Tasmanian School of Business and Economics
University of Tasmania

Discussion Paper Series N 2016-02

The Implications of Liquidity Expansion in China for the US Dollar

Wensheng Kang
Kent State University, USA

Ronald A Ratti
Western Sydney University, Australia
CAMA, ANU, Australia

Joaquin Vespignani
University of Tasmania,
CAMA, ANU, Australia,
Globalization and Monetary Policy Institute,
Federal Reserve Bank of Dallas, USA

ISBN 978-1-86295-883-8

The Implications of Liquidity Expansion in China for the US Dollar[Δ]

Wensheng Kang[a], Ronald A. Ratti[bd*], Joaquin L. Vespignani[cde]

[a]Kent State University, Department of Economics, US
[b]Western Sydney University, School of Business, Australia
[c]University of Tasmania, Tasmanian School of Business and Economics, Australia
[d]CAMA, Australian National University, Australia
[e]Globalization and Monetary Policy Institute, Federal Reserve Bank of Dallas, USA

Abstract

The value of the US dollar is of major importance to the world economy. Global liquidity has grown sharply in recent years with growing importance of China's money supply to global liquidity. We develop out-of-sample forecasts of the US dollar exchange rate value using US and non-US global data on price level, output, interest rates, and liquidity on the US, China and non-US/non-China liquidity. Monetary model forecasts significantly outperform a random walk forecast in terms of MSFE in the long run. A monetary model/ECM with sticky prices performs best. Rolling sample analysis indicates changes over time in the influence of variables in forecasting the US dollar. China's liquidity has a distinct, significant and changing influence on the US dollar exchange rate. Increases in the growth rate in the relative US-China M2 forecast a significantly higher value for the US dollar 1- and 6-month later.

Keywords: China's liquidity, trade-weighted US dollar, forecasting US dollar exchange rate

JEL Codes: E41, E51, F31, F41

[*]Corresponding author: Ronald A. Ratti; Western Sydney University, School of Business, Australia; Tel. No: +61 2 96859346;
E-mail addresses: wkang3@kent.edu (W. Kang), r.ratti@westernsydney.edu.au (R.A. Ratti), Joaquin.Vespignani@utas.edu.au (J.L. Vespignani).
Tel. Nos: +1 330 3087414 (W. Kang), +61 2 96859346 (R.A. Ratti), +61 3 62262825 (J.L. Vespignani).

[Δ]We thank Calla Weimer, Menzie Chinn and other participants at the 2016 Allied Social Science Annual Meetings in San Francisco for helpful comment on an earlier version of this paper presented at an American Committee on Asian Economic Studies/American Economic Association session.

The Implications of Liquidity Expansion in China for the US Dollar

1. Introduction

Much recent research has concentrated on the influence of global liquidity on commodity, goods and asset prices. Beckman et al. (2014) demonstrate that global liquidity factors influence commodity prices. D'Agostino and Surico (2009) show that change in global liquidity has predictive power for the US inflation rate. Belke et al. (2010) document that increases in global liquidity since 2001 raises the price of assets inflexible in supply. Ratti and Vespignani (2015) find that unanticipated increase in emerging countries' liquidity has a much greater influence on commodity prices than does that of developed economies.

In this paper we examine the influence of liquidity increases on the US dollar exchange rate value. Our focus is on the value of the US dollar relative to the currencies of the rest of the world, and not on a bilateral exchange rate between the US currency and that of another country. The value of the US dollar relative to the world's other currencies is of major importance to the US and the rest of the world. Emerging economies have companies with large US dollar denominated debt. The US dollar denomination is a high fraction in international bonds (Goldberg (2011) and Lo Duca et al. (2014)). Bruno and Shin (2015) and McCauley et al. (2015) associate appreciation of the US dollar with a decrease in bank capital flows and effective monetary tightening across the world.

The influence of liquidity increases on the US dollar exchange rate is examined within the context of monetary models of exchange rates.[1] These models suggest that the influence on the US dollar exchange rate of liquidity outside the US is to be distinguished from that of US liquidity. In assessing the impact of liquidity on the US dollar exchange rate we find it is useful to identify the origins of the changes in global liquidity. China, in

[1] Sarno and Taylor (2002) provide an authoritative review of the economics literature on exchange rates. Rossi appraisals the literature on forecasting exchange rates. Chinn (2012) reviews macroeconomic methods in modelling the determinants of exchange rates. Aizenman et al. (2009) review work that considers the connections between global liquidity defined in terms of international reserves, global imbalances and reserve management.

particular, has become an important provider of liquidity in recent years. The growing importance of China's money aggregates for global liquidity is illustrated in Figure 1a. In Figure 1a the log of M2 money supplies expressed in US dollars in China, US, Euro area, and Japan over 1996:01-2013:12 are presented. By August 2009, M2 in China exceeds that in the US, the Euro area, and in Japan. China's nominal M2 (in USD) increased on average by 19.6% per year from 1996 to 2013.[2]

Our work examining the forecast performance of monetary models of the overall US dollar exchange rate is facilitated by the availability of non-US global data in a new database, Database of Global Economic Indicators (DGEI), Federal Reserve Bank of Dallas. We develop out-of-sample forecasts of the US dollar exchange rate value using US and non-US global data on price level, output, interest rates, and liquidity in the US, China, and the non-US/non-China rest of the world. A monetary model with sticky prices framework significantly outperforms a random walk model in terms of out-of-sample forecasts in the long run. The best forecast from the model for the US dollar exchange rate is 60 months ahead. Monetary error correction models (ECM) with sticky prices achieve lower mean square forecast errors (MSFE) than a random walk model at horizons of 1-month ahead and afterwards. The monetary model with sticky prices generates much lower MSFE than the monetary models with flexible prices.

