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Abstract

This paper examines the potential impact of US monetary normalisation on sovereign bond yields in Asia Pacific. We apply the quantile vector autoregressive model with principal component analysis to the assessment of tail risk of sovereign debt, which may not be detectable using traditional OLS-based analysis. Our empirical evidence suggests that US Treasury bond yields can have a significant impact on sovereign bond yields in the region, an important channel through which monetary normalisation by the Fed can affect Asia-Pacific economies. Increases in sovereign bond yields will not only compromise the ability of the sovereigns in the region to service their debt but also translate into higher costs of borrowing for the rest of the economy. The results show how much the outsized impact could potentially be if US monetary normalisation somehow turns out to be much more disorderly than expected.

Keywords: Sovereign Credit Risk, Tail Risk, Value-at-Risk, Quantile Regression, Vector Autoregression, Impulse Response Function, Principal Components

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1. Introduction

Former Fed Chairman Ben Bernanke surprised global financial markets when he signaled the Fed's intention to taper its quantitative easing (QE) programme in his Congressional testimony on 22 May 2013. The US Treasury bond market was sold off, which coincided with a sharp rise in sovereign bond yields in Asia Pacific and abrupt capital outflows from the region (Figure 1). While financial markets have been a lot calmer since the Fed commenced its QE tapering, it is important for policymakers to be vigilant about a repeat of the turbulence over the course of monetary normalisation.

There has been a lot of research on the impact of Fed's monetary easing policy in recent years. However, studies on possible effects of US monetary normalization are scarce and mostly focus on the role of the country's economic fundamentals in explaining market reactions.[1] Mishra et al. (2014) study the impact on emerging markets. They find that countries with stronger macroeconomic fundamentals, deeper financial markets, and a tighter macroprudential policy stance in the run-up to the tapering announcements experienced smaller increases in government bond yields and smaller currency depreciations but less differentiation in their stock markets. However, Aizenman and Hutchison (2014) and Eichengreen and Gupta (2014) find that macro fundamentals are not important. In response to the Fed's tapering announcement, economies with more capital inflows would experience a larger exchange rate depreciation, declines in the stock market, and increases in sovereign CDS spreads. These responses may be attributable to investors' over-reaction.[2]

This study contributes to the literature by being the first to assess the tail risk of sovereign bond yields in Asia Pacific following a US monetary policy shock. Tail risk here refers to the likelihood of an extreme change in sovereign bond yields. This assessment is important because the region has received approximately 55% of total capital inflows to emerging markets in the past 5 years during which several rounds of quantitative easing were introduced in advanced economies.[3] Following the US's tapering announcement, sovereign bond yields increased sharply by 90 basis points on average between May and September 2013. These changes were all in the right hand tail of the yield distributions and some were in the 99th percentile (Figure 2). This suggests that the response of the yields may potentially be stronger-than-expected when the Fed eventually starts its monetary normalisation process.

This study also contributes to the literature of applied econometrics by proposing a new extension of

[1] For example, Bauer and Neely (2013) assess the impact of the three Fed's large-scale asset purchase programs on government bond yields of advanced countries using a dynamic term structure model; Moore et. al (2013) examine whether large-scale asset purchases by the Federal Reserve influenced capital flows out of the United States and into emerging market economies using a panel data regression; Rogers et al. (2014) examine the effects of unconventional monetary policy by the Federal Reserve, Bank of England, European Central Bank and Bank of Japan on bond yields, stock prices and exchange rates using a VAR specification.

[2] Poghosyan (2012) also suggests that investors' decisions can be largely explained by herding behaviour amidst increased risk aversion, rather than economic fundamentals, during periods of financial stress.

[3] See Sahay et al. (2014) for more information.

the vector autoregressive (VAR) model to quantile regression called the principal component quantile VAR (PC-QVAR) model. The model features both the SVAR model and quantile autoregression to capture the contemporaneous and lead-lag relationships, and the tail risk in one specification. Our data cover the past ten years encompassing two major financial crises and the tapering of US quantitative easing with considerable global impact. Our analysis therefore may provide regulators, policymakers, and sovereign bond investors with a better understanding of the likelihood of an extreme response of sovereign bond yields in the region under adverse market conditions.[4]

This remainder of the paper is organised as follows. Section 2 reviews some conventional methods and discusses technical details of the PC-QVAR models. Section 3 describes our endogenous variables and data on US Treasury yields. Section 4 reports and interprets our estimates of principal components, the OLS and quantile regression estimates of the two models, and one hypothetical scenario of US monetary normalisation. Section 5 concludes.

2. Methodology

2.1 Conventional Methods

To capture extreme changes in sovereign bond yields and other endogenous variables, conventionally, a structural vector autoregressive (SVAR) model can be considered. This is basically a vector autoregressive (VAR) model that captures lead-lag dynamics among the endogenous variables in the system and identifies contemporaneous relationship between the variables from the VAR model's residual. This method has been used by Bowman et al. (2014) to explain a vector of US and emerging markets' sovereign bond yields, corporate bond yields, stock prices, and exchange rates. Wright (2012) and Rogers et al. (2014) use the same approach to identify the effects of monetary policy shocks on various longer term interest rates since the US policy rate has been close to their zero lower bound. The model is generally regarded useful for capturing average changes in financial variables under the normality assumption. However, the true value of the variables associated with adverse market conditions tends to be underestimated since the distribution of the variables is usually fat-tailed. This implies that the true probability of extreme changes in these variables, known as tail risk, should be much larger than estimated under the normality assumption.

The quantile regression method proposed by Koenker and Bassett (1978) can be used to better assess tail risk. This method extends the notion of a sample quantile to a linear regression model, which is found to be more robust than ordinary least squares (OLS) estimators whenever the errors have a leptokurtic distribution. In the finance literature, Adrian and Brunnermeier (2008), and Fong and Wong (2012) use the quantile regression method to estimate the conditional value-at-risk (CoVaR) to gauge the systemic risks of international financial institutions and European sovereigns

[4] Empirical research studies on the spillovers from QE on emerging countries bond yields usually use regression-based approaches including panel data regression and VAR models to estimate the impact of US monetary shocks on the variables of interest, which may not be appropriate to assess tail risks in the countries.

respectively. Xiao (2009) applies the quantile regression method to cointegrated time series, generalising Engle and Granger (1987)'s cointegration model. Koenker and Xiao (2004) extend the autoregressive model to quantile autoregression (QAR) in a univariate case and apply to data on US commercial paper rates. Alternatively, Engle and Manganelli (2004) use an autoregressive process to specify the evolution of quantiles over time, which can be viewed as a VAR model for Value-at-Risk (VaR). White et al. (2012) further extend their idea to a multivariate case to capture the degree of tail interdependence among equity returns of different financial institutions, which is useful for developing measures of financial spillovers. Similarly, Cecchetti and Li (2008) incorporate the method of quantile regression directly into a vector autoregression (QVAR) model in an assessment of the tail distribution of US output growth when real housing prices are assumed to be considerably above the trend.

There are two significant concerns over the VAR model incorporated with quantile regression. First, unlike SVAR specifications, the VAR specification does not explicitly model the instantaneous relationships among the endogenous variables. Instead these variables are explained only in terms of their own history. Any instantaneous correlations are hidden in the correlation structure of the error term. Second, unlike VAR models, the quantile specification, which cannot be estimated equation-by-equation, requires all parameters to be estimated jointly, given that there is more than one equation in the system and the error terms are cross-correlated.

