted by the statistically significant (at the 1% level) coefficients corresponding to the lags of the monthly, quarterly and annual RVs. In other words, these results justify the use of the HAR-RV model. The coefficient of *ΔYield* is negative and statistically significant (at the 1% level), highlighting the existence of the leverage effect in the bond market. More importantly, as observed from Model 1, EQSOI anomalies increase RV in a statistically significant manner at the 1% level. The result continues to hold when we use SOI anomalies instead, and even a lag of EQSOI anomalies (giving the framework a predictive flavour) under Models 2 and 3 respectively. Furthermore, Model 4 depicts the case when we decompose the EQSOI anomalies into El Niño and La Niña events, and again as shown by the parameters corresponding to EQSOI1 and EQSOI2, the effects are positive and statistically significant at the 1% level, with El Niño-effects being slightly stronger than those of the La Niña phases. In summary, we find strong evidence in favour of our hypothesis that ENSO cycles capturing rare disaster risks increases US Treasury market volatility, controlling for persistence, multi-scaling behaviour and leverage.

Table 1. The Impact of the ENSO Cycle on Realized Variance (RV) of the Term-Structure of US Treasury Securities

	(1)	(2)	(3)	(4)
RV(-1)	0.200***	0.201***	0.201***	0.200***
	(32.87)	(32.94)	(32.96)	(32.62)
RV_q(-1)	0.224***	0.227***	0.228***	0.220***
	(28.27)	(28.37)	(28.52)	(27.96)
RV_y(-1)	0.340***	0.334***	0.335***	0.340***
	(40.88)	(39.88)	(40.54)	(41.77)
ΔYield	-0.00923***	-0.00885***	-0.00903***	-0.00946***
	(-3.07)	(-2.94)	(-2.99)	(-3.13)
EQSOI_Anomalies	0.00367***			
	(19.60)			
SOI_Anomalies		0.00155***		
		(7.68)		
EQSOI_Anomalies(-1)			0.000938***	
			(4.29)	
EQSOI1				0.00399***
				(8.66)
EQSOI2				0.00311***
				(4.29)
Constant	0.0174***	0.0178***	0.0176***	0.0181***
	(28.09)	(28.83)	(28.56)	(28.18)
N	187248	187248	187248	187248
χ^2(df)	4990.84	4998.92	5019.00	5344.54
Prob χ^2	0.00	0.00	0.00	0.00

Note: *t*-statistics in parenthesis, based on robust standard errors. The significance levels are represented by the asterisks (* for p<0.10, ** for p<0.05, and *** for p<0.01). χ^2 is a test for parameter constancy across the different maturities. The degrees of freedom (df) for the χ^2-statistics are 2154 for Models (1) to (3), and 2513 for Model (4).

Since we are using the RC model, in Figure 1 we see the impact of the EQSOI anomalies across all 360 maturities. In general, the impacts (which are actually all significant at the 1% or 5% levels, complete details of which are available upon request from the authors) of the ENSO cycle are quite stable across the maturities, though some peaks are observed around 16-, 30-, 51-, 94-, 122-, 163- to 180-, 238-month maturities, and a consistent rise in effect is observed from 288- to 360-month maturities. In other words, focussing on just 10-year bonds (as in Gupta et al., 2019), would lead to inaccurate portfolio allocation decisions. This is because the strongest impact is observed mainly for 16-month, and between 13- and 15-year and 30-year bonds, i.e., at the two ends and middle of the term-structure, indicative of high-trading at these maturities in the wake of increased rare disaster risks, and particularly El Niño events.