Rolling sample analysis indicates changes over time in the influence of variables in forecasting the US dollar exchange rate. China's liquidity does have a distinct, significant and changing influence on the US dollar exchange rate compared to non-US/non-China global liquidity. Relative US-China M2 growth from July 2004 to March 2007 forecasts increases in the US dollar 1-month to 60-months ahead. After March 2007 growth in US M2 relative to growth in China M2 predicts statistically significant higher values in the US dollar TWI 1-

[2] The behaviour of China's nominal GDP is also strongly upward over the period, increasing on average (in US dollars) by 15% per year.

month and 6-months ahead, with longer-term forecasts frequently not statistically significant. Relative US-China M2 growth is driven by growth in China's M2. A finding that China's liquidity expansion has negative effects on the US dollar is consistent with China intervening in the foreign exchange market to stabilize the pegged exchange rate. The outcomes obtained are consistent with China's exchange rate policy over 2005 to 2010 changing to consign less importance on the relative value of the renminbi to the US dollar.

Section 2 reviews China's exchange rate policy. Monetary models for the US dollar exchange rate are presented in Section 3.1 and data and variables (US and non-US) are defined in Section 3.2. Section 4 provides empirical results using the short-run first-difference and ECM models on out-of-sample US dollar exchange rate prediction. Section 5 presents a robustness check using 12-month moving average data. Section 6 concludes.

2. China's Exchange Rate Policy

The exchange rate policy of China is important in assessing the impact of China's liquidity on the US dollar. China tied its currency to the value of the US dollar from the Asian crisis in the late 1990s until July 2005. After July 21, 2005 the value of renminbi is determined with regard to a basket of currencies in which the dollar is of major importance. As illustrated in Figure 1b the value of the renminbi gradually increased versus the US dollar. Over three years following July 2005, the renminbi strengthened by about 21% versus the US dollar. Over an extended period from August 2008 to June 2010 the renminbi/dollar rate did not vary.[3] In June 2010, China's exchange rate became more flexible and gradually appreciated at about 5% per year. These developments are illustrated in Figure 1b.

A rise in China's liquidity facilitates domestic growth and increases demand for imports and foreign interest in investing in China. The currencies of the countries supplying

[3] Frankel (2009) provides a detailed examination of China's exchange rate regime. Dekle and Ungor (2013) note that the change in China's exchange rate policy in August 2008 was due China's export sector being under pressure following the US subprime crisis and the decline in world trade.

imports to China experience upward pressure as will the prices of the imported goods including commodities. Foreign investment flows also influences bilateral exchange rates. As these effects work their way through the financial markets, China intervenes in the foreign exchange market to stabilize the pegged exchange rate. The scale and mix of foreign currencies sold by China in the foreign exchange market will depend on the weights assigned to currencies in the reference basket of major currencies (against which the renminbi is allowed to float within a narrow margin).

The effects on the US dollar foreign exchange rate overall of monetary expansion in China depends on the above influences and there are likely to be consequences for the US dollar beyond that which would be expected upon monetary expansion in a small open economy operating a US dollar peg (with or without capital controls). Fratzscher and Mehl (2014) present evidence of a tri-polar global economy with the renminbi affecting exchange rate and monetary policies in Asia, distinctly so since the global financial crisis. China has achieved a size in terms of GDP on a PPP basis and level of monetary aggregates and in other dimensions that liquidity expansion in China might have consequences for the US dollar exchange rate.[4] Cai et al. (2012) and Fang et al. (2012) find that since 2005 the renminbi/US dollar value has overshadowed the renminbi exchange rate versus other currencies in shaping the overall value of the renminbi.[5] In contrast, Frankel (2009) argues that by mid-2007 the value of the euro had become an important focus in China's exchange rate peg and that the assumption of exclusive focus on the value of the dollar in China's exchange rate management would not be correct.[6]

---

[4] The IMF estimates that on a PPP basis China's GDP exceeds that in the US by about 4.30% in 2014. China's M2 exceeds that in the US by about 65% in December 2013 (Federal Reserve Bank of St. Louis statistics).

[5] A large literature has developed examining the increased economic influence of China on other countries. Chinn (2009) summarizes several papers examining the impact of China on the global economy including that of being a large net saver. Thomas et al. (2009) argue that China's rapid growth has had major effects on the configuration of global trade. Granville et al. (2011) examine the amount of price and exchange rate interaction between the G3 and China.

[6] The appropriate measurement of China's exchange rate and of effects of China's exchange rate on trade flows have also been topics of research. Whalley and Wang (2011) show that the effect on trade flows of Renminbi

3. Methodology

3.1. Monetary models of the exchange rate

In this paper we focus on predicting the value of the US dollar. The value of the US dollar is defined as the trade weighted US dollar index. The structural model utilized to predict the value of the US dollar encompasses leading monetary models of exchange rate determination. In this and the next section first difference and error correction specifications of the theoretical model will be estimated following work in Cheung et al. (2005) and Rossi (2013). We aim at tracking over the rate of growth of the trade weighted US dollar index with a simple reduced-form model. We construct h month ahead out-of-sample forecasts of the trade weighted US dollar index. We assess the effects on h month ahead trade weighted US dollar index of Chinese, US, and global liquidity expansion on the US dollar value by postulating the following '*single-equation lagged fundamental sticky price model*' in forecasting the h-step-ahead rate of growth of US-TWI exchange rate:

$$E_t(s_{t+h} - s_t) = \beta_0 + \beta_1 \Delta\widehat{p_t} + \beta_2 \Delta\widehat{i_t} + \beta_3 \Delta\widehat{y_t} + \beta_4 \Delta\widehat{m}_t^{US-China} + \beta_5 \Delta\widehat{m}_t^{US-(ROW-China)} + \varepsilon_t, \quad (1)$$

where s_t is the log of US-TWI exchange rate index, and p_t the log of consumer price index. The Δ denotes the first difference, the ^ indicates the US and rest of world (ROW) differentials of $p_t, i_t,$ and y_t, the US and China differentials of $m_t^{US-China}$, and the US and non-US/non-China rest of world differentials of $m_t^{US-(ROW-China)}$. The $\widehat{\Delta p_t}$ represents the rate of growth of relative price levels between US and the ROW for example. The i_t is the 3-month short-term nominal interest rate, and y_t represents the log of industrial productivity index. The m_t^{US}, m_t^{China} and m_t^{ROW} are the log of US, China and non-US/non-China ROW money stock $M2$ denominated in US dollars. The β_i for $i = 1,2,\ldots,5$ are regression coefficients, and ε_t is an error term which is assumed to be Gaussian.