To address the above concerns, in estimating the tail risk of sovereign bond yields, we propose a principal component quantile vector autoregressive (PC-QVAR) model in this paper. The new specification is a VAR model, in which the dependent variable is not a vector of the endogenous variables but a vector of principal components derived from these endogenous variables. It is also a quantile regression by which extreme changes in endogenous variables can be estimated under scenarios of hypothetical shocks. Therefore, the model features both the SVAR and quantile autoregression models by capturing the contemporaneous and lead-lag relationships, and tail risk in one specification. Given that the endogenous variables (i.e. principal components) are uncorrelated, the model can be estimated easily equation by equation using the conventional method introduced by Koenker and Bassett (1978). Moreover, similar to the VAR models estimating with the method of principal components (such as the factor VAR by Bernanke et al. (2005) and Bayesian VAR by Banbura et al. (2010)), our model does not suffer issues arising from dimensionality when estimating a large dataset of endogenous variables since the method principal components can distill a bulk of co-movement in the data into a small number of important factors.

2.2 The PC-QVAR Framework

Let Y_t be a vector of *d* endogenous variables including local sovereign bond yields at time *t*. We consider the following structural form of the VAR model to capture the dynamics of ΔY_t (Δ is the first difference operator) with a vector of exogenous variable X_t and an error term $\varepsilon_t \sim i.i.d.(0, \Sigma)$:

$$\Psi \Delta Y_t = \Theta_0 + \sum_{k=1}^{K} \Theta_k \, \Delta Y_{t-k} + \Phi_X X_t + \varepsilon_t. \tag{1}$$

We assume that Ψ is a $d \times d$ matrix determined from principal component analysis. More specifically, Ψ is a matrix of eigenvectors derived from Σ (i.e. the variance-covariance matrix of ΔY_t) which converts a set of possibly correlated variables (i.e. ΔY_t) into a set of principal components (i.e. $\mathbb{P}_t = \left(P_{1,t}, \ldots, P_{d,t}\right)'$) by the following relation:

$$\mathbb{P}_t = \Psi \Delta Y_t. \tag{2}$$

Therefore, Equation (1) can be rewritten as

$$\mathbb{P}_t = \Theta_0 + \sum_{k=1}^{K} \Theta_k^* \, \mathbb{P}_{t-k} + \Phi_X X_t + \varepsilon_t \tag{3}$$

where $\Theta_k^* = \Theta_k \, \Psi$. The specification in Equation (3) is known as the PC-VAR model of order K. Given that the principal components are contemporaneously uncorrelated with each other, Equation (3) can be viewed as *d* separate single autoregressive models so that the conditional quantile of $P_{i,t}$ can be estimated separately. Specifically, we rewrite Equation (3) as:

$$P_{i,t} = \theta_{i,0} + \sum_{k=1}^{K} \sum_{j=1}^{d} \theta_{j,k} \, P_{j,t-k} + \phi_X' X_t + \varepsilon_{i,t} \tag{4}$$

where $P_{i,t}$ is the *i*-th element of $\mathbb{P}_t$ for *i* = 1, …, *d*. The τ-th conditional quantile of $P_{i,t}$, denoted by $Q_{P_{i,t}}(\tau|\Omega)$ where $\Omega = (X_t$, past information up to time *t* – 1), can be written as:

$$Q_{P_{i,t}}(\tau|\Omega) = \theta_{i,0}(\tau) + \sum_{k=1}^{K} \sum_{j=1}^{d} \theta_{j,k}(\tau) \, P_{j,t-k} + \phi_X'(\tau) X_t + Q_{\varepsilon_{i,t}}(\tau|\Omega) \tag{5}$$

where $Q_{\varepsilon_{i,t}}(\tau|\Omega)$ is the τ-th conditional quantile of $\varepsilon_{i,t}$ and the estimator $\alpha(\tau) = \left(\theta_{i,0}(\tau), \theta_{j,k}(\tau), \phi_X'(\tau)\right)$ can be obtained by solving the following objective function:

$$\hat{\alpha}(\tau) = \arg\min_{\theta,\phi} \sum_{t=k+1}^{N} \rho_\tau \left(P_{i,t} - \theta_{i,0} - \sum_{k=1}^{K} \sum_{j=1}^{d} \theta_{j,k} \, P_{j,t-k} - \phi_X' X_t \right) \tag{6}$$

where $\rho_\tau(z) = z(\tau - I(z < 0))$ as given by Koenker and Bassett (1978) and $I(*)$ is an indicator function. We refer to Equation (5) as the PC-QVAR model. Note that τ can be different for the *d* principal components. Thus, Equation (5) is specified as:

$$Q_{P_{i,t}}(\tau_i|\Omega) = \theta_{i,0}(\tau_i) + \sum_{k=1}^{K}\sum_{j=1}^{d} \theta_{j,k}(\tau_i)\, P_{j,t-k} + \phi_X'(\tau_i)X_t + Q_{\varepsilon_{i,t}}(\tau|\Omega) \tag{7}$$

Hence, the conditional quantile of $\Delta Y_{i,t}$ given $Q_{P_{i,t}}(\tau_i|\Omega)$ and Ω can be rewritten as a sum of conditional quantiles of $P_{i,t}$ based on Equation (2), or specifically:

$$Q_{\Delta Y_{i,t}}(\tau_i^*|\Omega) = \sum_{i,j} \varphi_{ji}\, Q_{P_{i,t}}(\tau_i|\Omega) \tag{8}$$

where φ_{ij} is the (*i*, *j*)-th element of the $d \times d$ square matrix Ψ. The final conditional quantile τ_i^* depends on the choice of τ_i and it can be calculated by the following relations:

$$\begin{aligned}
\tau_i^* &= \Pr\left(\Delta Y_{i,t} > m_i \middle| P_{i,t} > n_i \ \forall i = 1, \dots d\right) \\
&= \Pr\left(\sum\nolimits_{i,j} \varphi_{ji} P_{i,t} > m_i \middle| P_{i,t} > n_i \ \forall i = 1, \dots d\right) \\
&= \int_{\sum_{i,j} \varphi_{ji} n_i = m_i}^{\infty} f_{P_{1,t} \dots P_{d,t}}\, dP_{1,t} \dots dP_{d,t} \\
&= \prod\nolimits_{i=1}^{d} \int_{n_i}^{\infty} f_{P_{i,t}}\, dP_{i,t} \\
&= \prod_{i=1}^{d} \tau_i .
\end{aligned}$$

where $f_{P_{1,t} \dots P_{d,t}}$ is the joint density function of $P_{1,t}, \dots, P_{d,t}$, $f_{P_{i,t}}$ is the density function of the $P_{i,t}$, and $m_i = Q_{\Delta Y_{i,t}}(\tau_i^*|\Omega)$ and $n_i = Q_{P_{i,t}}(\tau_i|\Omega)$ are defined to simplify the notation.

In this analysis, we assume that any shocks originating from US monetary normalisation are exogenous to the Asia-Pacific economies (denoted by X_t), which avoids imposing any restrictions on the matrix Ψ.[5] This assumption is probably not too restrictive because US monetary conditions have to a considerable extent dictated the direction of global financial markets, especially those in the Asia-Pacific region.[6] Therefore, the model can capture the impact of an exogenous shock from X_t on $\mathbb{P}_t$

[5] We can also assume the shock to be endogenous in the specification and follow the conventional model identification. However, this requires the coefficient matrix Ψ to be restricted by sign or magnitude so that the local government bond yields are assumed to have no directly impact on the US Treasury yield which makes the estimation process be more complicated in the tail risk analysis.

