Term at Risk Estimation for the Philippines

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ABSTRACT

Understanding the movements of the yields on key government securities and the risks associated with the downside of the distribution of the yield curve are crucial to understanding the movements of the markets influenced by short-term rates. Moreover, understanding how macrofinancial factors and domestic financial conditions can be linked to these yields is a crucial linkage which can deepen understanding on the transmissions and spillovers from the financial markets toward key economic variables. This study seeks to propose and implement a framework that quantifies the risks associated with the downside of yields and estimate a yield curve with these tail risks considered. Moreover, the framework can be used as a scenario analysis tool on seeing changes in the yield curve given changes in macrofinancial conditions in the economy.

JEL Classification E17, E43, E44

Keywords. Term at Risk, Term Premium, Yields, Quantile Regression

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Abbreviations

TaR	*Term at Risk*
GaR	*Growth at Risk*
GDP	*Gross Domestic Product*
GFC	*Global Financial Crisis*
AFC	*Asian Financial Crisis*
PCA	*Principal Components Analysis*
LDA	*Linear Discriminant Analysis*
FCI	*Financial Conditions Index*
EC	*External Conditions*
EU	*European Union*
ASEAN	*Association of Southeast Asian Nations*
IMF	*International Monetary Fund*
FED	*Federal Reserve Bank*

Introduction

The role of monitoring macrofinancial vulnerabilities and financial market uncertainties has increased significantly in the last decade. Given how these vulnerabilities have exacerbated previous crisis episodes and have made the road to recovery much tougher, there is a substantial desire to understand how these factors are linked with key economic indicators, such as the term yields. In particular, the framework developed by Adrian, Boyarchenko, and Giannone (2019) explored these macrofinancial linkages on GDP growth. This same framework served as the groundwork by which distributional impacts of macrofinancial vulnerabilities are determined. Other studies such as Lopez-Salido and Loria (2020) have also implemented the same framework[2] on inflation identifying key macrofinancial risks that could affect the upside and downside risks to inflation.

In recent financial crisis episodes, the impact of these macrofinancial risks also affects the yield curve and the yields of government securities across different term lengths. *Figure 1* shows the yields of various government securities by the different term lengths.

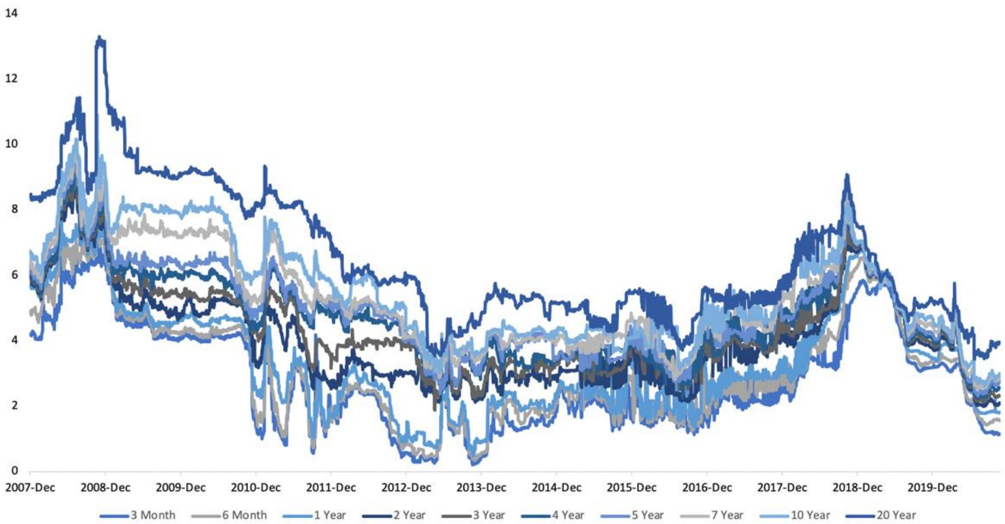

Figure 1. *Yields of Various Government Securities (by Maturity)[3]*

As seen in *Figure 1*, yields of various government securities have not really recovered after the Global Financial Crisis (GFC) to pre-GFC levels. While a modest strengthening had been seen in late 2017, the recent effects of COVID-19 brought the yields back to near all-time lows.

[2] The framework in Lopez-Salido and Loria (2020) utilized the Phillips Curve equation framework for the main regression, but a similar determination of the key macrofinancial risks was utilized.
[3] Data collected from Bloomberg until 31 October 2020

From the various yields of the different government securities, the yield curve can be derived. Given that the yield curve provides guidance on the direction of where short-term rates would be headed in the near future, it is of important consideration for central banks to monitor the potential downside risks to the yield curve.

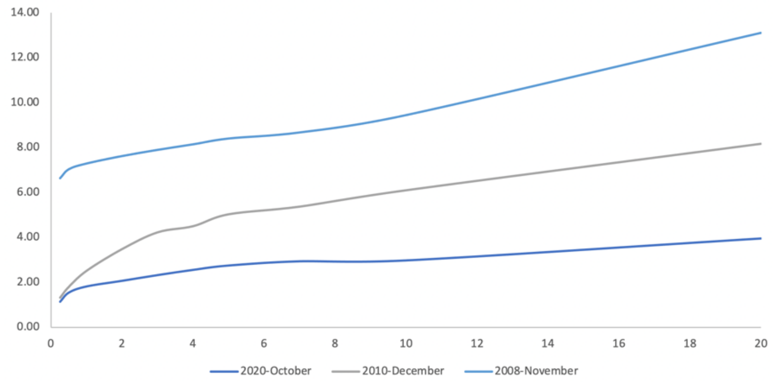

Figure 2. *Yield Curves of Philippine Government Securities (Select Years)*[4]