---

appreciation can be substantial. Cheung et al. (2015) investigate the effect of the bilateral real exchange rate for US-China trade flows and find the effect to be enhanced when the exchange rate is measured as the deviation from equilibrium values

The model in Equation (1) is associated with a particular monetary model with sticky prices specified in Cheung et al. (2005) and Rossi (2013) but adopted to account for the effect of China's liquidity. The variables are the main predictors used for out-of-sample exchange rate forecasting. Corresponding monetary models with flexible prices are as follows:

$$E_t(s_{t+h} - s_t) = \beta_0 + \beta_1 \Delta\hat{\iota}_t + \beta_2 \Delta\hat{y}_t + \beta_3 \Delta\hat{m}_t^{US-China} + \beta_4 \Delta\hat{m}_t^{US-(ROW-China)} + \varepsilon_t, \qquad (2a)$$

and

$$E_t(s_{t+h} - s_t) = \beta_0 + \beta_1 \Delta\hat{y}_t + \beta_2 \Delta\hat{m}_t^{US-China} + \beta_3 \Delta\hat{m}_t^{US-(ROW-China)} + \varepsilon_t. \qquad (2b)$$

These monetary models are derived from small open economy models by Frenkel (1976) and Mussa (1976) who argue that real money demand $(m_t - p_t)$ is a function of income y_t and the interest rate i_t and assume that a similar relationship holds for the foreign country. The bilateral nominal exchange rate fluctuations are then determined by two countries' relative price level, interest rate, real output and the money supply.[7]

3.2. Data and variables

We identify for the US and for the non-US rest of the world, variables relevant to monetary models of US dollar exchange rate determination. The non-US and US interest rate, price level and output variables are from Database from Global Economic Indicators (DGEI), Federal Reserve Bank of Dallas.[8] In DGEI, weights (based on shares of world GDP (PPP)) are applied to the official/policy interest rates in levels and are applied to headline price indexes and output indices in growth rates to construct indices representing the G40 economies (excluding the US). In 2012 on a GDP PPP basis, the G40 economies account for around 86% of global GDP (with the US accounting for 19% of global GDP). The non-US

[7] Greater detail on these models can be found in Bilson (1978, 1979), Frenkel (1976), Dornbusch (1976), Frankel (1979), and Meese and Rogoff (1983).
[8] The DGEI data was first released at the end of 2013 by the Globalization and Monetary Policy Institute at the Federal Reserve Bank of Dallas and is available at http://www.dallasfed.org/institute/dgei/index.cfm. For more details about this database construction, see Grossman et al. (2013).

part of the global economy is taken to be the 19 largest non-US advanced economies and the 20 largest emerging economies enclosed within the G40. The headline price indexes and output indices are for consumer prices and industrial production.

The trade weighted US dollar index and monetary aggregate data are from FRED, Federal Reserve Bank of St. Louis[9]. The monetary variables are the money stock in US dollar M2 for the US, China and the rest of the world. The (non-China/non-US) global liquidity is measured by the monthly growth rate of a broad monthly monetary aggregate constructed for the Euro area, UK, Japan, Brazil, Russia and India. The global monetary aggregate is based on M4 for the UK, L2 for India, and M2 for the other economies.

Figure 2 presents the log of nominal US-TWI exchange rate and the differential of log of a US variable and its counterpart ROW/China variable over the sample 1996.01-2013.12. In the first diagram of Figure 2, the relationship between US-TWI exchange rate and US-China M2 differentials varies, tending to be positive in the periods 1996.01-2002.2 and 2011.09-2013.12, negative over 2002.02-2008.08, and mixed during the global financial crisis, as the US-China M2 differentials decrease monotonically over time. In contrast, the association of US-TWI exchange rate with US-(ROW-China) M2 differentials shows a different pattern, tending to be negative between the late 1998 and the early 2004 and positive over rest of the sample period. In the third diagram of Figure 2, the price level differential drops sharply over 1996.01-2004.01 and becomes relatively stable over the recent decade. Before 2010 the fluctuation of interest rate differential is large, whereas the movement of industrial productivity differential away from that of the exchange rate has increased in the post global financial crisis period. These observations are indicative that the US-TWI exchange rate reflects the movements in countries' economic fundamentals and shows that their dynamic relationship is likely to be different from one episode to the next.

[9] The data is available at Federal Reserve Bank of St. Louis https://research.stlouisfed.org/fred2/.

4. Empirical Results

4.1. Out-of-sample exchange rate forecasting

We run our regression (1) over the sample 1996M1-2013M12. The MSFE is the metric for evaluating the forecast accuracy and for specifying the optimal forecast horizons in the model:

$$MSFE_{t_1}^{t_2}(h) = \frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} \left(s_{t+h|t} - s_{t+h} \right)^2, \tag{3}$$

where $s_{t+h|t}$ is the forecast of s_{t+h} from Equation (1), h is the month ahead forecast of the trade weighted US dollar index, and the summation of squared forecast errors runs over $1996M1 + h \leq t_1 \leq t_2 \leq 2013M12$. The rolling sample analysis estimates Equation (1) using 114-month rolling samples starting in July 2005. The summation of squared forecast errors in Equation (2) runs over the sample $2005M7 + h \leq t_1 \leq t_2 \leq 2013M12$.