[6] This can be briefly validated by checking yields' lead-lag relationship. One test is the granger causality test. Using the sample of sovereign bond yields described in Section 3, the test results show that the US Treasury yield does not granger cause only a few of advanced economies' sovereign bond yields.

and ΔY_t contemporaneously through the coefficient matrices of Φ_X and $\Psi'\mathbb{P}_t$.[7] The model can also capture the lead-lag dynamics among $\mathbb{P}_t$, and hence, the endogenous variables of ΔY_t through the coefficient matrices Θ_k.

Given that the shock is exogenous, we can define a specific impulse response function for this model to understand how the tail risk of the endogenous variables respond to a shock over time.[8] Specifically, assuming that there is a shock δ originating from US Treasury yields at time *t* only and other variables are constant, the τ-th quantile impulse response function (QIRF) for a local government bond yield is defined as the difference between the tail risk and the average risk of the *i*-th endogenous variable (for *i* = 1, …, *d*,). Specifically, the function is:

$$QIRF_{i,k} = Q_{\Delta Y_{i,t+k}}(\tau|X_t = \delta, \Omega_0) - \widehat{OLS}_{\Delta Y_{i,t+k}}(X_t = \delta, \Omega_0)$$

where Ω_0 denotes that all past information are zero upto time *t* – 1, and:

$$\hat{Q}_{\Delta Y_{i,t+k}}(\tau_i|X_t = \delta, \Omega_0) = \begin{cases} \sum_{i,j} \varphi_{ji} \left\{\theta_{i,0}(\tau_i) + \phi_X'(\tau_i)\delta\right\} & \text{for } k = 0 \\ \sum_{i,j} \varphi_{ji} \left\{\sum_{k=1}^{K} \sum_{l=1}^{d} \theta_{l,k}(\tau_i) P_{l,t-k}\right\} & \text{for } k > 0 \end{cases}$$

and

$$\widehat{OLS}_{\Delta Y_{i,t+k}}(X_t = \delta, \Omega_0) = \begin{cases} \sum_{i,j} \varphi_{ji} \left\{\theta_{i,0} + \phi_X'\delta\right\} & \text{for } k = 0 \\ \sum_{i,j} \varphi_{ji} \left\{\sum_{k=1}^{K} \sum_{l=1}^{d} \theta_{l,k} P_{l,t-k}\right\} & \text{for } k > 0 \end{cases}.$$

The rationale behind $\hat{Q}_{\Delta Y_{i,t+k}}(\tau_i|X_t = \delta, \Omega_0)$ and $\widehat{OLS}_{\Delta Y_{i,t+k}}(X_t = \delta, \Omega_0)$ is that the shock first seen at time zero will trigger an increase in the *i*-th endogenous variable and this change will gradually converge to its long term mean through the autoregressive process estimated in the specification over time. The difference therefore measures how large the "unexpected" risk of an economy deviates from the "expected" risk when US Treasury yields increases drastically, which is consistent with the idea of CoVaR measures, a popular measure of tail risks proposed by Adrian and Brunnermeier (2008).

2.3 Selected Endogenous Variables

Theoretically, borrowing costs in an economy, which has its own currency and runs its own monetary

[7] Based on Equation (2) and the property of principal components $\Psi\Psi' = \mathrm{I}$, $\Delta Y_t = \Psi^{-1}P_t = \Psi'\mathbb{P}_t$.

[8] The impulse response function tracks how the shock propagates through the system and how long it takes to absorb the shock. Under the autoregressive specification, the shock will be completely absorbed after the impulse response function converges to zero.

policy, should not be affected by those in another economy. Instead, these depend on the chances of the lender getting repaid or, in other words, the risk of default. However, a casual inspection of what has happened over the period from May to September 2013 (the first episode of market selloff since Bernanke's first hint of QE tapering) suggests that this is not the case (Figure 3). As can be seen, most of the economies do not lie on the 45-degree line, meaning that much of the increase in their sovereign bond yields cannot be explained by changes in their respective CDS spread alone. The fact that many lie way above the line and close to the y-axis suggests that there are other factors in play and one obvious candidate, especially for this period, is changes in US Treasury bond yields.[9]

Hence, in this study we postulate that local sovereign bond yields of an economy are determined by a world risk-free interest rate, own funding costs, and credit and exchange rate risks of the economy.[10] The reason for including a world risk-free interest rate is that global financial markets have become highly interconnected. Depending on infrastructural and regulatory constraints, individual capital markets are closely linked together. International investors would thus take advantage of arbitrage opportunities, having regard to credit and exchange rate risks tolerance.

3. Data Description

We analyze the eleven largest Asia-Pacific economies, comprising Australia, China, Hong Kong, Indonesia, Japan, Malaysia, New Zealand, the Philippines, Singapore, South Korea, and Thailand.[11] The GDP of these economies jointly accounted for an average of 86% of GDP of the Asia-Pacific region between 2005 and 2010.

The main interest of this study is how the 10-year local sovereign bond yield ($LSBY_{i,t}$) responds to the US monetary normalisation. Three closely related endogenous variables are incorporated in the specification, including (1) the domestic 3-month interbank interest rate ($IIR_{i,t}$) which is used to control for local funding costs; (2) the 5-year domestic sovereign CDS spread ($SCDS_{i,t}$) which is used as a measure for credit risks of the economy; (3) the risk reversal of the US dollar against the local currency ($RR_{i,t}$) which is used as a proxy for exchange rate risk. Note that, as opposed to most studies on the subject using spot and forward exchange rates, we use "risk reversal", the difference between call and put options' implied volatilities of currencies, as a barometer of currency movement, one that has been proved forward looking in analysing the crash risk of currencies (for instances, Brunnermeier et al. (2008) and Hui and Chung (2011)). Hence, $Y_{i,t}$ is a four-dimensional vector specified as $(LBY_{i,t}, IIR_{i,t}, SCDS_{i,t}, RR_{i,t})'$.[12] The 10-year US Treasury yield ($USBY_t$) is used to measure

[9] An empirical study found significant evidence that sovereign bond yields in emerging economies have moved much more closely with the US Treasury bond yield after 2005. See Turner (2013) for details.

[10] Such modelling of emerging market sovereign bond yields is not new. See similar model proposed by Edwards (1986).

[11] These economies are members of the Executives' Meeting of East Asia-Pacific (EMEAP), an organization of central banks and monetary authorities in the region.

[12] Some data alternatives or adjustment are employed in this analysis arising from incomplete market data. For the Philippines, the interbank call loan rate has been used to proxy for the local funding cost because the Bankers

the shock arising from US monetary normalisation. It is treated as an exogenous variable in the specification. Hence, X_t is simply $\Delta USBY_t$ in one dimension.

We use monthly data for the period from October 2004 to February 2014. Sovereign bond yields are drawn from Thomson Reuters and all other data from Bloomberg and JPMorgan Chase. Descriptive statistics are shown in Table 1. As can be seen, all endogenous variables have a very different range of fluctuations both within an economy and between economies. For example, in Hong Kong, the change in the sovereign CDS spread has a standard deviation of 10.7%, compared to other endogenous variables of less than 0.6%; South Korea's currency risk reversal has a standard deviation of 1.7%, while that of Thailand is only 0.45%; Indonesia's change in sovereign bond yield ranges from -3.79% to 3.97%, while Japan's ranges from -0.29 to 0.34. Thus, to make all economies more comparable, we compute the standard score (i.e., $z = (x - \mu)/\sigma$) for all variables so that all of them have mean zero and unity standard deviation.