The yield curve of the Philippines for end November 2008, end December 2010, and end October 2020 is shown in *Figure 2*. It can be noted that since the peak in the level of interest rates immediately post the GFC[5], overall yields across different terms declined. The yield curve can also be seen flattening across time progressively becoming flatter as yields continue to fall. This flattening of the yield curve is due to changing yields among various bonds with different maturity dates, which could signal indifference among investors between short-term and long-term bonds (investments). This continued flattening presents a challenge as interest rates are projected to be "low-for-long"[6]. A continued flattening could eventually lead to a yield curve inversion, which has been associated with the emergence of recession months after the inversion. As such, understanding the factors associated with the downside of yields is crucial in understanding how the bond market will move in the near term and potentially influence other economic variables as a result. While crisis episodes such as the GFC have shown that investors seek shelter in safer financial markets such as the bond market to mitigate their risks and losses from other types of investments, this behavior is not commonplace in all types of economic crises. Such can be said with the yields seen during the

[4] Figures were obtained from Bloomberg and used end-of-month values.
[5] Yields were high as investors sought shelter from the volatile equities market and diversified their portfolios toward safer financial investments.
[6] Cunliffe, J. (2019) suggests that interest rates across most economies are likely to remain low following the COVID-19 pandemic and the extraordinary measures done by central banks across the world.

COVID-19 pandemic. Bond yields remain low with the differential between longer and shorter maturities become smaller and smaller.

This paper seeks to propose the estimation of "Term-at-Risk"[7] which is the probability that future bond yield (at a given maturity) falls below a prespecified threshold. In probability notation, this is given as the form in (1)

$$\Pr\big(Yield_{t+h} \leq TaR_{t+h}(\alpha|\Omega_t)\big) = \alpha \tag{1}$$

where $TaR_{c,h}(\alpha|\Omega_t)$ represents the term at risk for a time $t+h$ quarters in the future at a tail α percent of the probability distribution of yields, given a set of information available at time t (Ω_t).[8] The factors that can affect and pose downside risks to these yields would be macrofinancial vulnerabilities, balance sheet weaknesses, and external conditions. The estimation follows the "Growth at Risk" specification by Adrian, Boyarchenko, and Giannone (2019) which was subsequently localized for a Philippine context by Arcin, Basilio, Eloriaga, Fernandez, and Guliman (2020). This study follows these specifications closely albeit with two key exceptions. First, the framework is applied to the estimation of bond yields instead of growth. While the linkages between domestic financial conditions, domestic leverage, and external conditions are used akin to the localized specification[9], a different focus variable is used with some modifications to the domestic financial conditions classification. Second, the framework is applied on multiple bond maturities, in particular, the 3-month, 1-year, 5-year, 10-year, and 20-year bonds. Having an estimation for different maturities allows the quantification of which term (whether long-term or short-term) is more affected by changes in the macrofinancial conditions.

This paper contributes to the existing pool of literature in two key ways. First, it serves as one of the first approaches to use the original Growth at Risk methodology applied to other economic variables, in this case, to the estimation of yields of different maturities. This will better the conduct of macrofinancial surveillance, especially in identifying the magnitude of

[7] While the more apt term would be "Yield-at-Risk", this is a concept that has a specific definition. Moreover, the use of "Term" allows the more general exploration on different maturities or different spreads.
[8] In essence, when targeting the worst-case scenario at some tail α percent of the probability distribution of a given yield, it is feasible to determine changes in the area α under the curve given any favorable or unfavorable financial conditions borne out of heightened or muted macrofinancial vulnerabilities.
[9] Specification of Arcin, Basilio, Eloriaga, Fernandez, and Guliman (2020).

key downside risks to the yields of various government securities. Using this method consistently enhances the ability of central banks to monitor emerging risks and identify which risks would need to be given more pertinence in the conduct of monetary policy such that no adverse consequences may be realized in various economic variables. Secondly, it proposes a methodology and a method of analysis on the totality of the yield curve rather than on specific maturities, thus proving to be a more generalized a measure of risk that the conventional indicators[10].

The paper is divided as follows. Section 2 discusses the data and the proposed subclassifications to be used in linking the conditions in the financial markets to the yields. Section 3 builds upon section 2 by discussing the methodology used in line with the original specification laid out by Adrian, Boyarchenko, and Giannone (2019). Section 4 discusses the key results and presents the estimated tail values of the yields of different government securities.

Data

Following the original Growth at Risk specification in Adrian, Boyarchenko, and Giannone (2019), various macrofinancial indicators are collected and are aggregated using Principal Components Analysis (PCA) or Linear Discriminant Analysis (LDA) into three broad categories. These categories are: (1) Domestic Financial Conditions, (2) Macrofinancial Imbalance[11], and (3) External Conditions.

- ***Domestic Financial Conditions.*** This category contains indicators representing misalignments in asset prices, ease of obtaining funds, the cost of funding, and the degree of financial market stress or volatility in the domestic environment.
- ***Macrofinancial Imbalance.*** This category contains indicators on macroeconomic balance sheet weaknesses, firm and bank leverage, indebtedness, debt-servicing, and growing systemic risk.
- ***External Conditions.*** This category contains indicators on prevailing external market behavior, commodity prices, balance of payments, and other external factors.

[10] Term Risk, Yield Curve Risk, and Value at Risk
[11] May also be referred to as domestic leverage.

Table 1 shows the different indicators which were used for the conduct of the estimation.

These indicators are grouped into the three categories outlined. The data used spans from Q1 2001 until Q3 2020[12]. The indicators used are similar to those used in Arcin, Basilio, Eloriaga, Fernandez, and Guliman (2020) with modifications done to the domestic financial conditions. These modifications were the removal of the real rates which would have been perfectly collinear to the dependent variable and the inclusion of some control variables to prevent omitted variable bias while at the same time explaining substantial variation in domestic financial conditions.