Table 1 reports the ratio of MSFE from estimating the regression in Equation (1) for different monetary models at different horizons, and for comparison, to MSFE from a random walk forecast at different horizons. The MSFE of the monetary models are lower than that of the random walk at the 18-month forecast horizons and afterwards. To assess the significance of the out-of-sample forecasting ability of the monetary models compared to the random walk model, we utilize the DM-statistics proposed by Diebold and Mariano (1995).[10] The MSFE of all monetary models significantly lower than that of the random walk at forecast horizons at 60 months at least in the significant level at 15%. The MSFE is lower for the monetary model with sticky prices than for the monetary models with flexible prices at the 6-month forecast horizons and afterwards, and is statistically significant at the 30, 42, 48, 54 and 60 months. For the monetary model with sticky prices in Equation (1) the lowest MSFE is with the forecast horizon at 60-month ahead. The monetary model with sticky prices in which

[10] Note that we can use Diebold and Mariano (1995) for testing the null hypothesis of equal predictive ability at the estimated in-sample parameter values even though our models are nested. Another testing method such as Clark and McCraken (2015) concerns forecast losses that are evaluated at the population parameter values. The discussion is in Giacomini and Rossi (2010).

differentials between the US and non-US global economy in interest rate, price level, and output influence the out-of-sample forecasts of the US dollar exchange rate is our preferred model.

4.2. Estimation of the basic model over full sample

Estimation of the monetary model with sticky prices version of Equation (1) with $h = 60$ months over the full sample appears in column (1) of Table 2. Adjusted R^2 is 0.114 in column (1). We choose to report the version of Equation (1) with $h = 60$ since this version of the estimated equation has the lowest $MSFE^{Stickey}/MSFE^{RW}$ in Table 1. Increases in the relative US-China M2 growth rates significantly reduce the rate of growth in the trade weighted US dollar in 60 months later. The result that increases in M2 growth in China relative to that in US raises the US dollar in the long run is explained by the more flexible exchange rate policy of China starting in July 2005 and followed over most of the subsequent period. Increases in growth in the relative US-(ROW-China) global liquidity has a positive coefficient but statistically non-significant in affecting the US dollar.

In column (1) of Table 2, the coefficient of the rate of growth of the relative price level is -0.356 and highly statistically significant. This implies that a rise in the price level outside the US is associated with an appreciation in the US dollar 60 months later. The inflation differential between the US and the rest of the world is statistically significant in all the regressions in Table 2. The coefficient estimates of the rates of growth of the relative interest rate and industrial productivity are insignificant in the period of analysis.

Estimation of the monetary models with flexible prices, Equations (2a) and (2b), with $h = 60$ months over the full sample appear in columns (2) and (3) of Table 2. The coefficient estimates of the relative US-China M2 growth rates for the monetary model with flexible prices are qualitatively and quantitatively similar to that with sticky prices. Adjusted R^2 of these models at 0.022 and 0.028 are far lower than the 0.114 in column (1) for the monetary model with sticky prices. The monetary model with sticky prices dominates the monetary models with flexible prices in terms of Adjusted R^2 and in terms of out-of-sample forecasting performance.

In columns (4) through (7) of Table 2 the effect of variation in the definitions of the liquidity variables are considered. In column (4) the liquidity variable is the growth in China's M2. The coefficient estimate of the Chinese money growth is statistically significantly and positive. In column (5) the liquidity variable is the growth in US M2. The coefficient estimate of the US money growth is statistically significantly and negative as expected. These results confirm that increases in the relative US-China M2 growth rates significantly reduce the rate of growth in the trade weighted US dollar in the long run as shown in column (1). In column (6) the effect of the liquidity variable measured by the growth in M2 in the rest of the world (other than the US and China), is statistically insignificant.

In column (7) the liquidity variable is the differential in growth in M2 between the US and the rest of world inclusive of China and is not statistically significant. This variable is the basic liquidity variable that would be included in a monetary model explaining the value of the US dollar with the emphasize on the US versus the rest of the world. In confirmation that growth in US M2 relative to growth in China's M2 is more important than the other monetary variables in predicting the US nominal exchange rate, the value of DM-statistic is relatively higher in column (1) than in columns (4) through (7) in Table 2.

4.3. Rolling sample analysis

To assess the extent and nature of parameter instability issues of the forecast starting in July 2005, a rolling sample analysis is followed. We estimate Equation (1) using 114-

month rolling samples. The first estimation sample uses data over 1996M1-2003M7, the second sample uses data over 1996M2-2003M8, etc., with each subsequent sample adding one new month and dropping the first month of the data in the preceding sample. The out-of-sample forecasting period begins in July 2005 and ends in December 2013.

Figure 3 shows the coefficient estimates of relative US-China M2 growth at the 1, 6, 12, 36, 48 and 60-month ahead forecast horizons of the rate of growth in the trade-weighted US dollar exchange rate. The coefficient estimate of the effect of the US-China money growth (β_4 in Equation (1)) for the 12 month ahead forecast labeled November 2011 in Figure 3, for example, is for the forecasted value of TWI in November 2012. For the 60 month ahead forecast labeled November 2011 in Figure 3, the forecasted value of TWI in November 2016. One standard deviation error bands appear around the parameter estimate.

The results in Figure 3 imply changing impact of growth in the relative US-China M2 on TWI at all forecast horizons over time. It is useful to consider the forecasts up 12 months ahead separately from the longer-term ahead forecasts. In Figure 3, the estimate of β_4 for the 1-month and 6-month ahead forecasts of TWI are positive (post July 2004) and for the most part statistically significant. For the 12-month ahead forecast, the estimate of β_4 is statistically significantly positive between April 2004 and March 2007 and virtually zero thereafter. These results suggest that for growth in US M2 relative to China M2 over the period July 2004 to March 2007, the US dollar TWI is forecasted to rise over the following 1, 6 and 12 months. For growth in US M2 relative to China M2 after March 2007, the US dollar TWI is predicted to be higher 1 to 6 months later, but to be not higher 12 months later.