4. Empirical Results

4.1 Principal Component Analysis

The results of the principal component analysis are reported in Table 2. Two driving forces are commonly seen in the first two principal components. One of them is a general market component, which is a positively weighted average of the four endogenous variables. The driving force is found in eight economies (see the bold figures) in which three of them (Indonesia, New Zealand, and Thailand) weight equally (roughly ranging from 0.3 to 0.5) on each endogenous variable. Another force is a financial sector component which captures the difference between an economy's creditworthiness (measured by the sovereign CDS spread and the currency's crash risk) and funding costs (measured by the sovereign bond yield and interest rates). It is found in nine economies (see the figures highlighted in yellow), which weights either (1) positively on sovereign CDS spreads and currency risk reversal and negatively on sovereign bond yields and interbank interest rate, or (2) positively on sovereign bond yields and interbank interest rate and negatively on sovereign CDS spreads and currency risk reversal.

4.2 Comparison between the OLS and QR Coefficients

The estimation results of the OLS regression are summarised in Table 3. Most of the F-statistics are found to be statistically significant, suggesting that each economy's estimated PC-VAR model has significant explanatory power on the principal components. The variable of $\Delta USBY$ significantly

Association of the Philippines has stopped the setting and publication of the Philippine Interbank Offered Rate since April 2013. Due to the absence of local sovereign CDS spreads data, the CDS spreads of Singapore Telecommunications Limited has been used as proxy for the local sovereign CDS spreads of Singapore. As for New Zealand, given limited data availability, the CDS spreads of Telecom Corporation of New Zealand Limited has been used to proxy for its local sovereign CDS spreads. For Indonesia, only data from December 2005 to February 2014 are available and have been used in estimation.

impacts the financial sector component but not the general market component.

The estimation results of the quantile regressions at the $\tau_1^* = 99.9$th percentile are summarised in Table 4. The standard error is found by a bootstrapped estimation with 100 repetitions. Quasi likelihood ratio test statistics are found to be statistically significant, suggesting that the estimated PC-QVAR model has significant explanatory power on the principal components. Unlike the results from OLS estimation, all the constant terms are found to be significantly different from zero, which suggests that part of the tail risk cannot be explained by US bond yields and lagged principal components.

4.3 Quantile Impulse Response Function

Figure 4 displays impulse responses illustrating the risks to the eleven economies of a one-standard-deviation shock to US Treasury yields. The horizontal axis measures the time in months, while the vertical axis measures the excess change in the 99.9th percentile of the individual economies as a reaction to the shock. As shown in the figure, the shock has a less-than-one-SD impact on Hong Kong, Indonesia, Malaysia, and South Korea at time zero. This impact becomes insignificantly different from zero within three months, other things being equal. Regarding the impact on other economies, the more-than-one-SD impact tends to be more drastic and is absorbed within 4 months.

4.4 Scenario Analysis

The model estimated at the mean and various quantiles is used to compute short-run changes in the 10-year sovereign bond yield in each of the economies based on the scenario seen between May and September 2013 during which the 10-year US Treasury yield increased by 94 basis points. The different quantiles can be considered as representing different levels of market distress: the higher the quantile, the greater the distress.

Figure 5 shows short-run responses in sovereign bond yields in Asia Pacific economies estimated at the mean and various quantiles along with their corresponding actual increases, with the economies ranked according to the size of their response at the 99.9th percentile. Take Hong Kong as an example, the actual increase in its 10-year sovereign bond yield was 1.2%, while the estimated increases at the mean and 99.9th percentile were 0.9% and 2.3% respectively.

First of all, it is apparent that the actual increases registered in the episode are mostly greater than the mean estimates except for the Philippines and Japan. This may reflect a knee-jerk reaction of international investors to ‘run for the exit’ in response to the news, given that these economies had received significant capital inflows after several rounds of QE by the Fed. The Philippines was a notable exception, with a much smaller increase attributable to the fact that its sovereign rating was upgraded to investment grade by Standard & Poor’s in May 2013. Japan, which introduced its own QE programme, also saw a slightly smaller increase. Second, the comparison of actual increases and estimates at two quantiles highlights the importance of assessing potential tail risks. The estimates at

the 99th and 99.9th percentiles are much larger than the actual increases or mean estimates. This means that the volatility and turbulence of financial markets could be far more disruptive than imagined in times of extreme adversity. Finally, the ranking of the economies suggests that under stressful market conditions, an increase in US Treasury yields has a much larger potential impact on sovereign bond yields in economies that are perceived to have weaker fundamentals.

5. Conclusion

This paper has examined the potential impact of US monetary normalisation on sovereign debt yields in Asia Pacific. We have applied a new set of tools to assess the tail risk of sovereign risk, which may not be detectable from conventional econometric methods.

Our empirical evidence supports the view that US Treasury bond yields have a significant impact on sovereign bond yields in the Asia Pacific region, and are an important channel through which QE tapering by the Fed could impact economic activity and financial intermediation in the region. Increases in sovereign bond yields will not only compromise the ability of sovereigns to service their debt but may also translate into higher costs of borrowing for the entire economy. The results also show how much an outsized impact could potentially be if US monetary normalisation turns out to be more disorderly than expected.

Our study has two potential key limitations. First, our framework implicitly regards a US monetary policy shock as unanticipated, which may potentially omit the effects of an anticipated monetary tightening. Although the anticipated impact may be moderate, Milani and Treadwell (2012) suggest that such impact could have persistent effects on global markets, while the impact of an unanticipated shock may be short-lived but stronger. Second, our empirical work assesses each economy individually without taking into account sovereign risks of other economies explicitly, which may underestimate the spillover effect in the region. These merit further research to enhance our methodology and build on our empirical findings.

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Table 1. Descriptive Statistics of Changes in Endogenous and Exogenous Variables

