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Global Liquidity Transmission to Emerging Market Economies, and Their Policy Responses*

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Abstract

This paper distills and identifies global liquidity (GL) momenta from the macro-financial data of advanced economies through a factor model with sign restrictions as policy-driven, market-driven, and risk averseness factors. Using a panel factor-augmented VAR, we investigate responses of emerging market economies (EMEs) to GL shocks. A policy-driven liquidity increase boosts growth in EMEs, elevating stock prices and currency values, while a risk averseness rise has an opposite effect. A market-driven GL expansion boosts stock markets and lowers funding costs, increasing competitiveness and current account. Inflation targeting EMEs fare better than EMEs under alternative regimes with respect to macro-financial volatility.

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Keywords: Global Liquidity, Panel Factor-Augmented VAR, Inflation Targeting

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I. INTRODUCTION

In efforts to ensure international financial system stability and the robust recovery of growth since the global financial crisis (GFC), growing attention has been paid to the role of global liquidity. Changes in global financial conditions have had increasingly larger impacts on not only domestic financial markets but also real economies as global financial markets become more integrated.

Global liquidity (GL) has become an integral concept in cross-border monetary transmission. Studies in this area have focused on particular economic variables such as interest rates (Frankel et al., 2002; Edwards, 2010, 2015; Kim and Yang 2009; di Giovanni and Shambaugh, 2008; Valente, 2009; and Kim and Shin, 2016), asset prices (Rigobon and Sack, 2004; Bluedorn and Bowdler, 2011; Ehrmann and Fratzscher 2009; Ammer et al., 2010; and Wongswan, 2009), inflation (Berger and Harjes, 2009), and capital flows (Cerutti et al., 2014; Cerutti et al., 2015; and Kim and Shin, 2016). The policy actions undertaken by the U.S. Federal Reserve (the Fed) after the onset of the GFC are instrumental in gauging the impacts of U.S. monetary policy on emerging-market economies (EMEs) (Glick and Leduc, 2012; and Bauer and Neely, 2014). Compared to existing studies, we broaden the scope of cross-border transmission by looking at a wider set of monetary and financial variables as well as real variables in the face of GL waves.

The ample GL generated by quantitative easing in advanced economies (AEs) is observed to have flowed into EMEs (IMF, 2010; and Bernanke, 2013). The waves of GL have had both positive and negative effects on EMEs. The expanded GL has stimulating effects on output and stock prices in EMEs at the receiving end. Such benign influences, however, are offset by the risks of overheated asset markets and heightened currency appreciation pressures.

Against this backdrop, this study investigates how GL affects macro-financial variables and policies in EMEs. GL has multifaceted momenta, since liquidity is generated by both government policies and financial markets. These momenta evolve in accordance with market developments such as financial integration, which strengthens the cross-border stream of GL, and financial innovations that intensify the role of endogenous or market-driven liquidity.

Identifying the key drivers of GL is crucial for examining the cross-border spillover effects of GL from a global economy perspective. This paper decomposes GL into an exogenous policy-driven momentum, and endogenous market-driven and risk momenta. We then investigate the impacts on EMEs of GL momenta and seek the policy implications on EMEs by means of a comparison between inflation targeting (IT) countries and alternative regimes (non-IT) countries.

Extensive research has been conducted to address a range of issues related to GL—its definition and measures, the main drivers of its cycles, its impacts on financial markets and the real economy, and its policy implications. D'Agostino and Surico (2007) introduce a GL measured by the simple mean of broad money growth in the G7 economies into the prediction of U.S. inflation, finding that, at horizons longer than two years, forecasts based upon GL are more accurate than the alternatives.[1] Kim (2001) finds from a vector autoregressive (VAR) model comprising the aggregates of the G-6 countries that U.S. expansionary monetary policy delivers booms to the rest of the world through the channel of the world real interest rate. Choi and Lee (2010) also find that AEs' expansionary monetary policies persistently boost output growth and inflation in Asian EMEs. The IMF (2010) offers an overview on the matter and evaluates policy options in response to the surge of capital inflows into capital-receiving economies. Kim (2001), and Choi and Lee (2010) use price measures of the monetary conditions of AEs. Recently, Bruno and Shin (2015) have suggested aggregate cross-border lending through the banking sector (i.e., non-core liabilities) as a GL measure. Kim and Shin (2016) examine the effect of the U.S. domestic credit on output and bond yields in EMEs through the onshore and offshore finance channels. Nonetheless, estimating GL with a single measure from a dominant country or a country group, regardless of whether price or quantity, has limitations. Chen et al. (2012) retrieve demand and supply shocks from price and quantity measures of GL, and analyze their impacts on GDP growth in the receiving countries. More recently, Eickmeier et al. (2013) have used a factor model to retrieve GL factors from a large set of data including price and quantity measures, and identified them as global monetary policy, global credit demand, and global credit supply.

While it is broadly similar to Eickmeier et al. (2013) in drawing out multiple components of GL, our approach has three innovative features. First, we identify the three momenta of GL from financial data of the G5 countries—the U.S., France, Germany, Japan, and the U.K.—rather than by incorporating both AEs and EMEs. We assume that GL comprises three momenta: policy-driven liquidity, market-driven liquidity, and risk averseness. Policy-driven liquidity is affected by discretionary policy actions of monetary authorities. Market-driven liquidity is generated through market developments and innovations within the financial systems of AEs and transmitted across borders in the spirit of Bruno and Shin (2015). Risk averseness reflects market participants' collective willingness to take financial risks, including price uncertainty and counterparty solvency. Second, we systematically investigate the impacts of GL momenta on EMEs. We apply a VAR model to data from EMEs, adding GL momenta derived from AEs as the exogenous variables.

Our approach enables us to identify distinctive GL shocks and the corresponding reactions of EMEs. To derive the three liquidity momenta, we select nine financial variables in each of the G5 countries, and then apply sign restrictions to characterize their principal components as economically meaningful factors. Minimal sign restrictions are imposed to identify these factors: for example, the policy-driven factor is set to increase the monetary base. We employ a factor-augmented vector autoregressive (FAVAR) model to incorporate the panel data of 10 EMEs for 1995:Q1-2014:Q3. This model includes the three factors as exogenous variables.

EMEs' policy responses to GL shocks and economic repercussions are derived from the impulse response analysis based upon the estimated panel FAVAR model. In response to positive GL shocks driven by G5 policies or their financial markets, EMEs appear to reduce policy rates and increase foreign reserves, thus mainly curtailing the shocks' impacts on their external fronts rather than on their real economies. Against a heightened risk averseness which

[1] Darius and Radde (2010) measure GL by adding the international reserves of G-7 countries to the U.S. monetary base and analyze the impacts of GL on asset prices in individual countries. Their findings suggest that GL has a limited impact on domestic housing prices.

accompanies capital outflows, EMEs furnish foreign-currency liquidity by running down foreign reserves while initial policy responses differ between IT and non-IT EMEs. Despite EMEs' policy responses, increases in global liquidity overall generate positive spillovers on equity markets and output, and a liquidity reversal owing to heightened risk averseness calls for negative spillovers. We also find that the responses of macro-financial variables to GL shocks are less volatile in IT countries than in non-IT countries.

The remainder of the paper is structured as follows. Section II presents the FAVAR model, and Section III estimates GL momenta from a factor model. Section IV examines forecast error variance decomposition and impulse responses of the estimated model for IT countries. Section V looks at GL impacts on non-IT EMEs for comparison. Section VI concludes.

II. Empirical Modeling of Global Liquidity Transmission

To measure the dynamic impacts of the GL momenta originating from AEs on key macro-financial variables in EMEs, we adopt a panel FAVAR model by extending the panel VAR models widely used in the literature.[2] Rebucci (2010) utilizes an 18-country panel using mean group estimators, which is the average of estimation for individual countries, to investigate whether growth of developing countries was driven by external shocks or domestic shocks. Ciccarelli et al. (2013) estimate a panel VAR model to find differences among euro area countries in monetary policy effects, allowing the slopes and contemporaneous impact matrix to differ between sub-country groups while assuming zero cross-country correlation.

This study also follows works on cross-border GL transmission such as Kim (2001), Canova (2005), Berger and Harjes (2009), Darius and Radde (2010), and Chen et al. (2012). Previous studies have employed GL metrics differing in coverage (country groups; banking sector vs. financial system) and scope (price vs. quantity measures; direct vs. indirect measures) to serve individual research purposes. To evaluate the transmission of GL originating from AEs into EMEs, we use both price and quantity data accounting for monetary policy at the zero lower bound.