Domestic Financial Conditions	**Domestic Leverage**	**External Conditions**
• Interbank Call Loan Rate (IBCL) • Equity Returns *(Log Difference of PSEi)* • PSEi Volatility • 5 Year Credit Default Swap • Makati Residential Real Estate Index *(Colliers)* • Emerging Market Bond Index (EMBI) for Philippines • Secondary Market Yield of a Three Month Government Security	• Debt to GDP • External Debt • Weighted Annual Cost of Capital *(Banks)*	• Chicago Board Options Exchange Volatility Index *(VIX)* • U.S. 10 Year Bond Yield • Purchasing Manager's Index of the US • Purchasing Manager's Index of China • Brent Crude Oil Price • Remittances • Log Difference of USD/PHP Exchange Rate • MOVE Index[13] • Current Account Balance

Table 1. *Subclassifications in the Term at Risk*[14]

The data points are grouped for two main reasons. First, the indicators are grouped so as to reduce dimensionality. While the estimation may be carried out with the variables not grouped together, there will be a severe multicollinearity problem that will be encountered given the similarity of the variables under study. Leaving the variables ungrouped leaves the likelihood of inflated standard errors a near certainty. Secondly, the

[12] Variables were transformed into a quarterly frequency by taking the datapoint on the last date of every quarter. Note however that some variables did not fully have observations that span the duration of the Q1 2001 to Q3 2020 time span.
[13] The MOVE index is a measure of volatility in the interest rates among different U.S. Treasuries. The MOVE index is generally the counterpart of the CBOE-VIX in the bond market
[14] A more detailed explanation of each indicator can be seen in the appendix.

indicators used in the Philippine case may not fully span the whole time-period. This is due to the fact that some indicators used were only conceptualized at some period after Q1 2001. Aggregating or grouping these variables into a single category or variable may provide more insight into the domestic financial conditions, macrofinancial imbalance, and external conditions.

Methodology

As mentioned previously, this paper shall closely follow the methodology developed by Adrian, Boyarchenko, and Giannone (2019) which had been localized for use in the Philippines by Arcin, Basilio, Eloriaga, Fernandez, and Guliman (2020). The approach is also the methodology used by the IMF in certain parts of its Global Financial Stability Report (GFSR)[15]. However, this methodology is applied to various term yields rather than real GDP growth. The TaR approach can be implemented using the following procedures.

- First, the approach starts with the construction of macrofinancial indices or financial conditions indices (FCI) based on the three partitions identified earlier in *Table 1*. The variables are aggregated per partition using LDA to reduce the dimensionality of the parameters.
- Second, a quantile regression is conducted to estimate some specification of future growth path given a set number of periods ahead and contingent on the three macrofinancial indices constructed in the first step.
- Third, after obtaining the conditional quantiles estimated at prescribed dates, a T-Skew distribution is fitted which is a parametric future growth distribution that is contingent on a specified set of macrofinancial conditions.
- Lastly, scenario analysis and multiple horizon projections are estimated. The methodology is detailed further in the succeeding sections.

[15]The GaR approach, for instance, was discussed in an analytical chapter based on in the 2017 GFSR.

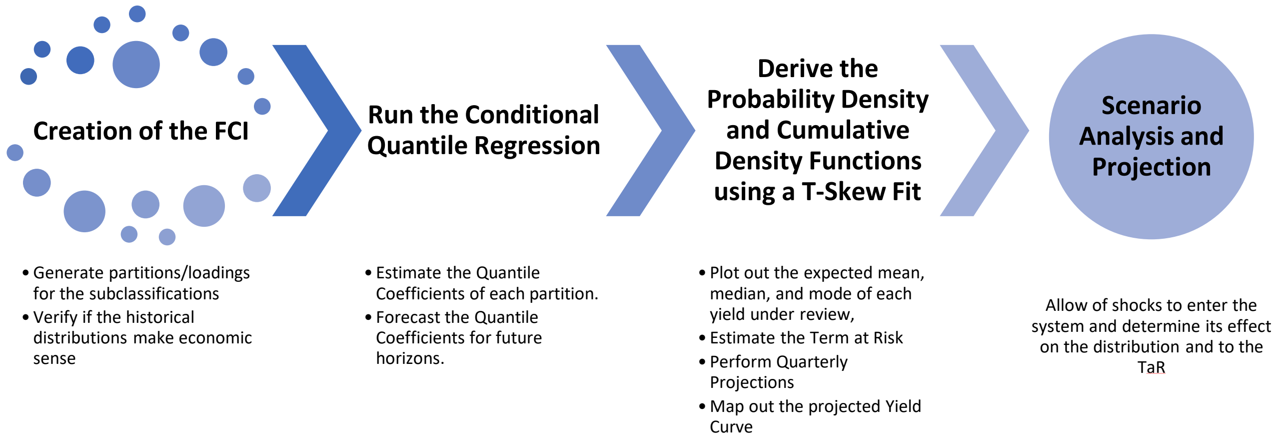

Figure 3. *TaR Methodology*

The methodology will only differ compared to the methodology in Arcin, Basilio, Eloriaga, Fernandez, and Guliman (2020) in the fact that the estimation is done for the yields of multiple government securities of different maturities. Most related literature on the said topic conducts the methodology on other real variables such as inflation. This study is likely the very first implementation of the said framework on a bond market financial indicator such as yields. While other measures such as the yield curve risk or yield risk measure the likelihood of these variables breaching a specified lower threshold, none of these indicators are as empirically rigorous or have the same explanatory power on the entire distribution of future yield as this framework proposed.

Creation of the Financial Conditions Indices

The FCIs are constructed using a procedure known as *linear discriminant analysis* (LDA). As mentioned previously, the data is aggregated into three categories, namely, domestic financial conditions, macrofinancial imbalance, and external conditions. LDA is used to account for the dimensionality issues typically encountered when dealing with data involving a multitude of variables. In this study, the indicators used are likely highly collinear with one another. This is due to the fact that these are indicators which can be moved in the same direction given the presence of various economic shocks. The movement of these indicators may also be somewhat contemporaneous in nature. Moreover, aggregating these macrofinancial variables into an index rather than just keeping them separated will theoretically improve estimations and filter idiosyncratic noises which potentially throw off forecasts or predictions.