The longer-term ahead forecasts of the effects of growth in US M2 relative to China M2 also suggest changes over time. For the 36-month ahead forecast, the estimates of β_4 are positive until September 2008 and virtually zero thereafter. With regard to 48-month forecast, the estimate of β_4 is mostly positive and statistically insignificant until September 2008, and negative thereafter with a statistically significant window between June 2010 and September 2011. The estimate of β_4 for the 60-month ahead forecast of TWI is positive from June 2005 until June 2010 and negative thereafter, with most estimates being statistically insignificant.

The overall pattern in Figure 3 is that relative US-China M2 growth over July 2004 to March 2007 forecasted increases in the US dollar TWI from 1-month to 60-months ahead (with many estimates being statistically significant). Growth in US M2 relative to China M2 after March 2007 continues to predict statistically significant higher values in the US dollar TWI from 1-month to 6-months ahead, but the longer-term forecasts of the effect on the US dollar TWI are mostly not statistically significant. The exchange rate policy of China is important in determining the effect of liquidity expansion in China on the value of the U.S. dollar. A focus on stabilizing the renminbi/US dollar value, an increase in China's M2 implies sales of US dollar assets with downward pressure on the US dollar relative to other currencies. These results are consistent with observations made in the literature concerning China's evolving exchange rate policy over 2005 to 2010 including a de-emphasis on the renminbi/US dollar value in shaping the overall value of the renminbi after mid-2007 (noted Frankel (2009)).

4.4. ECM estimation

In this subsection we follow Cheung et al. (2005) and Rossi (2013) and examine an error correction model (ECM). As Figure 2 suggests, both the exchange rate and the economic fundamentals in the monetary model are $I(1)$.[11] The ECM is expected to forecast better in long horizons in that the specification allows for the additional long-run interaction effect of the economic determinants of the exchange rate. We postulate the following '*single-*

[11] All these series were checked for the *I(1)* property before conducting the cointegration test. For the purpose of brevity, the stationarity test results are not reported.

equation lagged fundamental sticky price ECM model' in forecasting the h-step-ahead rate of growth of US-TWI exchange rate:

$$E_t(s_{t+h} - s_t) = \beta_0 + \beta_1 \Delta\widehat{p_t} + \beta_2 \Delta\widehat{\iota_t} + \beta_3 \Delta\widehat{y_t} + \beta_4 \Delta\widehat{m}_t^{US-China} + \beta_5 \Delta\widehat{m}_t^{US-(ROW-China)}$$

$$+\beta_6(s_t - \gamma_0 - \gamma_1\widehat{p_t} - \gamma_2\widehat{\iota_t} - \gamma_3\widehat{y_t} - \gamma_4\widehat{m}_t^{US-China} - \gamma_5\widehat{m}_t^{US-(ROW-China)}) + \varepsilon_t, \quad (4)$$

where the γ_i for $i = 0,1, \dots ,5$ are regression coefficients that capture the long-run relationship. The regression coefficient β_6 reflects the long-run gravitation towards the equilibrium relationship between the variables, in the sense that exchange rates revert back to their fundament value as long as $\beta_6 < 0$.

The estimates of the long-run cointegration relationship parameters γ_i vary as the data window moves. We utilize the Johansen method to test the null hypothesis of no cointegration. Table 3 presents the maximum eigenvalue statistics that reject the null hypothesis and show that there exists long-run relationship at different forecasting horizons. This study considers both first difference and ECM specifications, because it is difficult to determine unambiguously if these variables are cointegrated or not (as noted in Cheung et al. (2005) using the standard Johansen procedure). Following Cheung et al. (2005), the time-varying parameters γ_i are estimated without restriction. The long-run relationship using the full sample is estimated to be

$$s_t = 4.11(54.10) - 1.27(3.86)\widehat{p_t} - 0.01(3.14)\widehat{\iota_t} + 0.80(3.25)\widehat{y_t} + 0.17(3.57)\widehat{m}_t^{US-China}$$
$$- 0.26(3.73)\widehat{m}_t^{US-(ROW-China)}$$

with absolute t-statistic values in the parenthesis.

Table 3 shows the ratio of MSFE from estimating the regression in Equation (4) without short-run dynamic variables (for the monetary ECM model with sticky prices) to MSFE from a random walk forecast at different horizons. We exclude the short-run dynamic variables to make our exercise directly comparable with Cheung et al. (2005). The MSFE of the ECM model is lower than that of the random walk at all forecast horizons. The MSFE ratio in predicting nominal US TWI exchange rate is highly statistically significant at the forecasting horizon 60-month ahead. Estimation of Equation (4) with $\mathrm{h} = 60$ months over the full sample is reported in column (3) of Table 4. The signs of all coefficient estimates of the economic fundamentals are comparable to those in column (1) of Table 2. The coefficient estimate of error correction term β_6 is negative as expected in the monetary model.

In column (2) of Table 4 we utilize Chicago Board Options Exchange Volatility Index (VIX) as a proxy of contemporaneous short run dynamics. Matsumoto (2011) argues that the global liquidity can be measured by the price risk premium of risky assets. In column (2), VIX has a positive and statistically significant coefficient indicating that an increases in financial uncertainty is associated with a rise in the US dollar. However, in column (4) VIX is not statistically significant in the presence of the economic fundamental variables.

In column (1) of Table 4 we exclude all the short run macro dynamic variables as the monetary models specified by Cheung et al. (2005) and Rossi (2013), whereas all available variables are included in column (4). In general with variations in the definitions of the contemporaneous short run dynamics, the ratio of MSE from monetary ECM model with sticky prices to MSFE from a random walk is statistically significant in forecasting the exchange rate in the long run. The DM statistic of columns (3) and (4) including the growth of economic fundaments is relatively higher than that of columns (1) and (2) in particular. This implies that inclusion of the differentials in interest rates, price level, output and the relative money stocks between the US and China and the rest of the world is essential in the forecasting of the US dollar.