To measure GL, recent studies have begun to adopt indirect measures drawn from factor models or VAR models. The need for aggregating large sets of data emerges, because no clear measure is suggested by the theoretical work, and relevant data are of global coverage. Factor models excel in dealing with large sets of data, which are of low quality or high heterogeneity. Eickmeier et al. (2013) use a factor model to derive three components of GL while Chen et al. (2012) employ a dynamic factor model to measure the costs of noncore funding; and both studies use sign restrictions to identify different GL shocks.

Our empirical modeling of GL transmission entails two stages. In the first stage, we derive GL momenta from a static factor model. We employ data from AEs in deriving the momenta, an approach consistent with the notion that the AEs' liquidity conditions are governed by common factors and the fact that AEs have relatively higher mutual liquidity exposures. In the second stage, we estimate the impacts of the GL momenta on EME macro-financial variables by adding

[2] Canova and Ciccarelli (2013) provide a comprehensive overview on this empirical model including motivations, estimation issues and comparison with other empirical methods.

GL momenta shocks as exogenous variables to a VAR model of EMEs. This two-stage approach enables us to use variable sets suitable for the analysis of EME responses to GL, separately from the variable set used for identifying the GL momenta, and to take advantage of the parsimony of the panel FAVAR system.

In the first stage, we retrieve the GL momenta from a static factor model, employing a principal components analysis:

$$X_t = \Lambda F_t + u_t, \tag{1}$$

where X_t is a vector of financial variables of AEs, and F_t is a three-element vector of GL. Parameter matrix Λ contains factor loadings that relate the GL factors to the financial variables. Vector u_t comprises the idiosyncratic components that are not correlated with the GL factors. It has a mean of zero and covariance Ψ.

In the second stage, we add shocks to the momenta (v_t) as exogenous variables to a panel VAR model of EME variables (Y_t), incorporating the dynamic factor model of Stock and Watson (2005) into a panel VAR framework. For identification, shocks to the momenta (v_t) are assumed to be independent of individual shocks to EMEs, ε_t, in the following VAR model:[3]

$$Y_t = A(L)Y_{t-1} + B(L)v_t + \varepsilon_t, \tag{2}$$

$$F_t = C(L)\, F_{t-1} + v_t. \tag{3}$$

Like Bernanke et al. (2005), we incorporate factors retrieved from a large set of economic variables in a FAVAR model. Bernanke et al. (2005) used factors as conditioning information in measuring the impacts of monetary policy shocks on output and prices. In their study, the augmented factors work as proxies for otherwise missing variables, helping resolve the well-known empirical anomaly that monetary tightening leads to inflation—the so-called price puzzle.

In this study, we identify the motivating factors of GL. One factor is identified as the monetary policy stance measure of major countries, and the other two factors pertain to liquidity provision through global financial markets. We hence follow the spirit of Bernanke et al. (2005) in reducing the dimension of the conditioning variables. In addition, our factor-based approach allows us to incorporate into a single framework both the conventional and alternative measures of monetary policy to reflect that major central banks adopted balance-sheet operations in the face of constraints on interest rate lower bounds after the GFC.

Our model is an empirical counterpart to a theoretical small open economy model such as in Galí and Monacelli (2005). Therefore, it provides guidance on how EMEs respond to GL shocks, which will benefit both future works on small open economy models for EMEs and global forecast models such as in Carabenciov et al. (2013).

[3] Alternatively, one can place the GL momenta at the end in recursive identification, as is done by Darius and Radde (2010). This, however, would require a specification by which the endogenous variables interact among themselves. Since such a specification would complicate the matter while contributing little to the relevant questions of this study, we instead keep our model agnostic on the matter.

III. DERIVING GLOBAL LIQUIDITY MOMENTA

The factor model uses quarterly data for 1990:Q1-2014:Q3 from the G5: the U.S., the U.K., France, Germany, and Japan. For each country, nine variables—overnight call rates, government bill rates, real exchange rates, lending-rate spread against overnight call rates or policy rates, the monetary base, private domestic credit, international claims, stock prices, and stock market volatility—are used in deriving factors.[4] These variables capture the financial situations of the G5 countries driven by their policy authorities and market participants.

Financial data are processed in three steps. In the first step, following Stock and Watson (2005), outliers are replaced by the medians of previous observations.[5] The second step is filtering out the trend components of the time series. Given that interest rates of AEs have displayed a downward trend, a particular level of interest rates (for example, 4 percent) may have signaled monetary loosening in the early 1990s but not in the 2000s.[6] We thus apply the Hodrick-Prescott filter to interest rates.[7]

In extracting common factors among the G5 countries, to avoid a problem owing to heterogeneity one can consider the following two approaches. First, one can directly address the specific changes and varieties by employing various control variables at the cost of model complexity. Second, one can adopt a robust methodology applicable to most circumstances. We choose the second approach mainly because structural breaks or heterogeneity across the G5 countries are, in our opinion, not so well-established except for the downward trend of interest rates. Our study may err on the side of robustness, and we hope future studies will complement our findings with more elaborate models or specifications.

The final step is purging macroeconomic elements in the financial data to single out those that are unwarranted based on domestic fundamentals. Since the liquidity condition should be evaluated against macroeconomic situations, we regress the financial data on GDP growth and producer-price inflation, and then take the regression residuals as the processed data. This is consistent with the literature on monetary transmission such as Romer and Romer (2004). Each variable is weighted by GDP volume, accounting for differences in size among the G5 countries.

[4] Under financial frictions, stock prices are positively associated with market liquidity (e.g., Acharya and Pedersen, 2005), and asset market boom-bust cycles are related to credit expansion (Brunnermeier et al., 2012).

[5] Outliers are removed since their information content is largely outweighed by the loss of robustness caused by their involvement. In this study, an observation with a distance more than three times the interquartile range from the median is tagged as an outlier, and replaced by the median of its six previous observations.

[6] This trend may partly be attributable to financial innovations. As a supply shock to liquidity provision, it may have induced an expansion in credit and a decline in interest rates, a point made by Chen et al. (2012). Variables other than interest rates are not hampered by such an issue.

[7] This step is also taken to render the time series stationary. Alternatively, the original time series might be differenced to obtain stationary series. Considering the global downward trend of interest rates since the 1980s, we use the filtering method to preserve the information contents of the original series.

Momenta are estimated by the principal component method. We select three principal components as per the criterion of Ahn and Horenstein (2013).[8] Moreover, we believe that these three factors, which explain 48 percent of the variability of the underlying data,[9] sufficiently represent the relevant monetary and financial fundamentals of G5 countries.

The sign restriction approach allows us to postulate causality between the factors and observed variables.[10] Table 1 summarizes the restrictions used in this study: the three momenta—policy-driven liquidity, market-driven liquidity, and risk averseness—are assumed to cause the observed variables. Policy-driven liquidity is attributable to monetary policy actions, while market-driven liquidity is somewhat determined by the traditional banking sector and financial market conditions. Lastly, the risk averseness momentum aims to reflect the risk appetite of investors and related financial flows. Here we use minimal restrictions for identification, given the advantages relative to the use of additional restrictions. Employing many restrictions may help identify factors with a high degree of precision, but the outcome is not robust since a single wrong condition may exclude a true solution. With no consensus on valid restrictions having yet been reached in the literature, we opt for robustness.

The identification method of the momenta is in line with the tradition of empirical macroeconomics. The main contribution of the structural vector autoregression lies in the identification of the shock. Once all the relevant information on the shock is concentrated into the covariance matrix of the residuals, what remains to be done is identification through theoretical links between the observed variables and the latent shock. This is the same thing that we do with equation (1). The only difference is that the elements of X_t do not need to be controlled by their autoregressive components since they are fast-moving financial variables.

Table 1. Sign restrictions on factor loading

Factor	Underlying Variable
Policy-Driven Liquidity	M0 (+), Lending rate spread (+), Treasury bill rate (–), Real interest rate (–)
Market-Driven Liquidity	Private Domestic Credit (+), Stock Price (+)
Risk Averseness	Private Domestic Credit (–), Stock Volatility (+)

Notes: Sign restrictions are applied to the above variables for the U.S. only in pinning down Λ in equation (1). A positive sign attached to a variable means that the GL momentum in that row rises with the level of the variable.

[8] A widely-used approach in determining the number of factors, suggested by Bai and Ng (2002), renders five or six as the number of factors—close to the upper limit set by that approach. Breitung and Eickmeier (2005), however, argue that Bai and Ng's criteria may not be robust. The approach by Bai and Ng is prone to reporting local factors as well as global factors since multiple data series are used for each country. In contrast, the test based upon eigenvalues proposed by Ahn and Horenstein (2013) seems free from such an issue.