Economy	Change in variable	Mean	Maximum	Minimum	Std. Dev.	Observations
Australia	Δ*LSBY* (%pt)	-0.0121	0.7300	-0.7550	0.2483	112
	Δ*SCDS* (bps)	0.3784	46.7200	-36.0000	11.2447	112
	Δ*RR* (%pt)	0.0102	3.9490	-4.5433	0.8926	112
	Δ*IIR* (%pt)	-0.0251	0.6367	-1.5150	0.2598	112
China	Δ*LSBY* (%pt)	-0.0033	0.6720	-0.6339	0.1890	112
	Δ*SCDS* (bps)	0.5458	78.0000	-90.2400	19.8821	112
	Δ*RR* (%pt)	-0.0270	5.8180	-5.7430	1.0771	112
	Δ*IIR* (%pt)	0.0182	2.3500	-2.3000	0.7731	112
Hong Kong	Δ*LSBY* (%pt)	-0.0116	0.6740	-0.7880	0.2932	112
	Δ*SCDS* (bps)	0.4129	46.2000	-44.5000	10.6771	112
	Δ*RR* (%pt)	0.0173	1.5917	-4.5247	0.5227	112
	Δ*IIR* (%pt)	0.0003	1.4059	-1.3950	0.3483	112
Indonesia	Δ*LSBY* (%pt)	-0.0532	3.9730	-3.7860	0.8625	98
	Δ*SCDS* (bps)	-0.1867	358.3500	-139.2100	54.5171	98
	Δ*RR* (%pt)	0.0030	11.8543	-19.3274	2.8427	98
	Δ*IIR* (%pt)	-0.0671	1.5108	-1.5368	0.3960	98
Japan	Δ*LSBY* (%pt)	-0.0081	0.3390	-0.2920	0.0982	112
	Δ*SCDS* (bps)	0.3782	45.4800	-48.0000	11.9616	112
	Δ*RR* (%pt)	0.0078	4.1785	-3.4203	0.8298	112
	Δ*IIR* (%pt)	0.0011	0.1264	-0.1333	0.0295	112
Malaysia	Δ*LSBY* (%pt)	-0.0066	0.9990	-0.6100	0.2152	112
	Δ*SCDS* (bps)	0.6512	71.0000	-62.8200	21.4996	112
	Δ*RR* (%pt)	0.0042	3.2836	-3.1943	0.7360	112
	Δ*IIR* (%pt)	0.0040	0.2700	-0.7700	0.1085	112
New Zealand	Δ*LSBY* (%pt)	-0.0132	0.7650	-0.9400	0.2331	112
	Δ*SCDS* (bps)	0.3067	40.5300	-63.9400	13.8923	112
	Δ*RR* (%pt)	0.0069	3.6357	-4.4262	0.8905	112
	Δ*IIR* (%pt)	-0.0339	0.3200	-1.4550	0.2431	112
Philippines	Δ*LSBY* (%pt)	-0.0825	2.6160	-2.0150	0.5659	112
	Δ*SCDS* (bps)	-3.5539	192.5400	-84.9800	36.6446	112
	Δ*RR* (%pt)	0.0202	5.0763	-9.3672	1.2598	112
	Δ*IIR* (%pt)	-0.0460	0.5312	-0.9688	0.2638	112
South Korea	Δ*LSBY* (%pt)	-0.0040	1.0500	-1.3500	0.2621	112
	Δ*SCDS* (bps)	0.3067	216.0000	-105.0900	33.2575	112
	Δ*RR* (%pt)	0.0174	5.7491	-10.8186	1.6982	112
	Δ*IIR* (%pt)	-0.0079	0.3600	-1.4800	0.2121	112
Singapore	Δ*LSBY* (%pt)	-0.0057	1.0750	-0.6670	0.2353	112
	Δ*SCDS* (bps)	0.2445	55.3200	-59.4200	11.7886	112
	Δ*RR* (%pt)	0.0169	1.7685	-2.3416	0.5671	112
	Δ*IIR* (%pt)	-0.0087	0.6696	-0.6875	0.1611	112
Thailand	Δ*LSBY* (%pt)	-0.0109	1.2450	-1.3400	0.3811	112
	Δ*SCDS* (bps)	0.9759	87.0000	-64.8100	22.9163	112
	Δ*RR* (%pt)	0.0164	1.4269	-1.9789	0.4451	112
	Δ*IIR* (%pt)	0.0031	0.5640	-0.9506	0.1958	112
United States	Δ*USBY* (%pt)	-0.0122	0.6390	-1.0520	0.2644	112
	Δ*GFI*	-0.0033	6.9101	-3.6898	1.4302	112
	Δ*MOVE*	-0.2963	76.0000	-45.1000	13.3141	112

Table 2. Principal Components of Change in Endogenous Variables

Economy	Principal component	Δ*LSBY*	Δ*IIR*	Δ*SCDS*	Δ*RR*	Cum. Prop.
Australia	$P_{1,t}$	0.5468	0.5029	-0.5535	-0.3764	0.4867
	$P_{2,t}$	0.2898	0.2378	-0.1226	0.9189	0.6988
	$P_{3,t}$	-0.3397	0.8262	0.4471	-0.0471	0.8656
	$P_{4,t}$	0.7083	-0.0893	0.6919	-0.1079	1.0000
China	$P_{1,t}$	-0.4711	-0.1861	0.6501	0.5664	0.3499
	$P_{2,t}$	**0.2973**	**0.8828**	**0.2087**	**0.2978**	0.6015
	$P_{3,t}$	0.7530	-0.4206	-0.0155	0.5059	0.8293
	$P_{4,t}$	0.3503	-0.0956	0.7305	-0.5784	1.0000
Hong Kong	$P_{1,t}$	0.6715	0.5974	-0.2934	0.3258	0.3787
	$P_{2,t}$	-0.1785	0.3350	0.7964	0.4708	0.6454
	$P_{3,t}$	0.1885	0.4091	0.3545	-0.8194	0.8697
	$P_{4,t}$	0.6941	-0.6029	0.3924	0.0284	1.0000
Indonesia	$P_{1,t}$	**0.5066**	**0.3877**	**0.5468**	**0.5422**	0.6957
	$P_{2,t}$	-0.2943	0.9139	-0.1300	-0.2474	0.8686
	$P_{3,t}$	0.8079	0.0955	-0.4452	-0.3742	0.9548
	$P_{4,t}$	-0.0636	0.0727	-0.6971	0.7105	1.0000
Japan	$P_{1,t}$	0.3874	-0.5419	-0.1554	0.7295	0.3230
	$P_{2,t}$	0.6460	0.5332	-0.5427	-0.0625	0.6035
	$P_{3,t}$	**0.4459**	**0.3147**	**0.8202**	**0.1717**	0.8386
	$P_{4,t}$	-0.4836	0.5683	-0.0931	0.6592	1.0000
Malaysia	$P_{1,t}$	0.2471	-0.3443	0.7248	0.5432	0.3387
	$P_{2,t}$	-0.0422	0.8133	-0.0334	0.5793	0.5965
	$P_{3,t}$	0.9302	0.2438	0.0042	-0.2743	0.8483
	$P_{4,t}$	-0.2680	0.4006	0.6882	-0.5423	1.0000
New Zealand	$P_{1,t}$	-0.4828	-0.4708	0.5427	0.5007	0.3809
	$P_{2,t}$	**0.5228**	**0.5175**	**0.4350**	**0.5192**	0.6613
	$P_{3,t}$	-0.5174	0.5835	0.4487	-0.4365	0.8542
	$P_{4,t}$	0.4753	-0.4123	0.5612	-0.5378	1.0000
Philippines	$P_{1,t}$	**0.4468**	**0.0096**	**0.6532**	**0.6112**	0.4500
	$P_{2,t}$	0.4694	0.8483	-0.1598	-0.1857	0.7302
	$P_{3,t}$	-0.7254	0.5128	0.0631	0.4548	0.9078
	$P_{4,t}$	-0.2320	0.1314	0.7374	-0.6206	1.0000
South Korea	$P_{1,t}$	**0.1914**	**0.3964**	**0.6072**	**0.6614**	0.4415
	$P_{2,t}$	0.7110	0.5707	-0.3297	-0.2451	0.7591
	$P_{3,t}$	0.6368	-0.6353	0.4016	-0.1723	0.9309
	$P_{4,t}$	-0.2288	0.3371	0.6010	-0.6876	1.0000
Singapore	$P_{1,t}$	0.4529	0.5986	-0.5681	-0.3375	0.3649
	$P_{2,t}$	**0.5977**	**0.2395**	**0.3146**	**0.6974**	0.6574
	$P_{3,t}$	-0.2202	0.6219	0.6754	-0.3295	0.8414
	$P_{4,t}$	-0.6238	0.4445	-0.3495	0.5396	1.0000
Thailand	$P_{1,t}$	**0.4139**	**0.3149**	**0.5784**	**0.6285**	0.3736
	$P_{2,t}$	0.5657	0.6419	-0.4081	-0.3186	0.6704
	$P_{3,t}$	-0.6160	0.6486	0.3663	-0.2563	0.8639
	$P_{4,t}$	0.3594	-0.2612	0.6040	-0.6616	1.0000