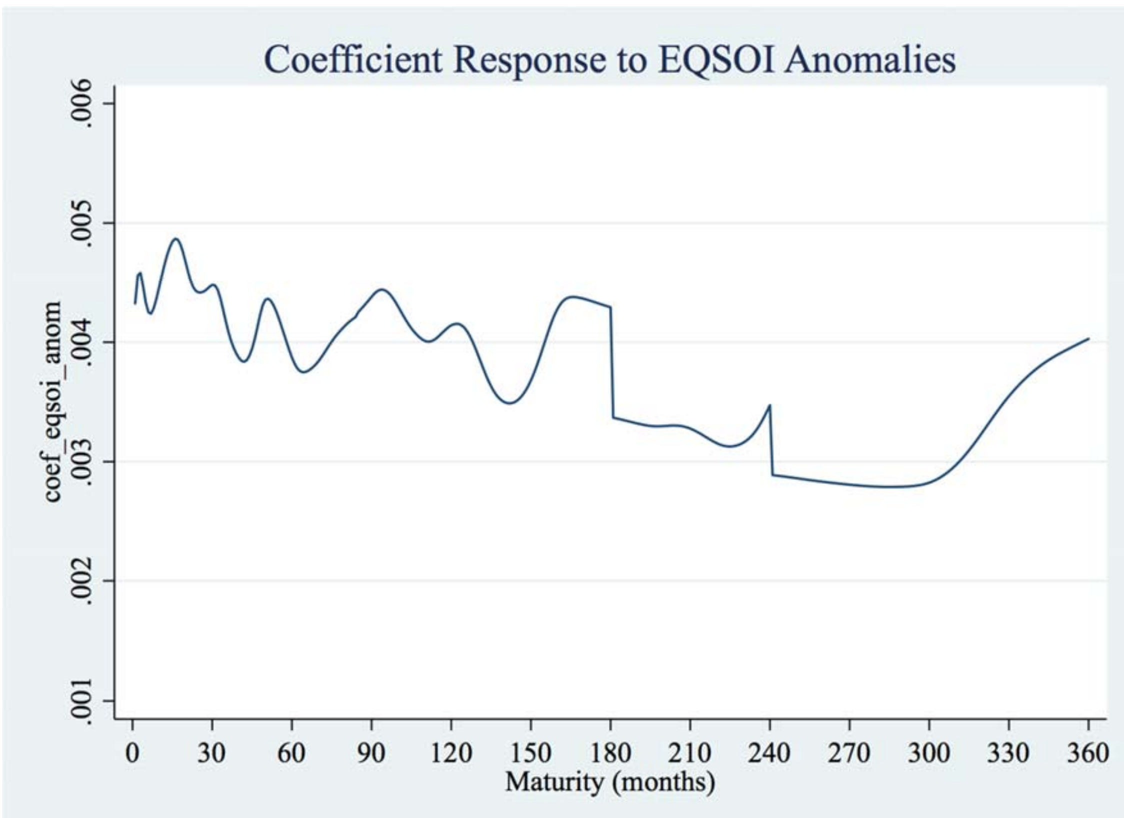

Figure 1. Random Coefficient Model Estimation Results for 1- to 360-Months Maturities due to EQSOI Anomalies

4. Conclusion

We provide evidence supporting the impact of rare disaster risks, as captured by the El Niño-Southern Oscillation (ENSO) cycle, on the realized variance (RV) of the entire term-structure of US Treasury securities. Given that US Treasury bonds are well-established safe-havens, we hypothesize a positive impact of the ENSO cycle on the volatility of the bond market. Using an extended heterogeneous autoregressive (HAR)-RV model applied to a panel involving the bonds of maturities of 1- to 360-months, we find that the ENSO cycle has a positive and statistically significant impact on bond market volatility, after controlling for long-memory-, multi-scaling- and leverage-effects. This result continues to hold, under alternative metrics of the ENSO cycle, its lagged values, and also when we distinguish between the El Niño and La Niña phases of the ENSO cycle, with El Niño having a stronger impact. Since our panel estimation method, based on a random coefficients model, allows for obtaining heterogeneous slope coefficients, we find that the impact on the entire term structure is positive, though stronger impacts are observed at the two-ends and the middle-part of the term-structure. This finding highlights the importance of using a random-coefficients model from the perspective of an academician. As volatility is a key input to investment decisions and portfolio choices in general, the fact that rare disaster risks in the form of the ENSO cycle can predict the volatility of the entire term structure of US Treasury securities is of paramount importance to bond fund managers and bond traders. The evidence of predictability also concerns policymakers who should care about rare disaster risks such as the ENSO cycle when taking decisions that involve US Treasury securities.

As part of future analysis, it would be interesting to extend our analysis to out-of-sample forecasting[7] and other international bond markets.

Declarations: Not applicable

Funding: No funding was received for conducting this study.

Conflicts of interest/Competing interests: None.

[7] While a full-fledged forecasting analysis based on recursive and/or rolling window for multi-steps-ahead of the entire yield curve involving maturities of 1 month to 360 months is beyond the scope of this paper, we have conducted a preliminary forecasting experiment, as suggested by an anonymous referee. In this regard, we estimated equation (1) with and without EQSOI over the in-sample period of 1961:06 to 2018:12, and produced one-month-ahead forecast for the entire yield curve over 2019:01 to 2019:12, i.e., using a fixed-scheme of estimation involving the model parameters. As can be seen from Figure A1 in the Appendix of the paper, the root mean square errors (RMSEs) for the entire yield curve with EQSOI included in the model are consistently lower than the corresponding RMSEs obtained from the model without the ENSO-predictor. In other words, we do find evidence of the role of EQSOI in producing forecasting gains for the US Treasury securities of maturities associated with 1 month to 360 months.