[9] Policy-driven liquidity explains 16%, market-driven liquidity 13%, and risk averseness 18% of AEs' variables.

[10] Sign restrictions are initially attempted in structural VAR models to identify shocks. For a survey of this application, see Fry and Pagan (2011).

To extract policy-driven liquidity, both the price and quantity variables largely associated with aggregate liquidity are assumed to reflect the AE policy stances. Specifically, a larger supply of base money (M0) is associated with expansions in policy-driven liquidity. Base money has come to play a prominent role in unconventional monetary policy. As major central banks set their policy rates at the lower bound after the GFC, their overnight call rates are no longer meaningful as an indicator of their monetary policy stances. The factor model treats as measurement error the gap between the lower bound and the unconstrained policy rates intended by policymakers that are very likely to be negative. Our approach aims to mitigate the influence of the measurement error by employing many other data and to derive a single indicator of the global monetary policy stances incorporating both pre- and post-GFC periods. We purposely exclude a sign restriction on the policy rate, while adding a sign restriction on the policy rate has little influence on the derived factors.

A subtle restriction with respect to the lending-rate spread is based upon the observation that, prior to the exercise of unconventional monetary policy, an expansion in policy-driven liquidity tends to widen that spread by reducing the funding cost of commercial banks through short-term instruments, including overnight loans.[11]

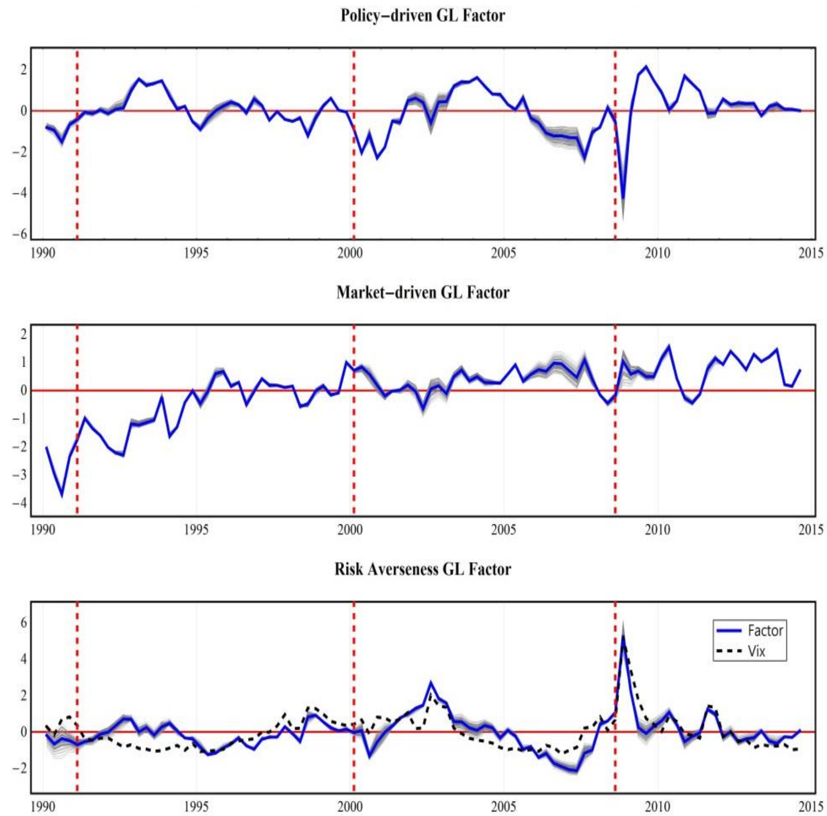
For market-driven liquidity, the main action involves domestic credit because the endogenous generation of liquidity within the banking system tends to foster credit advances to borrowers. Stock prices are also positively associated with market liquidity (e.g., Choi and Cook, 2006). In contrast, the heightened awareness of risk makes banks refrain from lending and tends to increase stock market volatility. Given the set of principal components, there are many possible choices of factors even under a specific set of sign restrictions. Among these possible candidates we choose the one closest to the median of the candidates, as suggested by Fry and Pagan (2011).

Figure 1 shows the three momenta constructed. Notably, after the recessions of the AEs in the early 2000s, policy-driven liquidity expanded rapidly until the Fed hiked its policy rate from 1 percent in mid-2004 to 5.25 percent in June 2006 before moving down after mid-2007. The tightening cycle is registered as a decreasing trend in policy-driven liquidity in the first panel. During the tightening cycle, market-generated liquidity continued to expand to its peak in early-2007. Meanwhile, the risk averseness of market participants declined. The confluence of these three momenta suggests an overall easing in GL for several years in the run-up to the GFC. With the culmination of the GFC in 2008:Q4, the policy-driven factor dropped to its lowest point; the market-driven factor slid down with the Lehman Brothers collapse (2008:Q3); and the risk averseness factor reached its highest point.

The debacle of the GFC appears to accompany the catalyzing effects of sudden deteriorations in major central banks' liquidity supply and market-driven liquidity, and a sharp spike in risk averseness. First, the supply of liquidity by major central banks during this quarter was not sufficient to backstop the sudden deterioration of output and weak prices. Especially, real interest rates (after controlling for producer price inflation and output growth) pointed to a record high

[11] The validity of these restrictions remains intact even after the federal funds rate was set at 0–25 basis points in December 2008, while the bank prime loan rate in the U.S. remained unchanged at 3.25 percent for 2009:Q1-2014:Q3.

Figure 1. Global liquidity momenta



Notes: Three momenta are derived from principal component analysis and identified by the sign restrictions in Table 1. All momenta are standardized. The solid blue lines depict the medians of all candidates as the corresponding momenta, and the shaded areas represent all candidate factors that pass the sign restrictions. (a) The three dashed-red (vertical) lines indicate the onset of the 1991 recession (1991:Q1), the bust of the dot-com bubble burst (2000:Q1), and the Lehman Brothers Bankruptcy (2008:Q3). (b) Notably, the correlation between the market-driven and risk averseness GL factors is very low at −0.04 (see Appendix A). The market-driven GL factor (second panel) is positively correlated with the domestic credit growth of the U.S., which is negatively associated with domestic credit growth of other G5 countries except the U.K. (c) The CBOE Volatility Index (VIX) is standardized and plotted with the risk averseness factor (bottom panel). The (simple) correlation between the risk averseness GL factor and VIX is 0.75. The risk averseness GL factor is a composite extracted from nine financial variables including cross-border and domestic-credit flows as well as stock price volatility for the G5, as opposed to the single measure of VIX.

except for the U.K. Second, the market-driven GL factor dipped owing to little excess liquidity for cross-border investments from the G5 with the acute shortage of liquidity during the quarter. Third, at the same time, the risk averseness factor reached its highest point, when investors' risk appetite in the U.S. stock markets plummeted to a record low as observed by the highest level of VIX (Figure 1, bottom panel).

The resulting sudden declines in GL were countered by the rapid rebound and expansion of policy-driven liquidity from early 2009—consistent with the policy actions undertaken by central banks in AEs, especially the U.S. Fed, upon the GFC. Concomitantly, resuming financial markets and tempering risk averseness helped endogenous liquidity recover.

IV. ASSESSING TRANSMISSION TO EMEs WITH IT

The three momenta derived from the observed financial data of AEs, denoted by F_t, are fed into the dynamics of EMEs' macro-financial variables as specified by equations (2) and (3). The econometric model comprising these equations for the EME panel is estimated by an equation-by-equation least squares method.

A. Connecting Global Liquidity Momenta to EMEs under IT

The panel data for 1995:Q1-2014:Q3 comprise 10 EMEs: the Czech Republic, Hungary, Israel, Korea, Mexico, the Philippines, Poland, Romania, Thailand, and Turkey.[12] We select IT countries among EMEs to focus on GL transmission into similar monetary policy environments.[13] For countries which adopted IT in the middle of the sample period, their data prior to the adoption are dropped. We also test whether the samples are homogenous with respect to an exchange rate regime (Rose, 2014), previous occurrences of financial crises (Laeven and Valencia, 2013), capital controls (Fernandez et al., 2015), or income level. Using the Chow tests, we could not reject hypotheses of homogeneity and the null that the parameters of equation (2) kept unchanged after the GFC.

The quarterly model includes eight variables: real GDP growth, CPI inflation, stock price growth, nominal effective exchange rate (NEER) growth, current account balance (as percent of GDP), capital inflows (as percent of GDP), foreign reserves (as percent of GDP), and overnight call rates. The lag structure of the model is determined by the Akaike information criterion, which performs better with small samples than other consistent information criteria including Hannan and Quinn (1979), according to Lütkepohl (2006). Two autoregressive lags and one contemporaneous and two lagged terms of the GL shock are selected.