The LDA procedure starts from individual variables $\{X_k\}_{k \in \{1,\ldots,n\}}$ being grouped into classes, where n is the number of variables for each class. These classes, defined as C, represent the three broad subclassifications, hence, $C = \{1,2,3\}$. Each class C contains individual variables X_k which are seen in *Table 1*. Using these variables and subclassifications, within-class and between-class matrices are created which represent the variability intra each class (within) and the variability between each class (between). The objective is to minimize the within-class variance so that the subclassifications are homogenous within themselves while maximizing the between-class variation such that the subclassifications are discriminated from one another. The specific advantages of LDA over PCA are highlighted in the appendix.

Quantile Regression Framework

The methodology uses a quantile regression framework which is a non-parametric estimation method which has distinct advantages over regular parametric estimation methods. First, the quantile regression framework captures the whole of the distribution of a dependent variable y_t. Conventional regressions such as those implemented using OLS are point centered regressions and can only produce coefficients at the mean of the distribution. By contrast, quantile regressions can capture and produce coefficient estimates at any quantile[16] allowing substantial variation in the coefficients as well as identifying the different magnitudes of how the independent variables correlate with the downside or upside of the distribution of the dependent variable. From this quantile regression coefficients, the probability distribution of future yields (at different maturities) may be estimated. Second, the quantile regression is inherently robust to outlying observations such as those that may be realized on crisis periods or on idiosyncratic episodes. As such, the quantile can be more accommodative to these observations which nonetheless explain the variation in yields compared to regular parametric estimation methods.

[16] Synonymous to percentile. The means that there are 99 quantiles (1st thru the 99th quantile).

The regression is specified with a generic government yield as the dependent variable $y_{i,t+h}^{\tau}$ against the independent variables which are the generated FCIs in addition to an autoregressive component $y_{i,t-1}^{\tau}$. The yield is estimated at a given quantile τ for a maturity i at some horizon h periods ahead. In the conventional estimation of the framework, h is usually set at four, eight, or twelve indicating 1, 2, or 3 year ahead projections[17]. The specification of the regression is seen below[18].

$$y_{i,t+h}^{\tau} = \alpha_0^{\tau} + \alpha_1^{\tau} y_{i,t-1}^{\tau} + \alpha_2^{\tau} DFCI_{i,t}^{\tau} + \alpha_3^{\tau} MI_{i,t}^{\tau} + \alpha_4^{\tau} EC_{i,t}^{\tau} + \beta Z_{i,t}^{\tau} + \varepsilon_{i,t}^{\tau} \tag{2}$$

The following are the key variables used in the regression above

- $y_{i,t+h}^{\tau}$ is the generic government yield with a maturity i for time $t+h$ at a given quantile τ;
- α_0^{τ} is the model intercept for a given quantile τ;
- α_n^{τ} are the slope coefficients for each independent variable n for a given quantile τ;
- $DFCI_{i,t}^{\tau}$ is the domestic financial conditions index for each τth quantile at some maturity i;
- $MI_{i,t}^{\tau}$ is the macrofinancial imbalance index for each τth quantile at some maturity i;
- $EC_{i,t}^{\tau}$ is the external conditions index for each τth quantile at some maturity i;
- $\beta Z_{i,t}^{\tau}$ is a vector of controls for yields including variables such as inflation, GDP growth, term premia, and other yield controls to account for potential unobserved factors for each τth quantile at some maturity i;
- $\varepsilon_{i,t}^{\tau}$ is some stochastic disturbance term at some period t for a given maturity i at some quantile τ

The lag length opted for shall be determined using the typical information criteria[19]. The inclusion of the autoregressive component $y_{i,t-1}^{\tau}$ is to mitigate any reverse causality concerns borne out of the model structure. The α_n^{τ} are the coefficients representing the

[17] Note that the data is of a quarterly frequency. As such, an $h = 4$ represents 4 quarters ahead. The same applies to all other specified h periods ahead.
[18] While the notation i, t precludes an estimate using panel data, the implementation done is a pure time series one where this methodology is run for each i where i could be 3-month, 1-year, 5-year, or 10-year.
[19] Akaike Information Criteria (AIC), Schwarz-Bayesian Information Criteria (SBIC), and the Hannan-Quinn Information Criteria (HQIC)

association between the financial conditions indices and the future yield. For this study, the 10th, 25th, 50th, 75th, and 95th quantiles are utilized. The corresponding α_n coefficients using a simples OLS are also shown.

Conditional Quantiles

From the conducted quantile regression, conditional quantile estimates of the future yield for a specified horizon, $y_{i,t+h}$ are obtained. This value for yield is contingent on financial variables $X_{i,t}$ which are the partitioned subclassifications from the LDA. The conditional quantile, $Q\left(y_{i,t+h}, \tau \middle| \{X_{i,t}\}_{i \in P}\right)$ for a specified time t is based on the estimated quantile model intercept, $\widehat{\alpha_0}^{\tau}$, and the slope coefficients, $\hat{\alpha}_i^{\tau}$, for each category P. The mathematical form of a conditional quantile is given below. As this estimation used a quantile regression, an estimate per quantile τ can be derived.

$$Q\left(y_{i,t+h}, \tau \middle| \{X_{i,t}\}_{i \in P}\right) = \widehat{\alpha_0}^{\tau} + \sum_{i \in P} \hat{\alpha}_i^{\tau} X_{i,t} \tag{3}$$

We use these conditional quantiles to estimate the conditional distribution of future yield. Compared to OLS, quantile regression coefficients are BLUE[20] when it comes to the estimation of a conditional quantile.