We present the fitted values of the natural logarithm of nominal US TWI exchange rate using various ECMs shown in Table 4 at 1, 12 and 60-month forecasting horizons over 2001:02 - 2013:12 in Figure 4. The fitted series at 1-month forecasting horizon mimics the nominal TWI exchange rate, while the predictions at 12-month forecasting horizons present the trend of nominal exchange rate using different ECMs in general. In particular, the first and second diagrams of Figure 4 shows that the fitted values at 60-month forecasting horizons is smoother when using the ECM without VIX and without contemporaneous short-run dynamic variables, in the sense that the ECM without the short-term dynamics captures the long-run trend of the US exchange rate. In contrast, the third and fourth diagrams of Figure 4 shows that the fitted series at 60-month forecasting horizons additionally reflect the fluctuation of the nominal exchange rate when using the ECM with the short-run dynamics and with/without the VIX.

5. A Robustness Check

To establish the robustness results of our analysis, we utilize a 12-month moving average of monthly data (MA(12)) for the interest rates and all other variables in the log levels before doing any empirical work. The moving average is commonly used with time-series data to smooth out short-term fluctuations and highlight longer-term trends or cycles (see Stock and Watson (2007) for forecasting inflation, Holt (2004) and Engel (2015) for forecasting the exchange rate). A criticism is that the moving-average will be auto-correlated, even if the original series is not auto-correlated. Thus, using the moving-average as a dependent variable is a potential violation of the subsequent causal model (that is to show a spurious causal relationship) in the short-term forecasting model. The advantage is to smooth out short-term fluctuations and highlight longer-term trends or cycles. It is superior to the mean model in adapting to the cyclical pattern and is superior to the random walk model in not being too sensitive to random shocks from one period to the next. Data averaging is adopted in time-series models generating long-term predictions when seasonality in data might be a problem. To overcome seasonality in quarterly data, Engel et al. (2015) average data over four quarters in models forecasting bilateral exchange rates.

Table 5 reports the ratio of MSFE from estimating the regression in Equation (1) for different monetary models at different horizons, and for comparison, to MSFE from a random walk forecast at different horizons using the MA(12) data over 1997.01-2013.12. The MSFE of the monetary models are lower than that of the random walk over all the forecast horizons. The MSFE of all monetary models significantly lower than that of the random walk at horizons of 30-month and more ahead at least at the 15% level, and at horizons of 48-month and more ahead at least at the 5% level.

Utilizing the MA(12) data we obtain similar but stronger results. It is consistent with Rossi' (2013) argument that 'data transformations (such as detrending, filtering and seasonal adjustment) may substantially affect predictive ability, and may explain differences in results across studies' (p. 1066).

6. Conclusion

Rossi (2013) observes in an extensive review of the literature on exchange rate predictability, that overall, empirical work does not find that customary predictors such as differentials in interest rate, price level/inflation and output variables do a very good job at out-of-sample prediction of the exchange rate.[12] We have found some success with using traditional predictors at global level in forecasting the US dollar exchange rate in the long run. Differentials between US and non-US global values for price levels and differentials between US and China's M2 are statistically significant in forecasting the US dollar exchange rate in the long run. The relative US-China money growth does have a distinct, significant and changing influence on the US dollar exchange rate.

[12] Rossi (2013) notes (contested) evidence that the monetary model at very long horizons and uncovered interest rate models at short horizons have some success at out-of-sample prediction of the exchange rate, and that it is thought that models based on Taylor rule gaps and net foreign assets have more encouraging out-of-sample forecasting capability for out-of-sample prediction for exchange rates.

We develop out-of-sample forecasts of the US dollar exchange rate value using US and non-US global data on price level, output, interest rates, and liquidity on the US, China and non-US/non-China liquidity. Growth in US M2 relative to growth in China's M2 is more important than the other monetary variables in predicting the US nominal exchange rate. The best forecast is from the monetary model with sticky prices for the US dollar exchange rate at 60 months ahead. Rolling sample analysis indicates changes over time in the influence of variables in forecasting the US dollar.

Consist with China intervening in the foreign exchange market to stabilize the pegged exchange rate, relative US-China M2 growth over July 2004 to March 2007 forecasts increases in the US dollar TWI from 1-month to 60-months ahead. Growth in US M2 relative to China M2 after March 2007 predicts statistically significant higher values in the US dollar TWI 1-month and 6-months ahead, but the longer-term forecasts of the effect on the US dollar TWI are mostly not statistically significant. These outcomes are consistent with China's evolving exchange rate policy over 2005 to 2010 from placing great importance on maintaining the US dollar value of the currency to consigning less importance on the relative value of the renminbi to the US dollar. These finding of influence of China's liquidity on the value of the US dollar exchange rate are consistent with the evidence presented by Fratzscher and Mehl (2014) of a tri-polar global economy with China's renminbi policy affecting exchange rate and monetary policies in Asia.

References

Aizenman, J., Chinn, M., Hutchison, M., 2009. Understanding Global Liquidity in a Volatile World. Review of International Economics 17, 651-654.

Beckmann, J., Belke, A., Czudaj, R., 2014. Does global liquidity drive commodity prices? Journal of Banking and Finance 48, 224-234.

Belke, A., Orth, W., Setzer, R., 2010. Liquidity and the dynamic pattern of asset price adjustment: A global view. Journal of Banking and Finance 34, 1933-1945.

Bilson, J.F.O., 1978. Rational expectations and the exchange rate, in: J. Frenkel and H. Johnson, eds., The economics of exchange rates (Addison-Wesley Press, Reading).

Bilson, John F.O., 1979. The deutsche mark/dollar rate -- A monetary analysis, in: Karl Brunner and Allan H. Meltzer, eds., Policies for employment, prices and exchange rates, Carnegie-Rochester Conference 11 (North-Holland Publishing Company, Amsterdam).

Bruno, V., Shin, H. S., 2015. Capital flows and the risk-taking channel of monetary policy. Journal of Monetary Economics 71, 119-132.