To establish the error band for impulse responses and forecast error variance decomposition, we trace each EME variable response to a GL shock. The error bands of the responses are constructed using the conventional Bayesian Monte Carlo integration method with some modification.[14] Since GL factors in equation (2) are estimated from the data rather than being directly observed, the error band may be subject to the issue of "generated regressors." To address this issue, (i) we resample GL factors, (ii) obtain estimated parameters for equation (2) for each realization of the GL factors, (iii) randomly pick a possible parameter set using Bayesian Monte Carlo integration from the estimation, and (iv) draw an impulse response based on the picked parameter set. Finally, the confidence interval and mean value of impulse responses are obtained from the empirical distribution of impulse responses. For real GDP, CPI, stock prices and exchange rates, we accumulate the responses of respective growth variables

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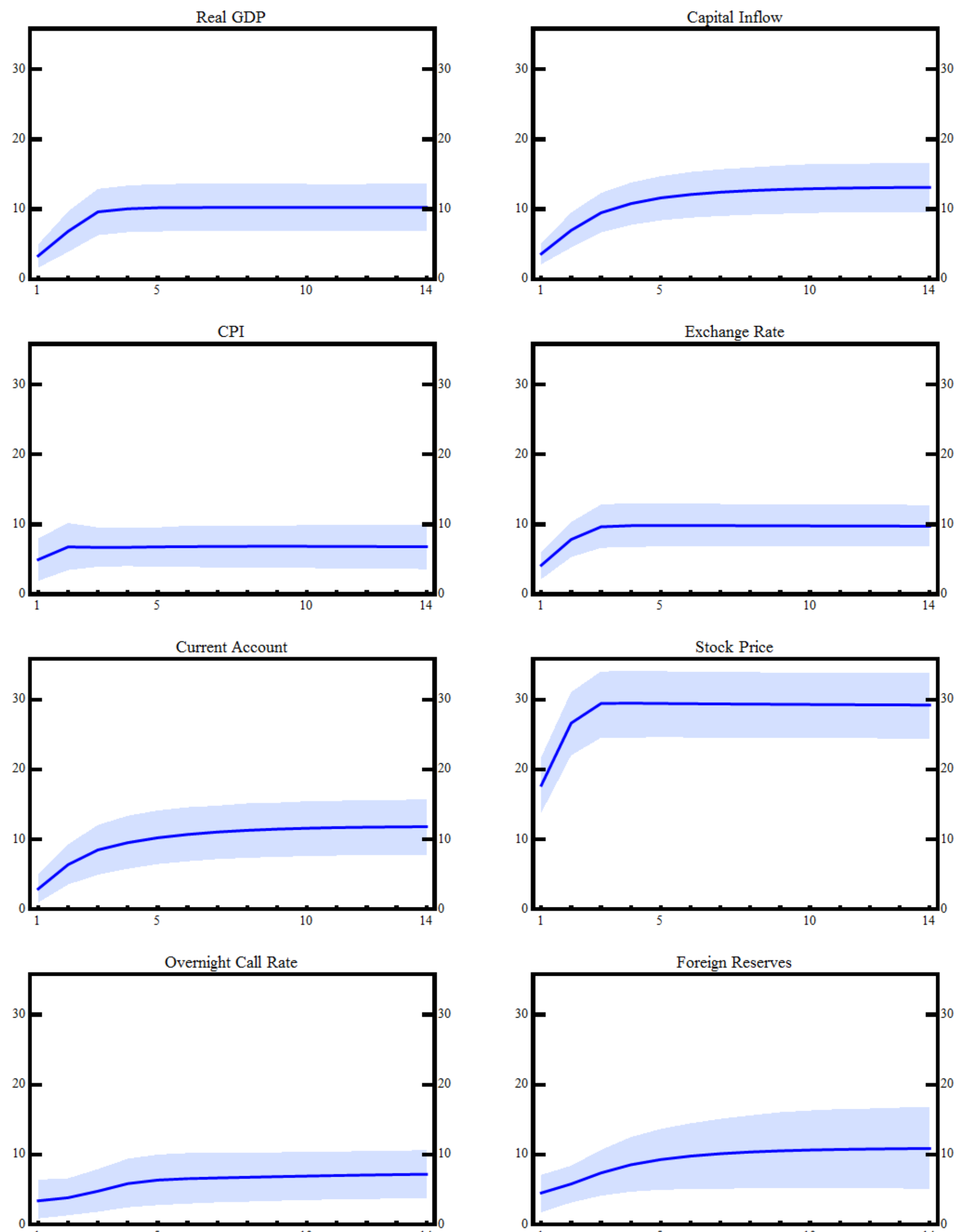
[12] We exclude commodity exporters because their responses to GL shocks may differ from other EMEs possibly because commodity exports are susceptible to changes in dollar strength and commodity price cycles which can be affected by supply factors such as shale gas and oil as well.

[13] We collect data on monetary policy regimes from Rose (2007), Roger (2010) and Hammond (2012), and our data are consistent with Brito and Bystedt (2010), although the latter only reports the year of adoption of inflation targeting.

[14] Canova (1991) adopts this method, simplified from Kloek and van Dijk (1978). Sims and Zha (1999) extend it to over-identified models, and Kilian (1998) offers a fix for small-sample bias. According to Kadiyala and Karlsson (1997), the posterior distribution based on the diffuse prior has a closed form. We therefore draw directly from the posterior distribution.

from the model to obtain the responses in their levels. We apply this method in deriving confidence intervals in Figure 2 as well.

Figure 2. Forecast error variance decomposition



Notes: This figure shows the percentage attributable to the three GL momenta out of the forecast errors of each variable. The responses of capital inflows, current account, and foreign reserves are measured as percent of GDP, and those of overnight call rates are measured in their levels, as in the model. For real GDP, CPI, stock prices and exchange rates, we accumulate the responses of respective growth variables from the model to obtain the responses in their levels. The shaded areas mark the bands between 16% and 84%, constructed by the Bayesian Monte Carlo integration method.

As we establish the three momenta of GL, the foremost interest would be placed on the question how powerful these factors are in explaining the economic and financial variability of EMEs. Figure 2 suggests that a moderate proportion of macro-financial variability in EMEs is attributable to GL momenta. About 10 percent of real GDP growth variability for the three-year horizon is attributable to GL momenta. About 13 percent and 30 percent of variability in capital inflows and stock prices, respectively, are found to be caused by GL momenta. NEER variability seems mostly swayed by domestic elements. Moreover, spillovers from AEs to EMEs' NEER are in general less than the case of their exchange rates against the U.S. dollar.

Table 2 provides the individual contribution of three momenta to the variability of EME variables. The policy-driven and risk averseness GL momenta play more important roles in the movements of EME variables than the market-driven GL momentum, except for current account, foreign reserves, and overnight call rates which entail substantial variability in response to the market-driven GL momentum. The policy-driven GL is found to dominate market-driven GL in terms of impacts on EME key variables except current account.

Table 2. Variability of variables attributable to the three momenta

Variable	All Factors	Policy-Driven Liquidity	Market-Driven Liquidity	Risk Averseness
Exchange Rate	10.0	2.9	1.9	5.2
Capital Inflow	13.2	2.5	1.9	8.8
Stock Price	29.6	12.1	6.9	10.9
Real GDP	10.5	3.3	2.3	4.9
CPI	6.8	2.3	1.8	2.6
Current Account	11.8	3.4	5.1	3.4
Foreign Reserves	10.7	4.6	3.9	2.4
Overnight Call Rate	7.1	3.0	2.7	1.5

Notes: This table reports three-year forecast error variance decomposition of equation (2). The second column represents the proportion in percent of variance caused by the three global liquidity momenta. The next three columns represent the proportion of each global liquidity momentum.

B. EME Responses to A Policy-Driven Global Liquidity Shock

Figure 3 depicts the macroeconomic responses of EMEs under IT against a policy-driven GL shock. The size of the shock is the one-standard deviation of the residuals from equation (3), which is at about the 89th percentile of the shock distribution. For the case of policy-driven GL, the years that saw shocks higher than a one-standard deviation are 1992, 1993, 2001, 2002, 2003, 2009 and 2011. The years in the early 1990s and the early 2000s coincide with U.S. monetary loosening, and other years after the GFC match the Fed's balance sheet expansion. The size of the policy-driven GL shock at the onset of the GFC (2009:Q1) was as big as 3.7 standard deviations.