Parametric Fit and T-Skew

The conditional quantiles can serve as a sufficient statistic for deriving the conditional cumulative distribution function (cdf). As in any cdf, a probability density function (pdf) may be derived using a parametric fit such as the one specified by Adrian et al. (2018). While non-parametric fits may be used, these fits can be inaccurate in the estimation of extreme quantiles which, in turn, may lead to inflated standard errors which subsequently produces inconsistency in the distribution.

The specific parametric fit uses a parametric T-Skew distribution function which has been extensively used in financial econometrics. Fitting the cdf estimated from the conditional quantiles using a T-Skew distribution will further reduce dimensionality even after the supervised partitioning conducted under LDA. The parametric T-Skew can be used to derive the probability density function which is some skewed version of a Student's t

[20] Best Linear Unbiased Estimator (Adrian et al., 2018)

distribution (Azzalini and Capitanio, 2003). This distribution is fully characterized using four parameters, namely; location (loc), degree of freedom (df), mean $(scale)$, and skewness (ζ).

The standardized version of the T-Skew function used for estimation is given below as equation 4. Each parameter represents statistical measures subject to the number of degrees of freedom (df) , a chosen level of significance α, and skewness ζ.

$$F^{*,-1}(\tau|\alpha, df, \zeta) = \frac{F^{-1}(\tau|\alpha, df, \zeta) - loc}{scale} \tag{4}$$

Following this, the T-Skew distribution parameters are estimated using an unconstrained optimization. This unconstrained optimization procedure (in equation 5) specifies a minimization of the distance between the empirical quantiles and the quantiles of the T-Skew following Giot and Laurant (2002).

$$\begin{aligned} loc^*, scale^*, skew^* \\ &= argmin\left[\sum_{\tau}\left\{TSkew.quantile(\tau, loc, df^{*11}, scale, skew)\right.\right. \\ &\left.\left. - Q\left(y_{t+h}, \tau \middle| \{X_{i,t}\}_{i\in P}\right)\right\}^2\right] \end{aligned} \tag{5}$$

This minimization procedure utilizes the Sequential Least-Squares Programming as the scale and skewness parameters are naturally bounded[21]. Once the T-Skew parameters are derived, the pdf of each yield may be estimated.

Scenario Analysis

Another key advantage of the TaR approach is the ability to perform scenario analysis that help determine conditions that change the probability distribution of each yield. Shocks may be calibrated as emanating from changes in a single variable, a subset of variables, a whole partition, or a mixture of all. For this section, shocks from the partitioned macrofinancial conditions are simulated to investigate the resulting changes in the distribution of future yields.

[21] The methodology is clearly outlined in Prasad et al. (2019)

A shock on a partition (i.e. on financial conditions, external conditions and, domestic leverage) is done via an adjustment on the conditional quantiles (in equation 3). This means introducing counterfactual partitions given as $\tilde{X}_{i,t} = X_{i,t} \cdot (1 + \Phi)$ where Φ represents a shock based on a percentage change or standard deviation change. As a result, the adjusted conditional quantile is given in the form of equation 6 below.

$$\tilde{Q}\left(y_{t+h}, \tau \middle| \{X_{i,t} \cdot (1 + \Phi)\}_{i \in P}\right) = \hat{\alpha}^{\tau} + \sum_{i \in P} \hat{\beta}_i^{\tau} \tilde{X}_{i,t} \tag{6}$$

Shocking a certain variable requires accounting for the change in the partitions if one or more of the variables are shocked. As such, the adjustment in the conditional quantiles will have to be calibrated based on the correlation between a raw variable given as $\tilde{X}_{i,t} = X_{i,t} \cdot (1 + [\Phi \times \phi])$ where ϕ represents the correlation between the entire input and a specific variable or variables inside that input.

Results and Discussion

This section is divided into three main parts. First, the estimated yield curve and the term at risk based on the derived pdf are discussed as well as how these results feed into the larger financial markets. Secondly, the conditional quantile estimates are explored so as to ascertain the macrofinancial factors which may greatly affect or pose downside risks to the pdf of each yield at a given maturity. Lastly, a scenario analysis simulating a moderate financial crisis akin to the specification of Adrian et al. (2018) is conducted.

The results show a recovery in the longer-term yields for Q4 2020 - Q3 2021 likely due to factors relating to the recovery efforts as COVID-19 continues to subside. Meanwhile, short term uncertainty pushed shorter term yields further down providing a lower outlook on the recovery of shorter-term yields. This seems to suggest that the uncertainties emanating from the pandemic is still continuing to depress the shorter-term outlook while developments on longer term cures and vaccines have likewise caused longer-term yields to increase. While longer term yields are projected to increase, there is considerably greater uncertainty in these yields as the derived pdf suggests a greater scale and skewness to the distribution.

From the conditional quantile estimates, it may be inferred that the main factors affecting the downside of yields at shorter maturities emanate from domestic financial conditions. This can be seen consistently across all the shorter maturities (3-month, 1 year) as a change in domestic financial conditions is heavily associated with the tail of the distribution as compared to macrofinancial imbalance and external conditions. Conversely, macrofinancial imbalances factor more into the narrative of downside risks in medium- or longer-term yields while external conditions heavily influence the longer-term yields.

Lastly, the scenario analysis suggests an improvement across all yields at different maturities when financial conditions are looser. While the improvement in the yield is fairly consistent, the improvement in the short-term yield is the highest of all of the yields under review, while long-term yield also increased albeit with a higher uncertainty and skewness compared to the other yields.

Estimated Yield Curve and Term at Risk

Estimating the yield curve and the term at risk is essentially done by running the quantile regression and deriving the T-Skew fit at different yield maturities. Running the methodology yields the results in *Figure 4*. The grey and light blue lines represent the projection for the next four quarters ahead (Q4 2020 to Q3 2021) and the term at risk associated with that projection respectively. The darker blue line represents the yield curve as of Q3 2020.