Availability of data and material: Data will be available upon request.

Code availability: Estimation code will be available upon request.

Authors' contributions: RE: Model estimation and writing; RG: conceptualization, supervision, writing; JN: Model estimation and writing; EB: data curation and writing.

Ethics approval: Not applicable

Consent to participate: Informed consent was obtained from all individual participants included in the study

Consent for publication: Data and codes will be available upon request.

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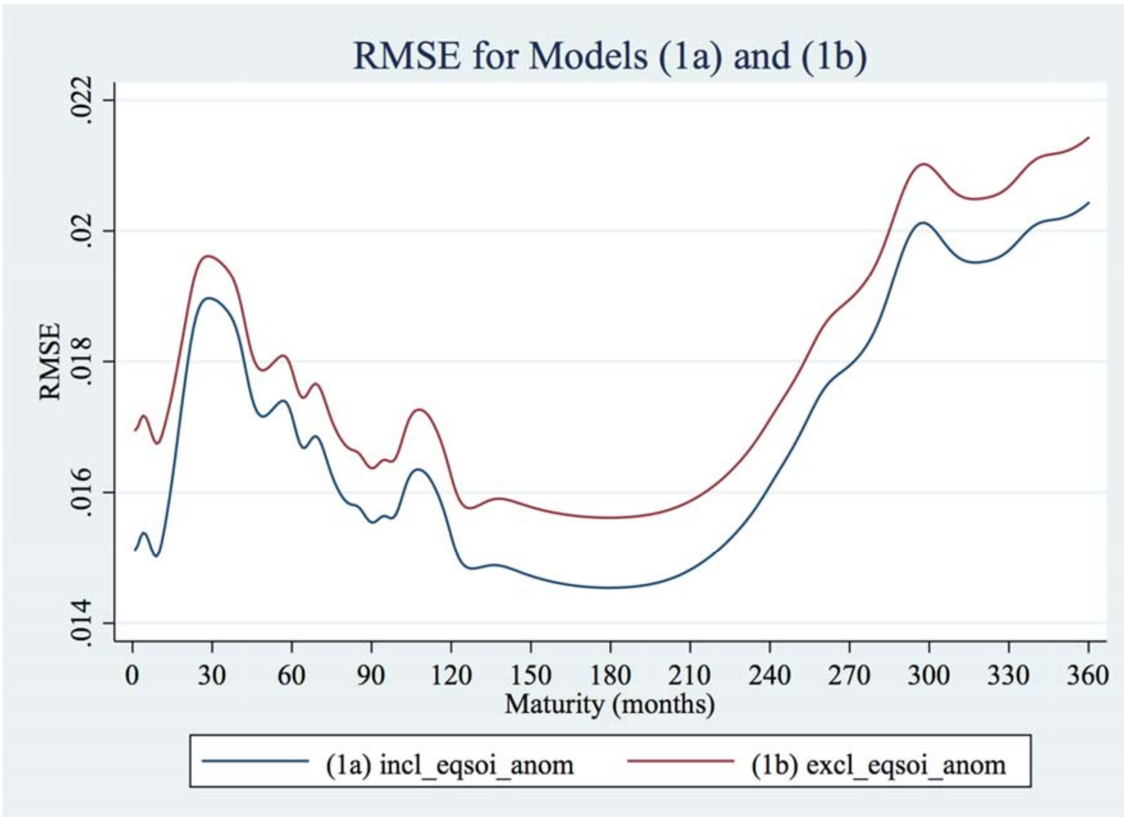
APPENDIX:

Figure A1. Out-of-Sample Forecasting of US Treasury Securities with 1- to 360-Month Maturities due to EQSOI Anomalies



Note: See Table 1 column number 2, i.e., Model 1, and also Note to Table 1. Model 1(a) includes EQSOI anomalies (incl_eqsoi_anom), while Model 1(b) excludes (excl_eqsoi_anom) the same to produce out-of-sample forecasts over 2019:01-2019:12, using an in-sample of 1961:06-2018:12. RMSE is the root mean square errors of these two models.