A positive policy-driven GL shock accompanies capital inflows and brings about a boosting effect in EMEs' GDP by increasing output by 0.25 percentage point three years after the shock.[15] During the same period we see a 6.5 percentage point increase in stock prices.[16] The local currency appreciation and stimulated domestic demand with capital inflows exert downward pressures on current account balance. On the price level, positive pressures from the expansion of policy-driven liquidity and increasing output elevate CPI, while such an inflationary effect of liquidity expansions is diffused over time by the disinflationary effect of exchange rate appreciation.

Policy authorities use policy rates and/or foreign reserves to counteract the impacts of GL momenta on their economies. In response to a policy-driven liquidity shock, EME policy authorities cut policy rates and absorb the incoming liquidity as part of their foreign reserves.[17] Despite these policy efforts, local currencies appreciate while stock markets see a boom partly attributable to increasing investment by foreigners.

EMEs appear to accommodate the AEs' overall monetary policy stance. The reconciliation of the EMEs' policy stances with AEs' reflects trade linkages and financial integration. First, if AEs' policy decisions are associated with global business cycles, small open economies closely linked to the global markets through trade channels should assimilate major economies in terms of their policies. Second, most EMEs do not exercise full autonomy over monetary policy despite their de jure flexible regimes and capital account openness in favor of the dilemma argument by Rey (2016), as opposed to the macroeconomic trilemma.[18] Small open economies may attempt to temper the exchange rate volatility heightened by GL shocks—depending on their policy space dictated by the availability of foreign reserves.

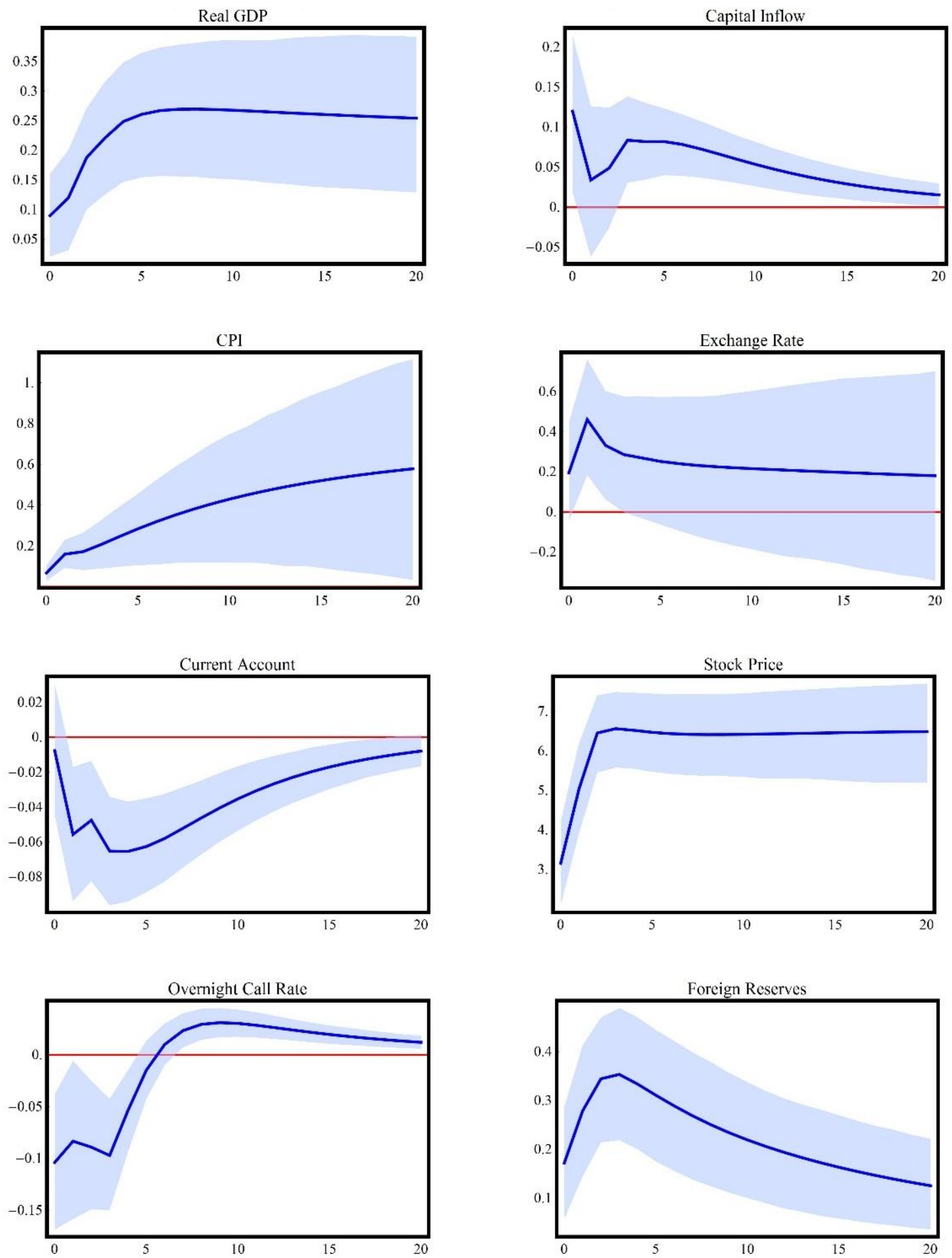
[15] This monotone response contrasts with Carabenciov et al. (2013), which report a swing in the output gap after a positive U.S. monetary policy shock. In their work, the shock decreases the output gap in EMEs in a short period and then reverses the previous effect.

[16] This result is consistent with the finding of Sun and Psalida (2011) that global liquidity, measured by the M2 aggregates of G4 countries, spills over to EMEs through increased inflows to equity, raising their equity returns.

[17] Sun and Psalida (2011) find that receiving countries accumulate foreign reserves and bring about a decline in their real interest rates in response to incoming global liquidity.

[18] Frankel et al. (2002) find that in the 1990s U.S. interest rates were fully transmitted to the rest of the world including countries with flexible exchange rates. Edwards (2010) finds that Latin American countries adjust to changes in the U.S. monetary policy stance more rapidly than Asian countries, citing capital mobility as a cause.

Figure 3. Responses of EMEs to a policy-driven GL shock



Notes: This figure shows the responses (in percentage change) of key macro-financial variables in percent to a positive, one-standard-deviation shock to policy-driven GL momentum. (a) The responses of capital inflows, current account, and foreign reserves are measured as percent of GDP, and those of overnight call rates are measured in their levels, as in the model. For real GDP, CPI, stock prices, and (nominal effective) exchange rates (increase=appreciation), we accumulate the responses of respective growth variables from the model to obtain the responses in their levels. (b) The shaded areas mark the bands between 16% and 84%, constructed by the Bayesian Monte Carlo integration method.

Chen et al. (2012) report a similar result with respect to growth. Although it is not fully articulated, their reported figures suggest that a "noncore" GL demand shock has a negative impact on EME growth but that a noncore GL supply shock has a positive impact, consistent with our findings.[19] Their noncore GL demand shock corresponds to a positive shock to risk averseness in this study, and their supply shock to a market-driven or policy-driven liquidity shock. The latter match is not one-to-one, since we divide the supply of GL by its source, either policy or markets.

Previous studies are in line with our finding that GL expansions boost output and inflation in the recipient EMEs but show some differences in their effects on current account balances. Bernanke (2013) argues that monetary expansion of AEs has almost no impact on current account of EMEs due to offsetting two effects: appreciation of EME currencies and stronger demand of AEs.[20] Bergin (2006) finds from an estimated two-country DSGE model that upon a U.S. monetary easing the foreign country, which is all G7 countries but U.S. in his model, experiences a minuscule degree of worsening in the current account. Kim (2001) finds that U.S. monetary expansions have positive impacts on growth and inflation and an initial negative impact, followed by positive effects with lags, on trade balances in G6 countries. We find that EMEs experience negative impacts on their current account balances from the monetary expansions in AEs, but the negative impacts remain significant for 20 quarters after the shock. The prolonged impact on EMEs' current account balances might be attributable to the relaxed perennial funding shortage of domestic buyers as well as to reduced competitiveness following local currency appreciations.[21]