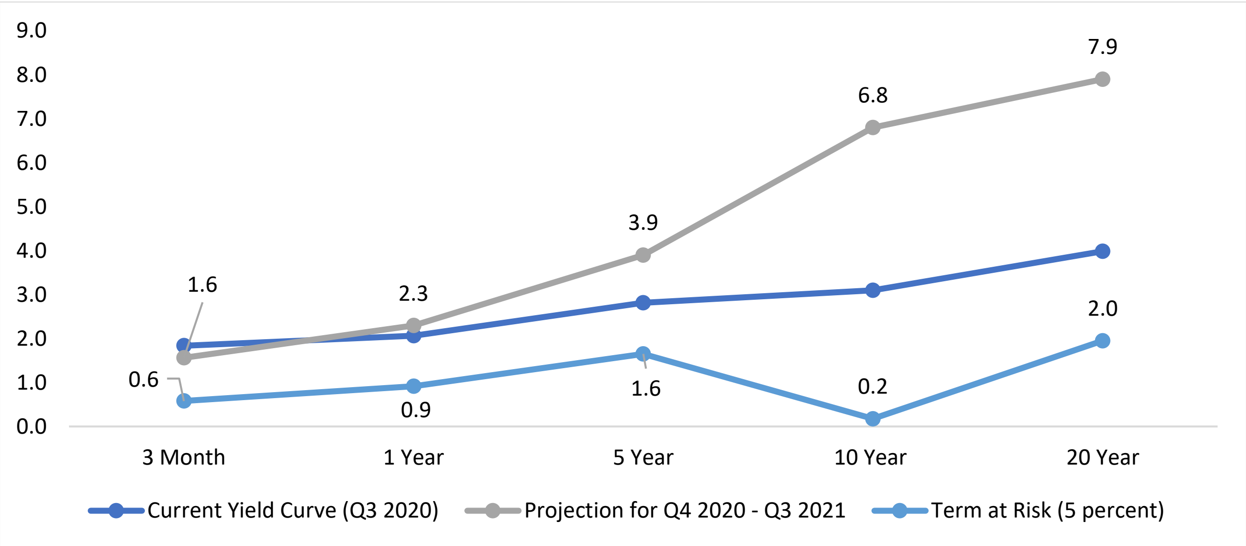

Figure 4. *Q4 2020 – Q3 2021 Conditional Projection and Term at Risk*

The projection for Q4 2020 – Q3 2021 suggests a recovery in the longer term yields while a slight decline further is seen in the short term yield. Because of the COVID-19 pandemic, yields have generally declined following the reductions in the policy rate. While the longer-term yields continue to recover post the start of the pandemic[22], the yields are still below normal as the effects of the pandemic continue to wane on the bond market. Interesting to note is that the 3-month bond yield is projected to fall further as more investors shift their investments to longer term securities given renewed confidence as more news on vaccines and pandemic mitigating measures come in.

One aspect of the results to consider is the large uncertainty in the distribution of the 10 year and 20-year yields. Compared to the shorter-term yields, the associated distribution with these longer-term yields has a larger scale and a greater skewness. This suggests that the macrofinancial factors utilized in deriving the pdf is associated with a greater uncertainty in the value of the longer-term yields. This is consistent with the view that crisis events generally cause great uncertainty in futures as prospects initially after an economic shock may seem very limited. These yields start to improve as considerable progress is made in handling the crisis. As the pandemic has not been fully contained as of time of reporting, it is reasonable to expect considerable uncertainty from the estimation of the longer-term yields.

Lastly, the estimated yield curve and the yield curve at risk do not show any glaring signs of a potential inversion, suggesting stable financial conditions are expected for the period projected. While there is considerably higher uncertainty in the 10-year yield, the lower 10-year yield value at risk compared to the 5-year may just be due to the volume by which the bond is subscribed to and not due to other underlying macrofinancial factors. As a yield curve inversion generally indicates the likelihood of a recession, this result suggests that no immediate or prolonged recession should be expected.

Conditional Quantile Estimates at Each Yield

The conditional quantile estimates are seen in *Figure 5*. All quantile coefficients for each year are detailed and separated by the quantile under consideration. The results using a simple OLS are also given. First, it can be seen that domestic financial conditions are heavily associated with all yields, especially the shorter-term yields at all quantiles. In terms of the lowest quantile, domestic financial conditions appears to be the most significant determinant followed by macrofinancial imbalance and external conditions. Second, medium-term yields

[22] Since the BSP reopened the GS purchase window in late February, normal market activity returned as investor confidence has been restored. This was seen in the decline in GS yields in the secondary market following marked increase in early March particularly for the longer tenors, as well as increase in the volume of transactions in the secondary market

are generally affected by all factors but the macrofinancial imbalance is the highest and most significant determinant for these yields. Third, external conditions seem to be highly associated with downside risks to longer-term yields as evidenced by the quantile regression coefficients associated with the 20 year yield.

The significance of the domestic financial conditions is an expected result as movements in the bond markets have been shown to have been responsive to monetary policy adjustments which are heavily affected by financial conditions in the domestic economy. Moreover, the significant association of the macrofinancial imbalance and external conditions on medium and longer-term yields suggests that movements in this yields are heavily influenced by the developments in the global economy.

Scenario Analysis Results

Results of the scenario analysis simulating the impact of a two standard deviation change in domestic financial conditions suggest that all yields across different maturities will increase with this change. A considerable increase is seen in shorter term bonds which is to be expected given the high degree of association between domestic financial conditions and shorter-term yields.

It is important to note that given the shock, the relative direction of how the yields responded are all the same, albeit with varying magnitudes. This response is likely due to the consistent response of yields of different maturities when economic shocks occur. It is more likely that the recovery post these shocks would vary, likely having a different recovery path post a crisis for a given yield. Nevertheless, the scenario analysis reflect the estimated magnitudes in the quantile coefficients suggesting a consistency between the two aspects of the estimation and is consistent with the larger economic story.