Note: A bolded row refers to the component of general market condition, while a highlighted one refers to the financial sector component

Table 3. Ordinary Least Square Estimates of the PC-VAR Model

Economy	Dep.var	Constant	Independent variable $P_{1,t-1}$	$P_{2,t-1}$	$P_{3,t-1}$	$P_{4,t-1}$	Δ*USBY*	F-stat
Australia	$P_{1,t}$	0.00	0.13	0.12	0.03	0.10	0.59**	6.0**
	$P_{2,t}$	0.00	0.14**	0.04	0.29**	-0.12	0.21**	5.4**
	$P_{3,t}$	0.00	0.21**	0.09	0.05	-0.24**	-0.33**	7.9**
	$P_{4,t}$	0.00	-0.10**	0.13**	-0.14*	-0.06	0.38**	8.4**
China	$P_{1,t}$	0.02	0.00	-0.11	-0.23**	-0.11	-0.20*	1.8
	$P_{2,t}$	0.02	-0.04	-0.12	0.15	-0.01	0.07	0.9
	$P_{3,t}$	0.03	-0.10	0.17*	-0.14	0.05	0.07	2.0*
	$P_{4,t}$	-0.02	0.07	0.09	0.10	-0.21**	-0.12	2.3*
Hong Kong	$P_{1,t}$	0.00	-0.03	-0.05	-0.14	0.01	0.74**	12.4**
	$P_{2,t}$	0.00	0.04	0.04	0.07	-0.11	-0.15	0.6
	$P_{3,t}$	0.01	0.12*	0.19**	0.00	-0.18	0.11	2.5**
	$P_{4,t}$	-0.01	-0.03	-0.03	0.04	0.28**	0.26**	4.5**
Indonesia	$P_{1,t}$	0.01	0.28**	0.57**	0.20	0.43	0.31*	3.8**
	$P_{2,t}$	0.01	0.22**	0.35**	0.43**	-0.07	0.01	12.2**
	$P_{3,t}$	0.00	-0.02	-0.10	0.15	-0.09	0.18**	3.9**
	$P_{4,t}$	0.00	-0.02	0.02	0.03	-0.24**	0.09*	3.1**
Japan	$P_{1,t}$	0.00	0.02	-0.34**	-0.16	-0.05	0.36**	5.8**
	$P_{2,t}$	-0.01	-0.22**	0.03	0.12	0.06	0.58**	9.1**
	$P_{3,t}$	0.00	0.00	0.16*	-0.08	0.10	0.10	1.2
	$P_{4,t}$	-0.01	-0.15**	0.15**	0.04	0.07	-0.06	2.5**
Malaysia	$P_{1,t}$	0.00	-0.05	-0.09	-0.13	-0.11	-0.13	0.8
	$P_{2,t}$	0.00	-0.14*	0.29**	0.33**	0.29**	-0.16*	8.0**
	$P_{3,t}$	-0.01	0.05	-0.06	0.16*	-0.28**	0.37**	6.6**
	$P_{4,t}$	0.00	0.07	0.19**	-0.01	0.01	-0.16**	3.3**
New Zealand	$P_{1,t}$	0.00	0.13	-0.12	0.00	0.09	-0.35**	3.0**
	$P_{2,t}$	0.00	-0.20**	0.26**	0.26**	-0.16	0.24**	6.6**
	$P_{3,t}$	0.00	-0.06	0.08	0.06	-0.32**	-0.37**	7.6**
	$P_{4,t}$	0.00	0.22**	-0.19**	-0.26**	0.18**	0.19**	10.8**
Philippines	$P_{1,t}$	0.00	0.01	0.02	-0.13	0.48**	0.01	1.2
	$P_{2,t}$	-0.01	0.28**	-0.15*	-0.01	-0.12	0.36**	4.9**
	$P_{3,t}$	0.01	-0.11*	0.10	0.16*	-0.02	-0.21**	2.3**
	$P_{4,t}$	0.01	-0.06	0.00	0.09	-0.14	-0.10	1.5
South Korea	$P_{1,t}$	0.00	0.17*	0.19*	-0.30*	0.10	0.05	2.0*
	$P_{2,t}$	0.00	0.17**	0.11	-0.10	0.52**	0.51**	6.2**
	$P_{3,t}$	0.00	-0.11**	-0.38**	0.28**	-0.13	0.09	13.8**
	$P_{4,t}$	0.00	-0.05	0.04	0.08	0.10	0.03	1.1
Singapore	$P_{1,t}$	0.00	0.11	0.02	-0.31**	0.21	0.46**	7.2**
	$P_{2,t}$	0.00	0.13	-0.07	0.02	0.08	0.15	1.4
	$P_{3,t}$	-0.01	0.08	0.13*	0.06	0.07	-0.24**	2.4**
	$P_{4,t}$	-0.01	0.05	-0.02	0.27**	-0.09	-0.28**	5.4**
Thailand	$P_{1,t}$	0.00	-0.01	0.21*	0.04	-0.08	0.04	0.9
	$P_{2,t}$	0.00	0.16*	0.15*	0.24**	-0.22*	0.43**	5.9**
	$P_{3,t}$	-0.01	0.26**	0.32**	0.30**	-0.10	-0.20**	19.5**
	$P_{4,t}$	0.01	-0.07	-0.14**	-0.10	-0.27**	-0.11	3.5**

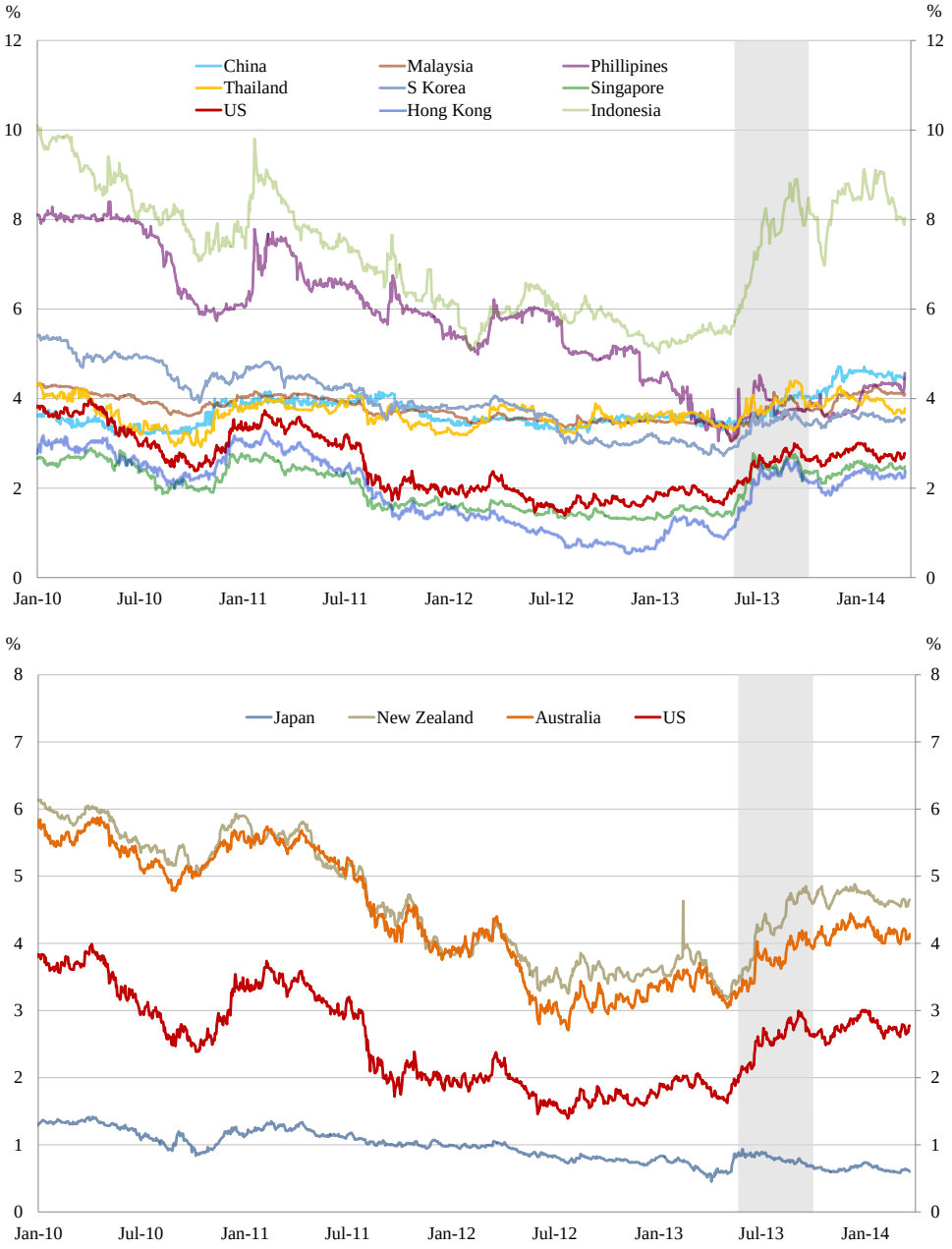
Note: ** and * indicate the significance levels of 5% and 10% respectively.