C. EME Responses to A Market-Driven Global Liquidity Shock

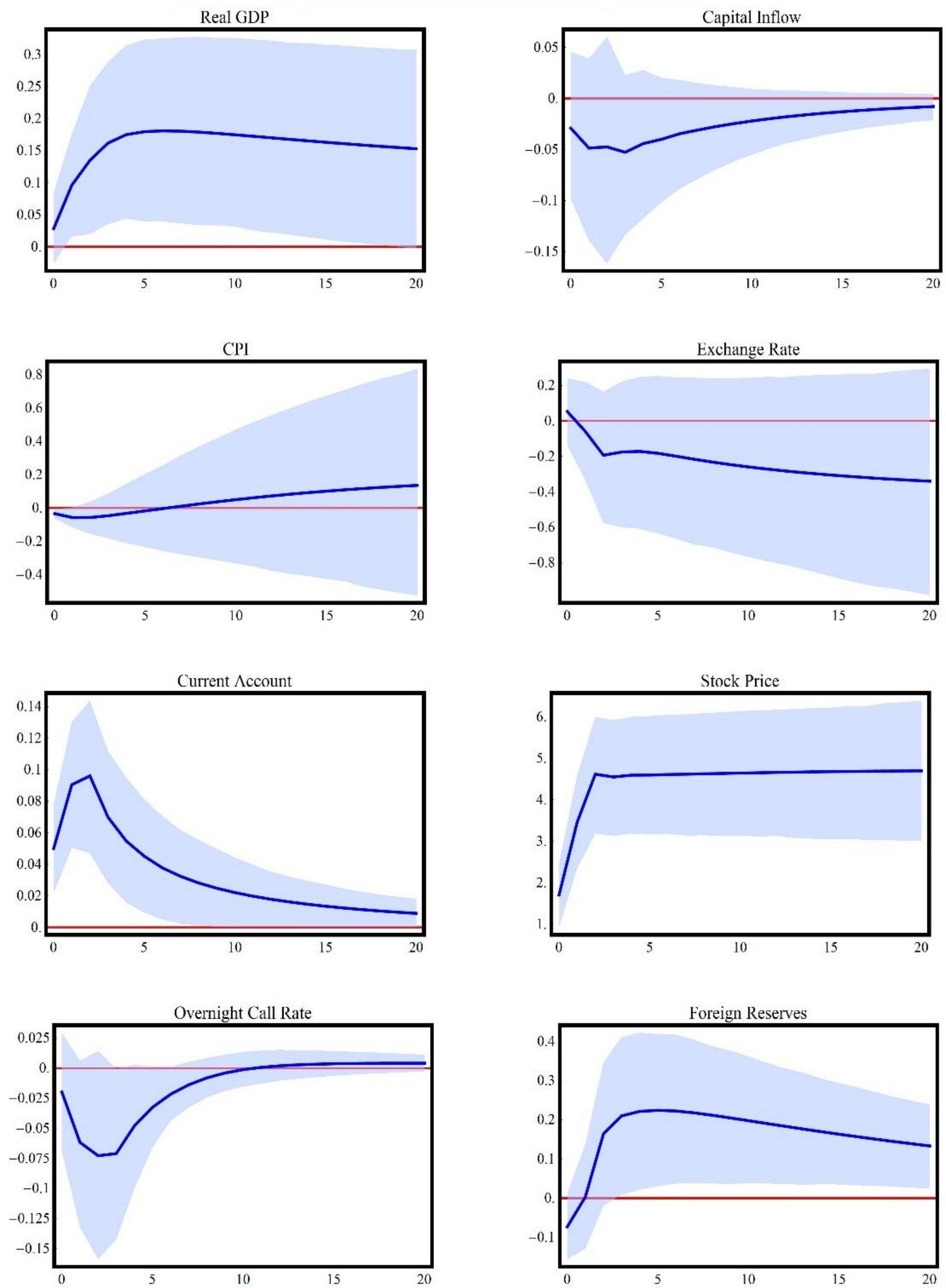
Figure 4 shows EME responses to a positive market-driven GL shock. The shock size is the one-standard deviation of the shock distribution, which corresponds to the 81st percentile. The market-driven GL factor could be associated with financial market conditions including financial innovations, funding situations, and institutional changes. Its fluctuations are less clearly associated with business cycles but entail a rising trend reflecting the degree of financial deepening. We note that the magnitude and persistence of responses of some variables to market-driven GL shocks are not well pronounced.

[19] Chen et al. (2012) retrieve demand and supply shocks of noncore GL. They define noncore liquidity as total nonresident deposits in commercial banks and other deposit corporations, plus loans and securities of commercial banks, nonbanks, and other financial intermediaries.

[20] Bernanke (2013) also argues that heavy and volatile capital inflows to EMEs from AEs are not only caused by the latter group's monetary expansions but also influenced by the growth prospects of receiving countries and investor risk sentiment.

[21] The monetary transmission that renders EMEs' borrowing costs cheaper can dominate the external demand from AEs, resulting in lingering negative impacts on current account balances in EMEs. Kim (2001) argues that the transmission channel through real interest rates is more critical than the trade channel.

Figure 4. Responses of EMEs to a market-driven GL shock



Notes: This figure shows responses of policy and financial variables in percentage change to a positive, one-standard-deviation shock to market-driven global liquidity momentum. See notes (a) and (b) to Figure 3.

A plausible story for EME responses to the rise in market-driven GL involves increased market liquidity and lower funding costs. A prospective financial easing, conducive to positive business sentiments, boosts strongly stock prices. Corresponding increases in market liquidity reduce funding costs and induce policy rates to catch up lowered market rates. A working capital channel (Christiano et al., 2011) for open economies implies that lower funding costs increase export competitiveness and thus current account balance, leading to foreign reserve accumulation. Disinflationary pressures stemming from lower funding costs largely offset inflationary pressures from rising GDP and depreciations owing to capital outflows accommodative of rising current account balance.

D. EME Responses to A Risk Averseness Global Liquidity Shock

Figure 5 shows EME responses to heightened risk averseness. A one-standard deviation of the shock distribution, which corresponds to the 92nd percentile, is applied to the exercise. Three years before and after the GFC witnessed higher shocks than this level: 1998 (the Russian financial crisis), 2002 (the dot-com bubble bust), and 2011 (the European debt crisis). At the height of the GFC, the shock to the risk averseness GL momentum amounts to 6.5 standard deviations.

Heightened risk averseness weakens EMEs' output, CPI, stock prices, and local currencies. These contrasting effects are attributable to the reversal of capital flows. The current accounts of EMEs rise, possibly owing to weakening domestic absorption and gaining price competitiveness with exchange rate depreciations.

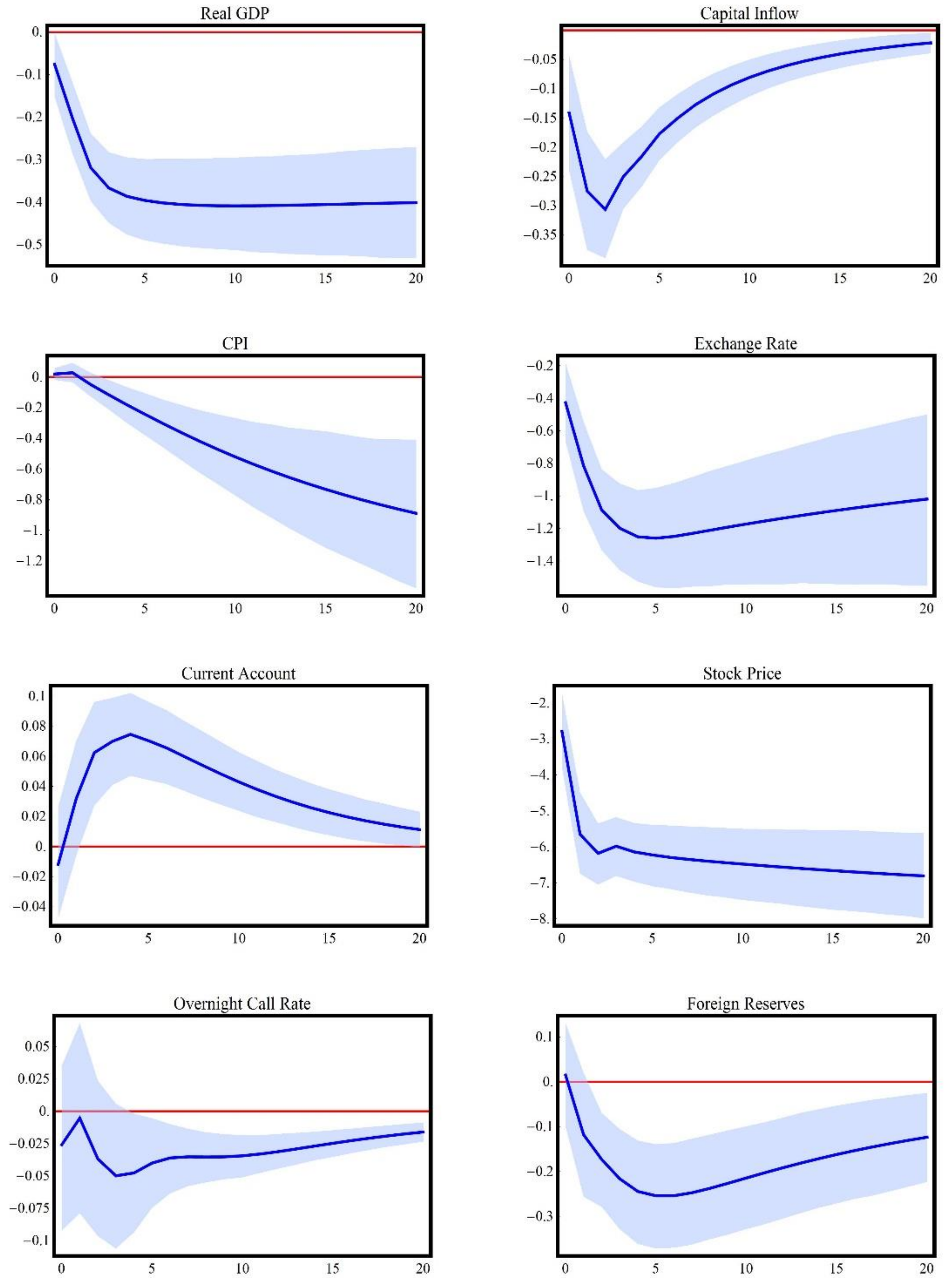
A shock to risk averseness causes EMEs to embark on policy responses to dampen its impact. They can deploy foreign reserves to counteract the stop of foreign investment inflows. However, EMEs' decisions on policy rates could differ depending on their economic fundamentals and policy space. As experienced with the QE tantrum in 2013, some EMEs did not raise their policy rates in the face of a risk of capital outflows, while others did. Lowering policy rates with a lag can be understood as the average policy actions of EMEs with a higher concern on capital outflows in the short run and a typical domestic-oriented policy reaction against the sluggishness of their economies in the medium run.