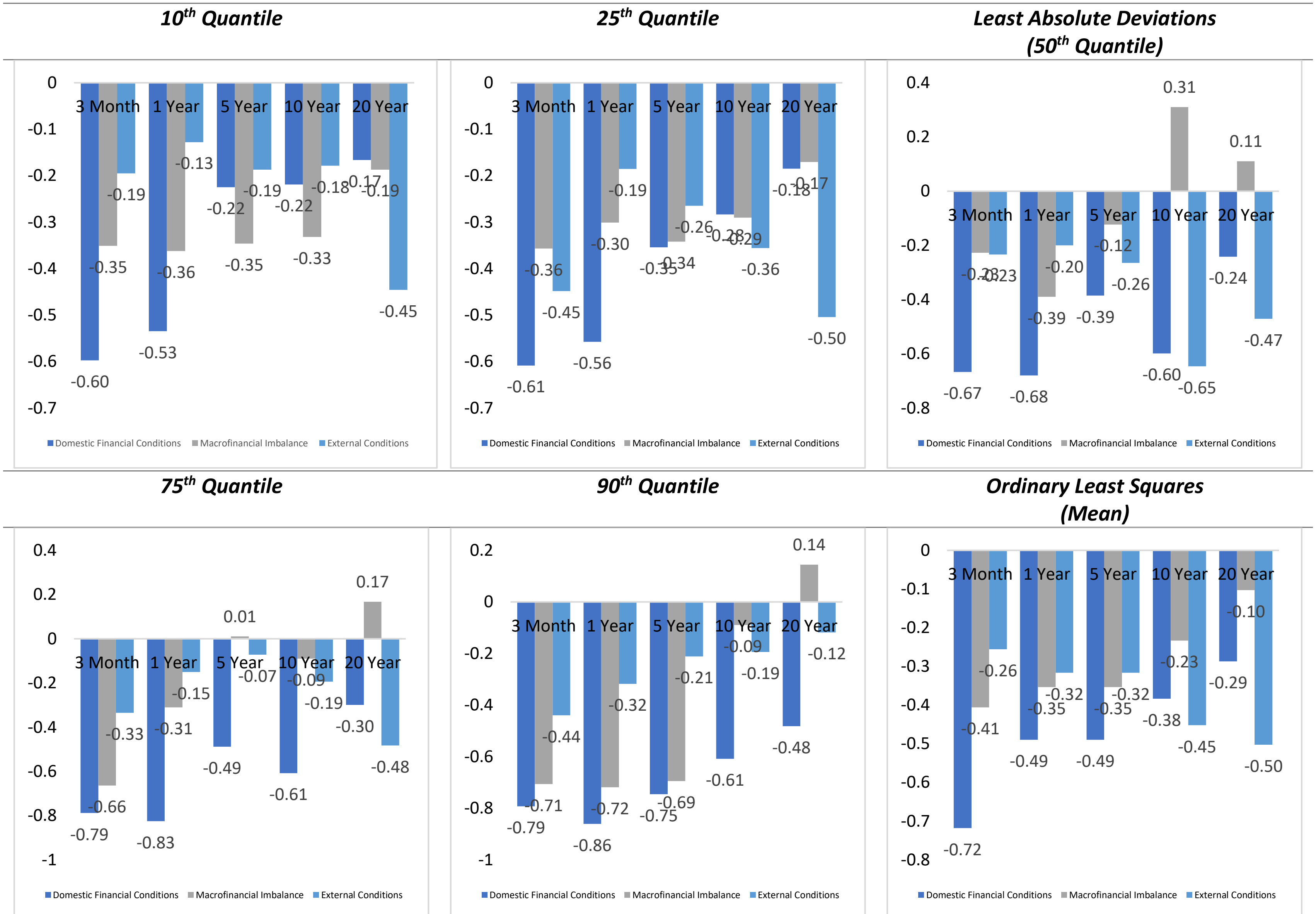

Figure 5. *Conditional Quantile Estimates*

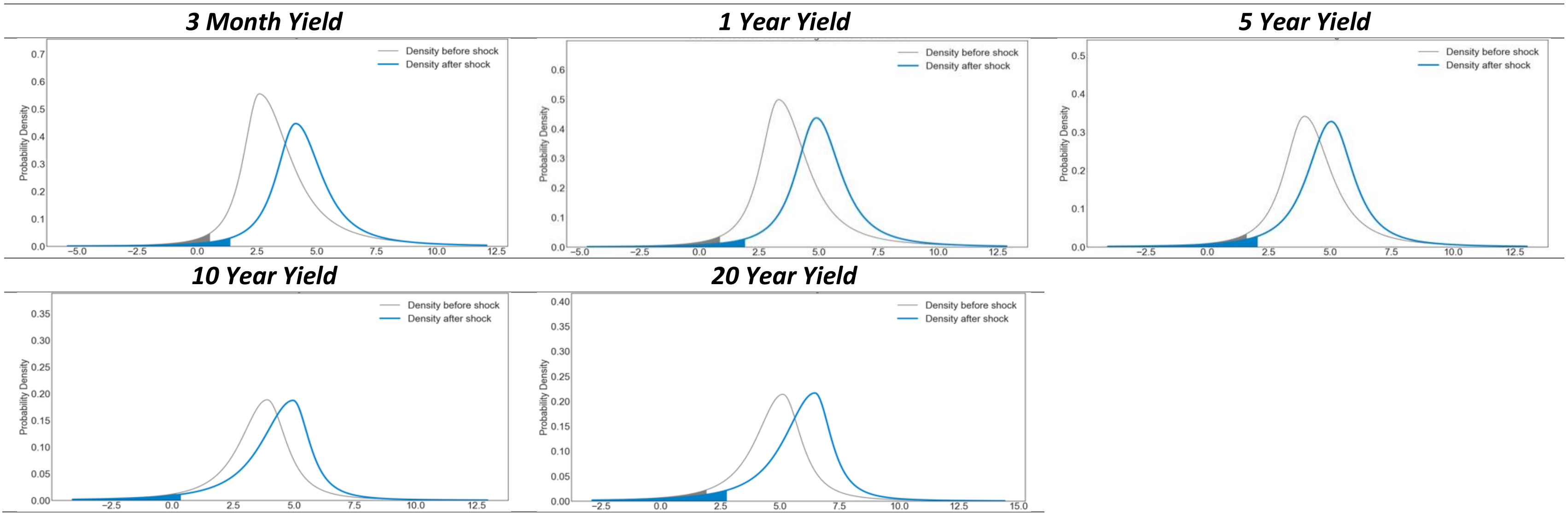

Figure 6. *Scenario Analysis Estimates*

Conclusion

The TaR framework links financial conditions to the yields of an economy and serves as a useful macrofinancial surveillance and analytical tool. The results obtained from the estimation likewise give substantial insight on the outlook and distribution for each yield. The results show that longer-term yields are projected to rise in the coming quarters while a slight decline is to be expected in the shorter-term yields. There is no considerable risk as to a yield curve inversion for the next few quarters as yields continually recover from the impact of the pandemic. Factors to consider in the assessment of the downside risks to the yields mainly emanate from the movements in the domestic financial markets for shorter-term yields while external conditions are likely to play a larger role for longer-term yields.

Overall, the Term at Risk framework can directly enhance the capacity of a country to conduct macrofinancial surveillance and to anticipate macrofinancial risks as these arise. There are several key policy implications that can be taken from the initial TaR application for the Philippines.

First, the linkage between the financial markets and the real economy is clearly seen in the framework. It has been shown that both domestic financial conditions and external conditions have a significant impact on the the yields under review. The results of the quantile regressions clearly show that changes in these conditions affect the distribution of yields at varying maturities. Zeroing in on the downside risks to yields, the current analysis confirms the need to be vigilant about buildups in external market stress and in domestic financial conditions as these pose the highest downside risk to yields. The term at risk estimates also help differentiate whether the sources of risks to growth are coming from the macrofinancial sector or from the pandemic, or both.

Second, even as a non-parametric approach, the TaR analysis can serve as a sensitivity analysis for point yield forecasts. With this comparison, the TaR analysis provides a means for empirically validating yields estimates obtained from standard models. Moreover, the TaR analysis provides a perspective of the bond market that is directly linked with (or sensitive to) the economy's macrofinancial conditions.

Third, the TaR analysis is very useful and most relevant in cases when rare events occur since the analysis involves results or estimates of growth that are "at risk", i.e. at the lower-end of the distribution of yields. Specifically, empirical results assign probabilities to the various growth numbers across a distribution. For the current pandemic period, for instance, COVID-19 is seen to have a significant impact on the economy and is expected to hamper domestic yields as rates are projected to be low for longer. Analysis and policy evaluations should therefore focus on the "at risk" part of the yield distribution.