Table 4. Estimates of the PC-QVAR Model at a Quantile of 0.999

Economy	Dep.var	Independent variable						Quasi LR stat
		Constant	$P_{1,t-1}$	$P_{2,t-1}$	$P_{3,t-1}$	$P_{4,t-1}$	Δ*USBY*	
Australia	$P_{1,t}$	0.85**	-0.03	0.09	0.01	-0.20	0.62**	14.8**
	$P_{2,t}$	0.62**	0.02	-0.11	0.19	-0.34**	0.04	10.9*
	$P_{3,t}$	-0.63**	0.28*	0.07	0.18	-0.14	-0.29	10.4*
	$P_{4,t}$	0.52**	-0.26**	0.24**	-0.24	0.03	0.40**	40.9**
China	$P_{1,t}$	-0.63**	-0.04	0.02	-0.17	0.11	-0.12	3.5
	$P_{2,t}$	0.78**	-0.22	0.07	-0.05	0.17	0.17	7.5
	$P_{3,t}$	0.70**	-0.08	0.20	-0.33*	0.02	0.14	11.3**
	$P_{4,t}$	0.39**	-0.03	0.02	0.09	-0.21	-0.15	2.2
Hong Kong	$P_{1,t}$	0.64**	0.04	-0.03	-0.15	0.23	0.54**	27.3**
	$P_{2,t}$	-0.53**	0.11	0.04	-0.07	-0.06	-0.28	7.6
	$P_{3,t}$	0.54**	0.10	0.13	-0.11	-0.20	0.00	5.7
	$P_{4,t}$	0.52**	-0.07	-0.10	-0.03	0.15	0.31**	11.3**
Indonesia	$P_{1,t}$	0.78**	0.24	0.33	0.59	0.10	-0.01	8.7
	$P_{2,t}$	-0.53**	0.18	0.47**	0.66**	-0.11	0.06	28.7**
	$P_{3,t}$	0.49**	0.06	-0.12	0.14	-0.05	0.26	4.7
	$P_{4,t}$	-0.27**	0.00	-0.08	0.08	-0.33*	0.05	7.3
Japan	$P_{1,t}$	0.59**	-0.06	-0.29**	-0.20	-0.21	0.35**	27.7**
	$P_{2,t}$	0.75**	-0.19*	0.12	0.24*	0.08	0.56**	34.9**
	$P_{3,t}$	0.82**	0.08	0.27*	-0.23	0.06	0.19	4.6
	$P_{4,t}$	-0.59**	-0.19*	0.23*	-0.02	0.03	-0.04	8.2
Malaysia	$P_{1,t}$	1.01**	0.16	-0.37	-0.08	-0.21	-0.22	9.2
	$P_{2,t}$	-0.39**	-0.15**	0.08	0.22**	0.11	0.06	22.8**
	$P_{3,t}$	0.53**	0.07	-0.11	0.07	-0.12	0.34**	16.9**
	$P_{4,t}$	-0.38**	-0.01	0.24*	0.03	0.05	-0.21	16.4**
New Zealand	$P_{1,t}$	-0.62**	-0.12	-0.08	-0.03	0.13	-0.34*	11.9**
	$P_{2,t}$	0.72**	-0.03	0.35*	0.12	-0.08	0.04	4.6
	$P_{3,t}$	-0.60**	-0.30*	0.26*	0.27	-0.46**	-0.38**	36.0**
	$P_{4,t}$	0.46**	0.30**	-0.20**	-0.18**	0.17	0.25**	40.1**
Philippines	$P_{1,t}$	0.70**	-0.17	-0.05	-0.18	0.49**	-0.10	11.4**
	$P_{2,t}$	0.71**	0.16	-0.17	0.22	-0.08	0.23*	17.2**
	$P_{3,t}$	-0.68**	-0.09	0.11	-0.02	0.02	-0.37*	4.3
	$P_{4,t}$	-0.61**	-0.05	0.13	0.08	0.18	-0.14	5.0
South Korea	$P_{1,t}$	0.56**	-0.04	0.00	-0.10	0.04	-0.20	5.3
	$P_{2,t}$	0.65**	0.12	0.02	-0.02	0.34	0.32	6.0
	$P_{3,t}$	0.50**	-0.10	-0.46**	0.49**	-0.09	0.05	39.2**
	$P_{4,t}$	-0.29**	0.00	0.21*	-0.20	0.05	-0.05	9.3*
Singapore	$P_{1,t}$	0.64**	-0.06	0.00	0.08	0.36*	0.46**	32.8**
	$P_{2,t}$	0.82**	0.17	0.06	0.00	0.27	0.03	0.8
	$P_{3,t}$	-0.46**	0.09	0.23**	0.08	-0.03	-0.20	20.4**
	$P_{4,t}$	-0.63**	0.21	-0.11	0.10	-0.05	-0.20	9.8*
Thailand	$P_{1,t}$	0.93**	0.12	0.11	0.14	0.09	0.14	3.6
	$P_{2,t}$	0.69**	0.07	0.02	0.10	-0.31	0.35*	10.8*
	$P_{3,t}$	-0.50**	0.31**	0.37**	0.23*	-0.13	-0.32**	45.3**
	$P_{4,t}$	0.64**	-0.15	-0.13	0.01	-0.36*	-0.23	8.7