Cai, Z., Chen, L., Fang, Y., 2012. A new forecasting model for USD/CNY exchange rate. Studies in Nonlinear Dynamics & Econometrics 16 (3).

Cheung, Y.-W., Chinn, M.D. and Pascual, A.G., 2005. Empirical exchange rate models of the nineties: Are any fit to survive? Journal of international money and finance 24, 1150-1175.

Cheung, Y.-W., Chinn, M.D., Qian, X., 2015. China–US trade flow behavior: the implications of alternative exchange rate measures and trade classifications. Forthcoming Review of World Economy. DOI 10.1007/s10290-015-0232-y.

Chinn, M.D., 2009. The symposium on 'China's impact on the global economy'. Pacific Economic Review 14, 342-345.

Chinn, M.D., 2012. Macro Approaches to Foreign Exchange Determination. Chapter 2 Handbook of Exchange Rates, J. James, I.W. Marsh, L. Sarno (Eds.), John Wiley & Sons Inc., 45-71.

Clark, T.E., McCracken, M.W. (2015). Nested forecast model comparisons: A new approach to testing equal accuracy. Journal of Econometrics 186, 160-177.

D'Agostino, A., Surico, P., 2009. Does global liquidity help to forecast US inflation? Journal of Money, Credit and Banking 41, 479-489.

Dekle, R., Ungor, M., 2013. The real exchange rate and the structural transformation (s) of China and the US. International Economic Journal 27, 303-319.

Diebold, F. X., Mariano, R.S., 1995. Comparing predictive accuracy. Journal of Business and Economic Statistics 13, 253-263.

Dornbusch, R., 1976. Expectations and exchange rate dynamics. Journal of Political Economy 84, 1161-1176.

Engel, C., Mark, N.C., West, K.D., 2015. Factor model forecasts of exchange rates. Econometric Reviews, 34, 32-55.

Fang, Y., Huang, S., Niu, L., 2012. De facto currency baskets of China and East Asian economies: the rising weights. Bank of Finland BOFIT Discussion Papers, 2-2012.

Frankel, J. A., 1979. On the mark: A theory of floating exchange rates based on real interest differentials. American Economic Review 69, 610-622.

Frankel, J. A., 2009. New estimation of China's exchange rate regime. Pacific Economic Review 14 (3), 346–360.

Fratzscher, M., Mehl, A., 2014. China's dominance hypothesis and the emergence of a tri-polar global currency system, Economic Journal 124, 1343–1370.

Frenkel, J.A., 1976. A monetary approach to the exchange rate: Doctrinal aspects and empirical evidence. Scandinavian Journal of Economics 78, 200--224.

Giacomini, R., Rossi, B., 2010. Forecast comparisons in unstable environments. Journal of Applied Econometrics 25, 595-620.

Goldberg, L.S., 2011. The international role of the dollar: Does it matter if this changes? FRB of New York Staff Report 522.

Granville, B., Mallick, S., Zeng, N., 2011. Chinese exchange rate and price effects on G3 import prices. Journal of Asian Economics, 22 (6), 427-440.

Grossman, V., Mack, A., Martinez-Garcia, E., 2013. Database of global economic indicators (DGEI): a methodological note. Federal Reserve Bank of Dallas Globalization and Monetary Policy Institute Working Paper 166.

Holt, C.C., 2004. Forecasting seasonals and trends by exponentially weighted moving averages. International journal of forecasting, 20, 5-10.

Lo Duca, M., Nicoletti, G., Vidal Martinez, A., 2014. Global corporate bond issuance: what role for US quantitative easing? ECB Working Paper Series, no 1649.

Matsumoto, A., 2011. Global liquidity: Availability of funds for safe and risky assets. International Monetary Fund working paper (No. 11-136).

McCauley, R.N., McGuire, P., Sushko, V., 2015. Global dollar credit: links to US monetary policy and leverage. Bank for International Settlements, BIS Working Paper No 483.

Meese, R.A., Rogoff, K., 1983. Empirical Exchange Rate Models of the Seventies: Do they fit out of sample? Journal of International Economics 14, 3-24.

Mussa, M., 1976. The exchange rate, the balance of payments and monetary and fiscal policy under a regime of controlled floating. Scandinavian Journal of Economics 78, 229–48.

Ratti, R.A., Vespignani, J.L., 2015. Commodity prices and BRIC and G3 liquidity: A SFAVEC approach. Journal of Banking & Finance 53, 18-33.

Rossi, B., 2013. Exchange rate predictability. Journal of Economic Literature 51, 1063-1119.

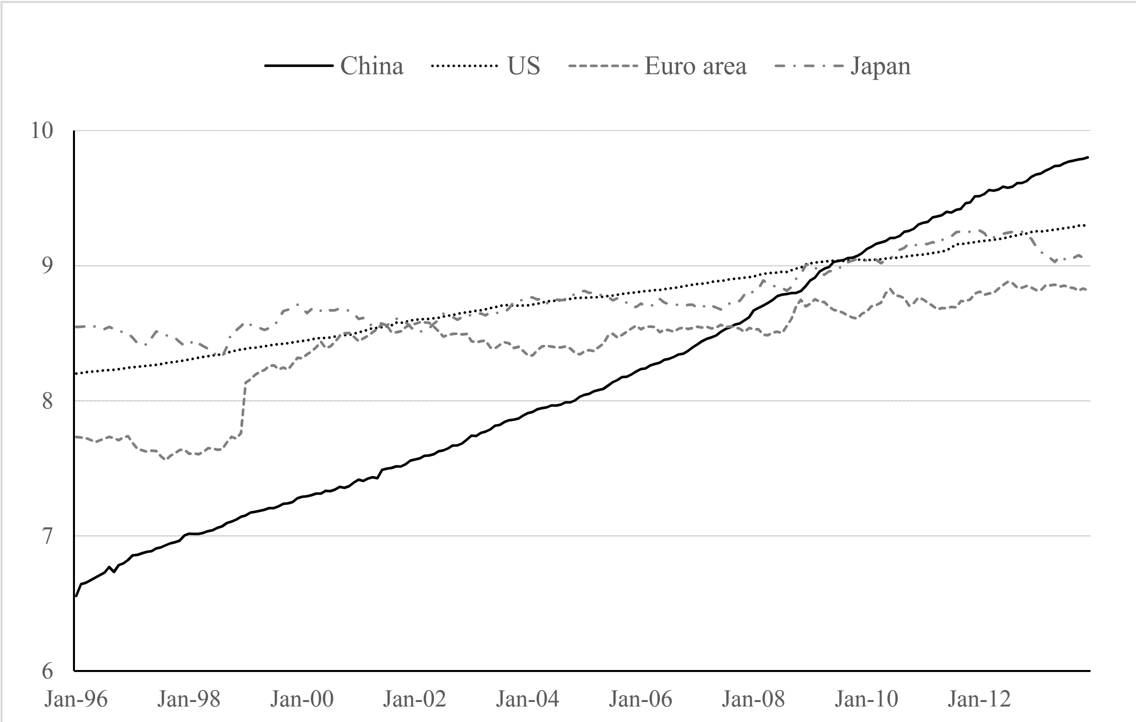
Sarno, L., Taylor, M.P., 2002. The economics of exchange rates. Cambridge University Press.