V. Comparison with Non-IT Countries

In light of policy authorities' concerns about price stability and possibly business cycle stabilization, one could take into account the volatility of inflation and growth to assess monetary policy effectiveness. Also, integral in evaluating macroeconomic performance for small open economies is the transmission of external variables into the domestic economy.

To estimate our FAVAR model for non-IT EMEs, we create a panel of non-IT country-period data by gathering data of the 10 sample countries prior to their adoption of IT. Since the sample countries adopted IT in the latter part of the sample period and no country retracted their decisions to adopt IT, any result from the comparison between the IT panel and non-IT panel may partly be attributable to possible structural shifts. To mitigate this concern, we added three countries—Hungary, India, and Malaysia—which remained in policy regimes other than IT. We demean the data at the country level, removing a potential fixed effect.

Figure 5. Responses of EMEs to a risk averseness GL shock



Notes: This figure shows responses of policy and financial variables in percentage change to a positive, one-standard-deviation shock to risk averseness global liquidity momentum. See notes (a) and (b) to Figure 3.

Table 3 shows the forecast error variance decomposition of the non-IT panel. The variability of key variables attributable to GL momenta is largely similar across the two panels with two noteworthy points. First, the stock price movements of the non-IT panel are less influenced by GL shocks than those of the IT panel, perhaps because non-IT countries have more constraints on capital mobility and market developments. Second, a disproportionately high variability in overnight call rates and foreign reserves is attributable to GL factors in the non-IT panel than in the IT panel.[22]

Table 3. Variability of variables attributable to the three momenta for non-IT countries

Variable	All Factors	Policy-Driven Liquidity	Market-Driven Liquidity	Risk Averseness
Exchange Rate	9.0	3.1	3.1	3.1
Capital Inflow	14.4	2.6	2.8	9.1
Stock Price	21.9	11.2	4.6	6.1
Real GDP	14.4	5.5	4.2	4.6
CPI	8.0	1.6	2.7	3.7
Current Account	10.9	2.8	4.7	3.0
Foreign Reserves	16.0	1.9	3.0	11.1
Overnight Call Rate	13.5	4.2	4.9	4.1

Note: This table replicates Table 2 for non-IT countries.

[22] Our finding that monetary policy is more responsive to GL factors in non-IT EMEs than IT EMEs reconciles Taylor's (2013a, 2013b, and 2016) argument that the optimal cooperative equilibrium can be reached if each economy pursues monetary policy to achieve domestic objectives with little consideration of foreign factors (such as the exchange rates, capital flows, and policy rates of other countries.)

Responses to GL shocks of non-IT EMEs, as depicted in Appendix B, are very similar to those of IT EMEs with a few exceptions. The exceptions pertain to the policy responses of non-IT EMEs in contrast with those of IT EMEs. First, in response to the policy-driven GL shock, lowering interest rates with a lag releases moderate upward pressures on inflation. Second, in response to the market-driven GL shock, mild capital inflows accompany local currency appreciations reducing current account balance and accommodative interest rate policy with sharp interest rate cuts, which nonetheless seem to have a limited effect on price competitiveness perhaps because of weak links to the funding costs of exporters. Third, in response to the heightened risk averseness, the initial hike of interest rates to deter sharp capital outflows helps attenuate currency depreciations, exerting stronger downward pressures on prices.

We now probe the expected volatility of key variables in term of forecast errors. A comparison between the IT panel and the non-IT panel reveals that IT EMEs fare better than non-IT EMEs in terms of expected volatility in macro-financial variables: see Appendix C (the first two columns). Our findings are threefold. (i) Non-IT countries are exposed to higher volatility in exchange rates and capital flows than their IT counterparts, suggesting that regimes that do not target inflation are not necessarily better suited to reducing volatility in exchange rates and capital flows. (ii) The variability of policy variables is greater in non-IT (rather than IT) EMEs, partly owing to higher responsiveness to GL shocks. (iii) Non-IT EMEs are prone to higher volatility of output and inflation, compared to IT EMEs.[23]

We also look for the possible culprit of higher volatility through a counterfactual analysis. Our counterfactual analysis suggests that the higher volatility of non-IT EMEs is largely attributable to the greater domestic shocks including monetary policy shocks rather than to differences in structural parameters. See Appendix C (the last three columns) for more details.

Our comparison between countries under IT and those under alternative regimes suggests that IT helps reduce the susceptibility of inflation and GDP as well as policy measures (interest rates and foreign reserves) to GL shocks and the volatility of key variables as a whole. This finding reconciles the argument that rule-based monetary policy provides better outcomes (Taylor, 2013a, 2013b, and 2016; and Nikolsko-Rzhevskyy et al., 2014), while existing studies offer mixed results on macroeconomic performance of inflation targeting in EMEs (e.g., Brito and Bystedt, 2010; and Gonçalves and Salles, 2008).

[23] IT can be credited with preventing extremely bad economic outcomes through e.g., the Taylor principle (more than a one-to-one response of the policy rate to inflation). Vegh and Vuletin (2012) find that the counter-cyclicality of monetary policy in EMEs has strengthened in the 2000s, compared to the preceding 40-year period.

VI. CONCLUSION

This study delves into the cross-border transmission of GL stemming from AEs. Using various monetary and financial series of AEs, we distill multifaceted GL into three momenta and incorporate them into a panel FAVAR model to investigate their effects on EMEs' economies and policy responses. To address the challenge of applying major countries' policy rates, close to the zero lower bound, as driving factors, we complement them with other monetary and financial series. We identified GL factors with economic interpretations employing minimal sign restrictions, an approach widely used in structural VAR models.

Our empirical findings provide a clearer picture of how GL generated from AEs produces spillover impacts on the real and financial fronts of EMEs. We find that the additional provision of external liquidity to EMEs through a policy-driven GL shock boosts EMEs' stock prices and output with capital inflows and causes local currency appreciation, which are partially absorbed by EMEs' policy rate cuts and foreign reserve accumulations. A market-driven GL expansion boosts stock markets and is translated into lower funding costs, which help raise competitiveness and current account balance. Heightened risk averseness pulls foreign liquidity out of EMEs regardless of different initial policy reactions between IT and non-IT EMEs, weakening their local currencies and slowing down their economic activities. We also find that IT EMEs fare better than non-IT EMEs in terms of macro-financial volatility.