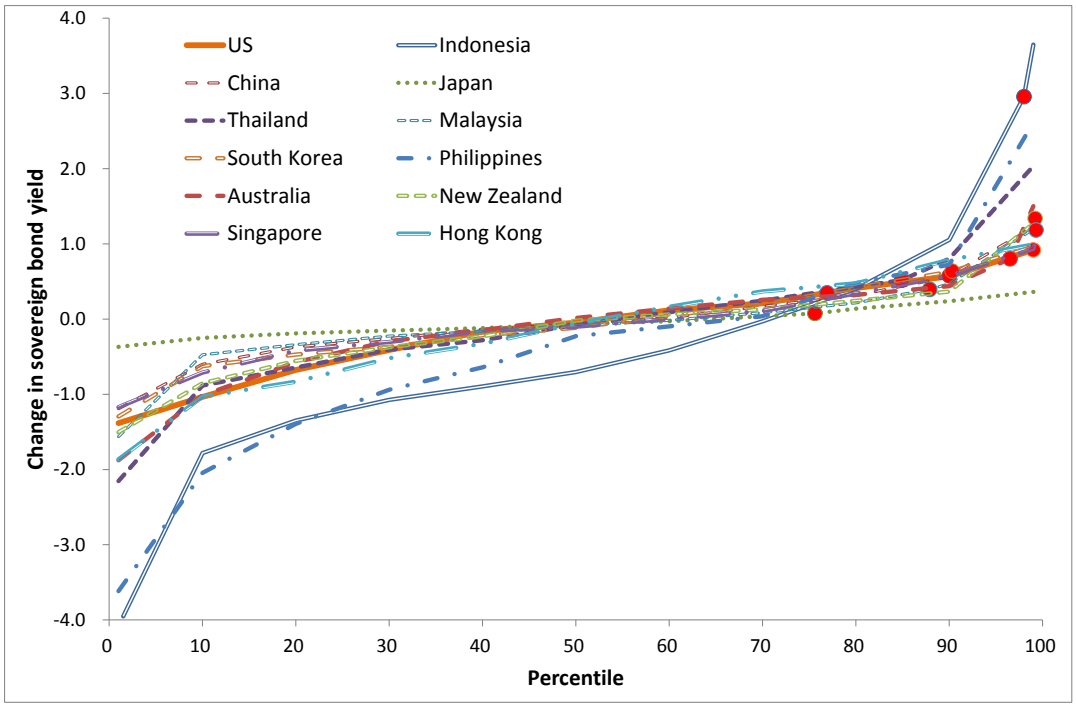
Note: ** and * indicate the significance levels of 5% and 10% respectively.

Figure 1. Yields of 10-Year Local Sovereign Bonds



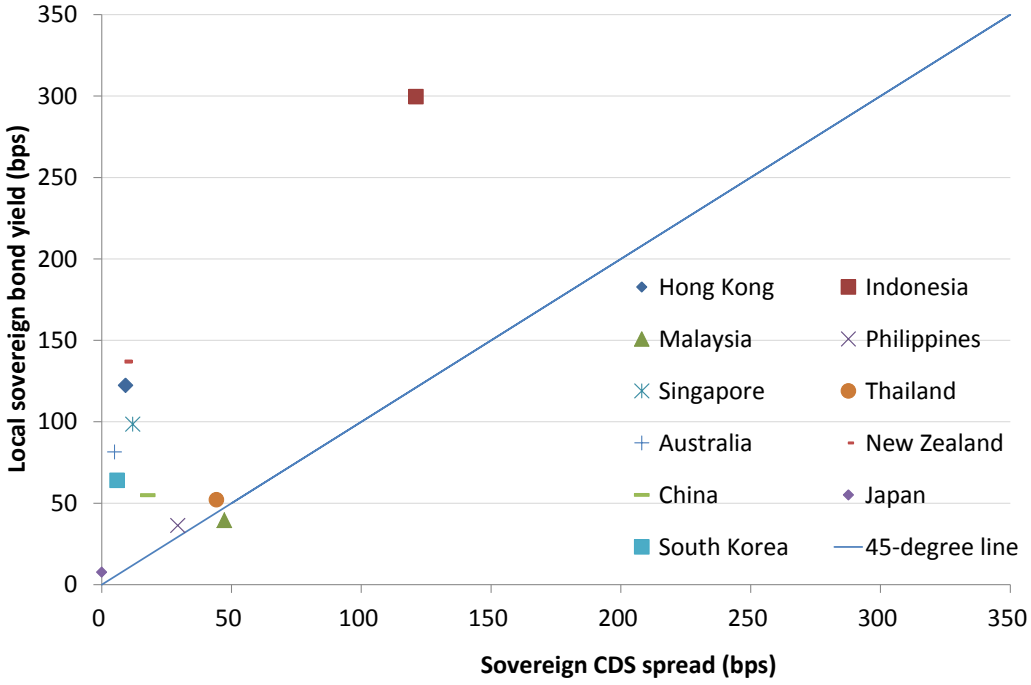
Source: Thomson Reuters.

Figure 2. Unconditional Percentiles of Sovereign Bond Yield Changes in Asia Pacific



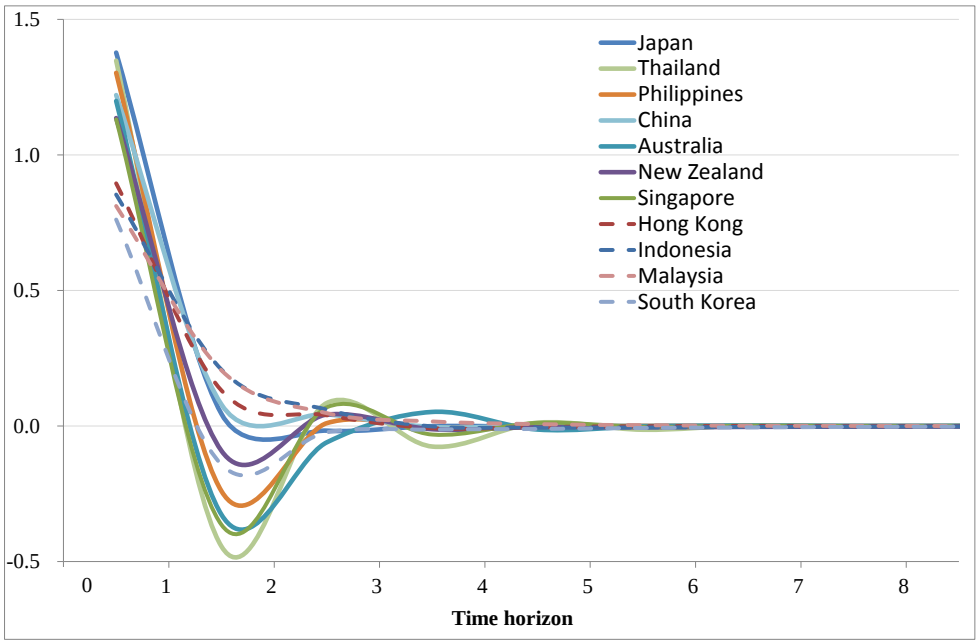
Notes:
1. The red dot represents the actual change in each sovereign bond yield in the region
2. The yield distribution is constructed based on the sample period from October 2004 to April 2013 which is right before the signal of tapering of US quantitative easing.

Figure 3. Scatter Plot of Changes in Local Sovereign Bond Yields and Sovereign CDS Spreads (From May 2013 to September 2013)



Source: Bloomberg.

Figure 4. Quantile Impulse Response of Local Government Bond Yields at the 99.9th Percentile Given a Shock of One-SD Increase in US Treasury Yields



Notes: (1) The quantile impulse response shows how the excess response, which is the difference between the impulse responses estimated at the 99.9th percentile and estimated by the OLS method, evolves over time. (2) The order of economies shown in the legend is based on the size of response at time zero.

Figure 5. Estimated Short-Run Changes in Local Sovereign Bond Yields Based on the Scenario Seen between May 2013 and September 2013 (During Which the 10-year US Treasury Bond Yield Rose 94bps)