In light of the results, it is imperative that the conduct of macrofinancial surveillance using TaR be made a staple in a policy evaluation toolkit. The TaR Framework has many uses to further enhance the BSP's toolkit on monitoring developments in the economy. As shown in the empirical exercises, the TaR is a useful, flexible, and comprehensive macrofinancial surveillance tool. Using the TaR analysis, policymakers can identify what the key indicators to look at and how these are doing at any point in time. Moreover, the TaR can provide forward guidance on key downside risks to yields and anticipate events such as yield curve inversions. This framework can provide guidance on which indicators pose greater downside risks to yields compared to others. Summing these reasons up highlights the TaR's role as an essential guide in macroprudential policy given that it can be used to quantify the impact of systemic and financial market risks or developments on future yields.

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Appendix

	3 Month	1 Year	5 Year	10 Year	20 Year
Current Yield Curve (Q3 2020)	1.835	2.062	2.81	3.093	3.985
Projection for Q4 2020 - Q3 2021	1.5618	2.294	3.9546	3.9085	5.1226
Term at Risk (5 percent)	0.5765	0.9169	1.6495	0.1751	1.9502
Term at Risk (10 percent)	0.962	1.4343	2.5298	2.5981	4.1318

Appendix Table 1. *Specific Point Estimates of the T-Skew Fit*

Advantages of the LDA. This study uses LDA rather than Principal Components Analysis (PCA) due to several key benefits. Firstly, under PCA, the data reduction is realized via a maximization variance principle and applied to a set of individual variables that are not necessarily important or relevant for estimating the probability distribution of GDP. More specifically, under LDA, the variance is maximized among a set of variables (classes) while ensuring linear separability between the classes of a dummy (categorical) variable Y.

Since PCA and LDA results are heavily affected by missing values, a process called chain-indexing is used. Recursive retropolation (interpolation by backward differences) is implemented in chain-indexing such that problems of absent data from the beginning or at the end of the sample are solved. Following the IMF framework, the dummy (categorical) variable is set equal to 1 when the yield at a one-year level is below the 35th historical country-specific percentile and 0 elsewhere. The percentile cutoff for the Philippines is set slightly higher at 30 percent[23].

Secondly, LDA implores a classification partitioning that allows linking financial variables to yields in the data reduction process. Third, LDA is considered robust even when homoscedasticity and the normality of the distribution of the data are violated. Akin to principal components analysis, the input variables are normalized through a z-score to avoid distortions due to heterogeneity with regards to the scaling of each variable.

[23] The benchmark percentile cutoff was increased given that Philippine data compared to developed country data is relatively more incomplete and less long-span. As such, a higher compensation or cutoff would increase the precision of the estimates.