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APPENDIX

A. Macro-Financial Data Used in Estimation and Correlations among Selected Variables

The underlying data to retrieve global liquidity momenta are financial data of the U.S., the U.K., Japan, Germany, and France. The price measures of liquidity are overnight call rates, Treasury bill rates, real interest rates measured by overnight call rates subtracted by CPI inflation rates, the lending rate spread (lending rate minus overnight call rate), stock prices, and stock price volatility. The quantity measures of liquidity are the monetary base, private domestic credit, and international claims. The data cover the period from 1990:Q1 to 2014:Q3, and all data except for interest rates are seasonally adjusted and differenced quarter over quarter if necessary. For the macro-financial series of EMEs, the seasonally adjusted quarter-over-quarter differences are used for the following series: private domestic credit, international claims, stock prices, and the monetary base. Overnight call rates, Treasury bill rates, and real interest rates are filtered to remove downward trends.

The data sources of AEs are as follows: overnight call rates are from the IFS, Bank of Japan, and Bloomberg; lending rates, government bond rates, domestic credit, and stock prices are from the IFS; international claims are from BIS; stock price volatility is measured by the (quarterly) standard deviation of daily changes in the stock price index for each country from Bloomberg; real GDP, CPI, and PPI are from the IFS; and the monetary base is from the IFS, DataStream, Bank of England, and Bank of Japan.

The data sources of EMEs are as follows: real GDP is from DataStream; the CPI is from CEIC; stock prices are from Bloomberg and DataStream; nominal effective exchange rates are from BIS; current account balances and foreign reserves are from the IFS; overnight call rates are from the IFS and DataStream; and capital flows are sums of inbound direct investments, inbound portfolio investments and inbound other investments, which are obtained from the IFS.

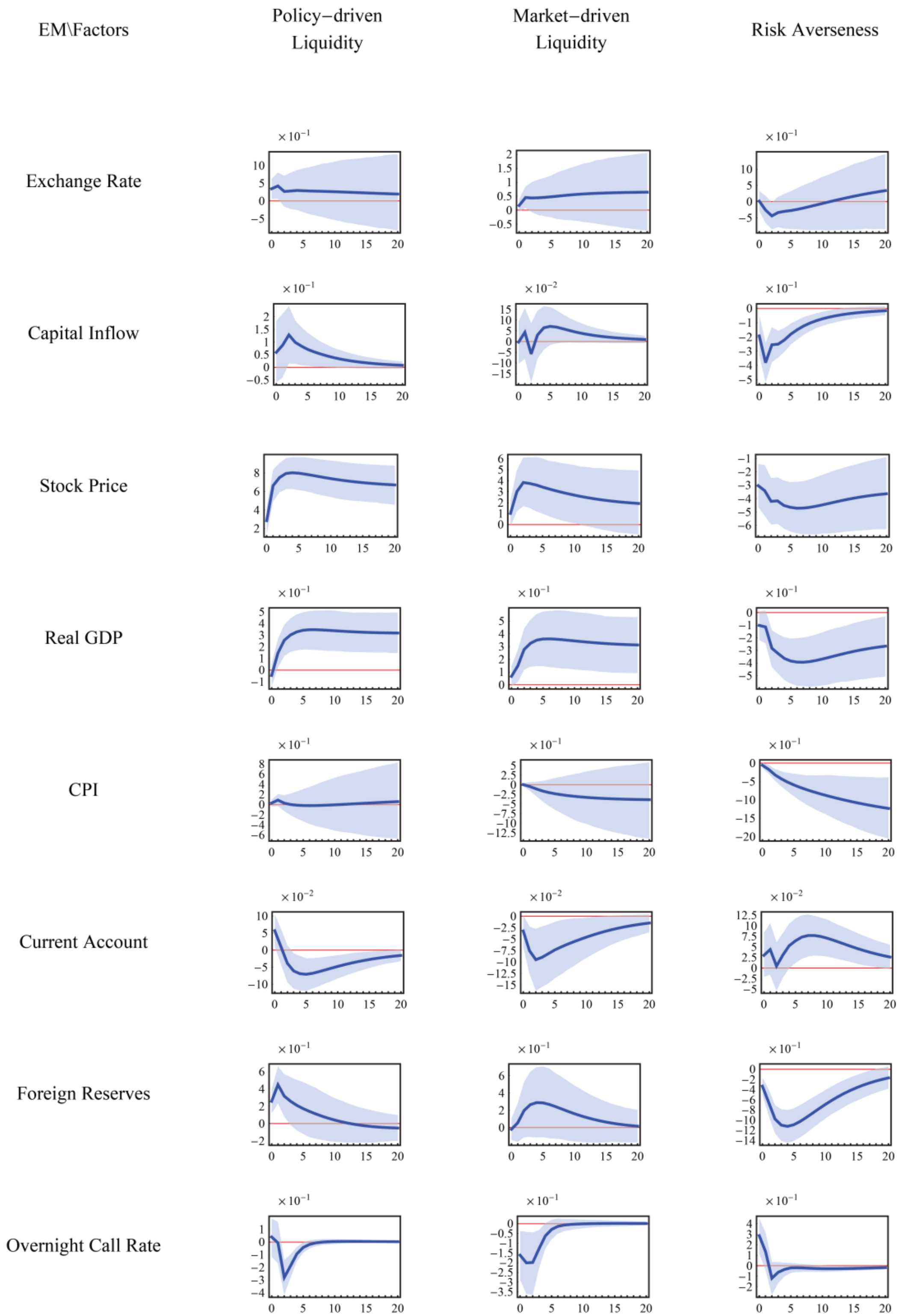
Table A1 shows how market-driven and risk averseness GL factors are correlated with their key drivers of domestic credit growth and stock market volatility.

Table A1. Simple correlations between variables

	Market-driven GL	Risk Averseness GL	VIX	DC Growth (G5 Avg)	DC Growth (U.S.)	SMV (G5 Avg)	SMV (U.S.)
Market-driven GL	1.00	–0.04	0.06	–0.32	0.56	0.03	0.18
Risk averseness GL	–0.04	1.00	0.75	–0.18	–0.06	0.79	0.77
VIX	0.06	0.75	1.00	–0.14	0.02	0.92	0.89
DC Growth (Avg)	–0.32	–0.18	–0.14	1.00	0.17	–0.08	–0.20
DC Growth (U.S.)	0.56	–0.06	0.02	0.17	1.00	0.08	0.14
SMV (Avg)	0.03	0.79	0.92	–0.08	0.08	1.00	0.92
SMV (U.S.)	0.18	0.77	0.89	–0.20	0.14	0.92	1.00

Notes: The table reports the simple correlations between selected variables for the 1990:Q1-2014:Q3 period. The variables are the market-driven GL factor, risk averseness GL factor, VIX, domestic credit (DC) of the U.S. and G5 average (Avg), and stock market volatility (SMV) of the U.S. and G5 average.

B. Responses of Non-IT EMEs to GL Shocks



Notes: This figure shows the non-IT EME responses of key macro-financial variables in percentage change to a positive, one-standard-deviation shock to each GL momentum. See notes (a) and (b) to Figure 3.

C. Comparison of Forecast Errors between IT and Non-IT Countries

Table A2 reports the three-year forecast errors (in standard deviation) using the estimated FAVAR model comprising equations (2) and (3) for the IT and non-IT panels (the first two columns).

To understand the source of the high expected volatility of non-IT countries, we attempt a simple counterfactual exercise (a la Stock and Watson, 2003). The three-year forecast errors from the counterfactual exercise for non-IT EMEs are also shown: in the estimated result of equation (2) of the non-IT panel, the estimate of $A(L)$ matrix (third column), $B(L)$ matrix (fourth column), and covariance of domestic shock ε_t (fifth column), respectively, are replaced by the counterpart of the IT panel estimation. The replacement of the variance-covariance matrix reduces the forecast errors more than other alternatives for most variables.

Table A2. Comparison of forecast error variance between IT and non-IT EMEs and counterfactual analysis

Variable	IT	Non-IT	$A(L)$ replaced	$B(L)$ replaced	$Cov(\varepsilon_t)$ replaced
Exchange Rate	3.3	3.7	3.7	3.8	3.5
Capital Inflow	2.1	2.3	2.3	2.3	2.2
Stock Price	12.9	17.0	16.8	16.8	13.8
Real GDP	1.0	1.3	1.3	1.3	1.1
CPI	1.2	1.7	2.0	1.7	1.3
Current Account	1.1	1.5	1.3	1.5	1.4
Foreign Reserves	5.2	8.8	6.6	8.3	7.6
Overnight Call Rate	1.5	2.3	2.9	2.2	1.4

Notes: This table reports the three-year forecast errors (in standard deviation) using the estimated FAVAR model comprising equations (2) and (3) for the IT and non-IT panels (the first two columns) and the outcome of counterfactual analysis for the non-IT panel (the last three columns).