Stock, J.H., Watson, M.W., 2007. Why has US inflation become harder to forecast? Journal of Money, Credit and banking 39, 3-33.

Thomas, C.P., Marquez, J., Fahle, S., 2009. Measures of international relative prices for China and the USA. Pacific Economic Review 14 (3), 376–397.

Whalley, J., Wang, L., 2011. The impacts of Renminbi appreciation on trade flows and reserve accumulation in a monetary trade model, Economic Modelling 28, 614-621.

Figure 1a. M2 Money Supply, January 1996-December 2013.

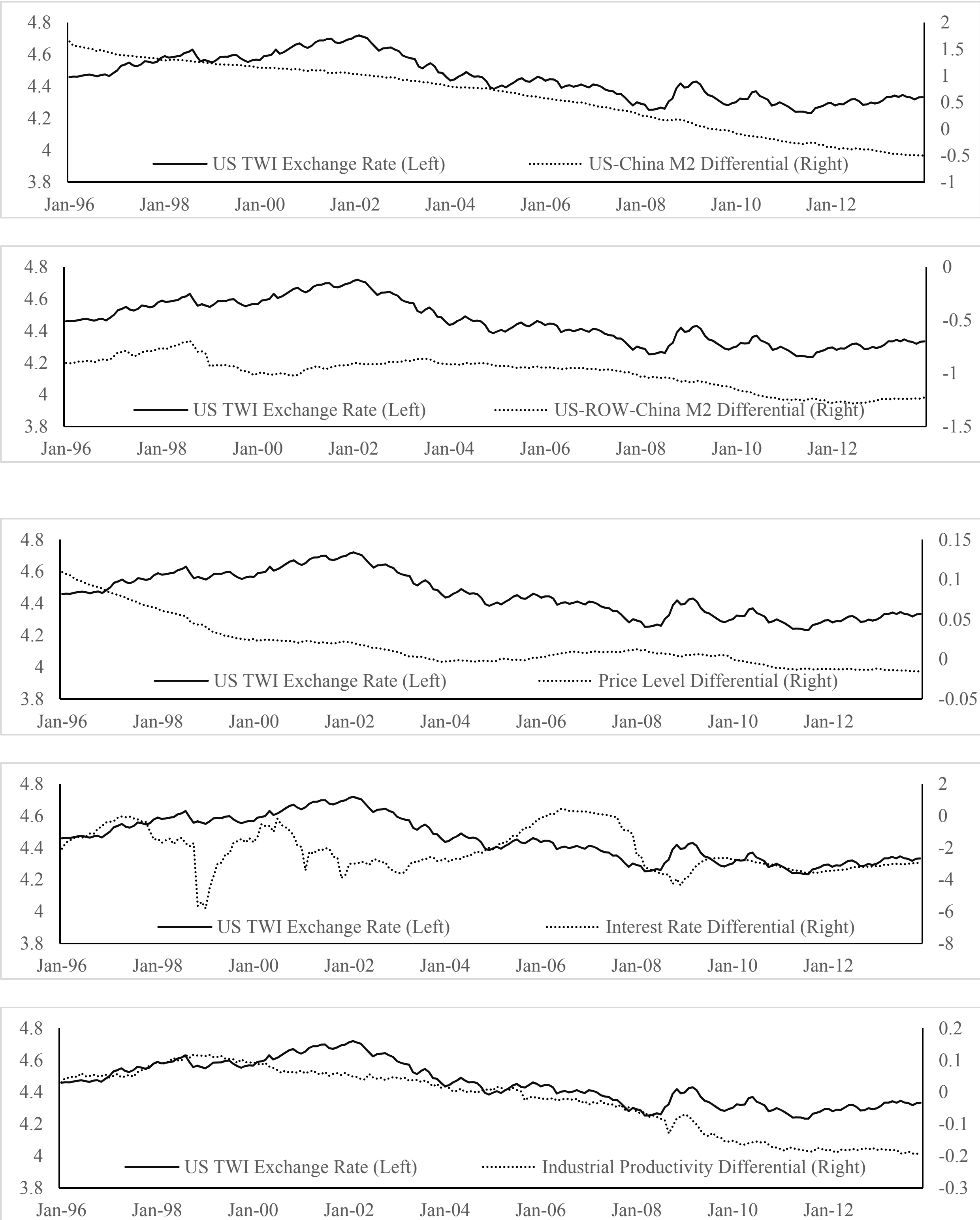


Notes: The log of M2 money supply expressed in US dollars for China, US, Euro area, and Japan over 1996:01-2013:12.

Figure 1b. US-TWI and Chinese Yuan to USD.

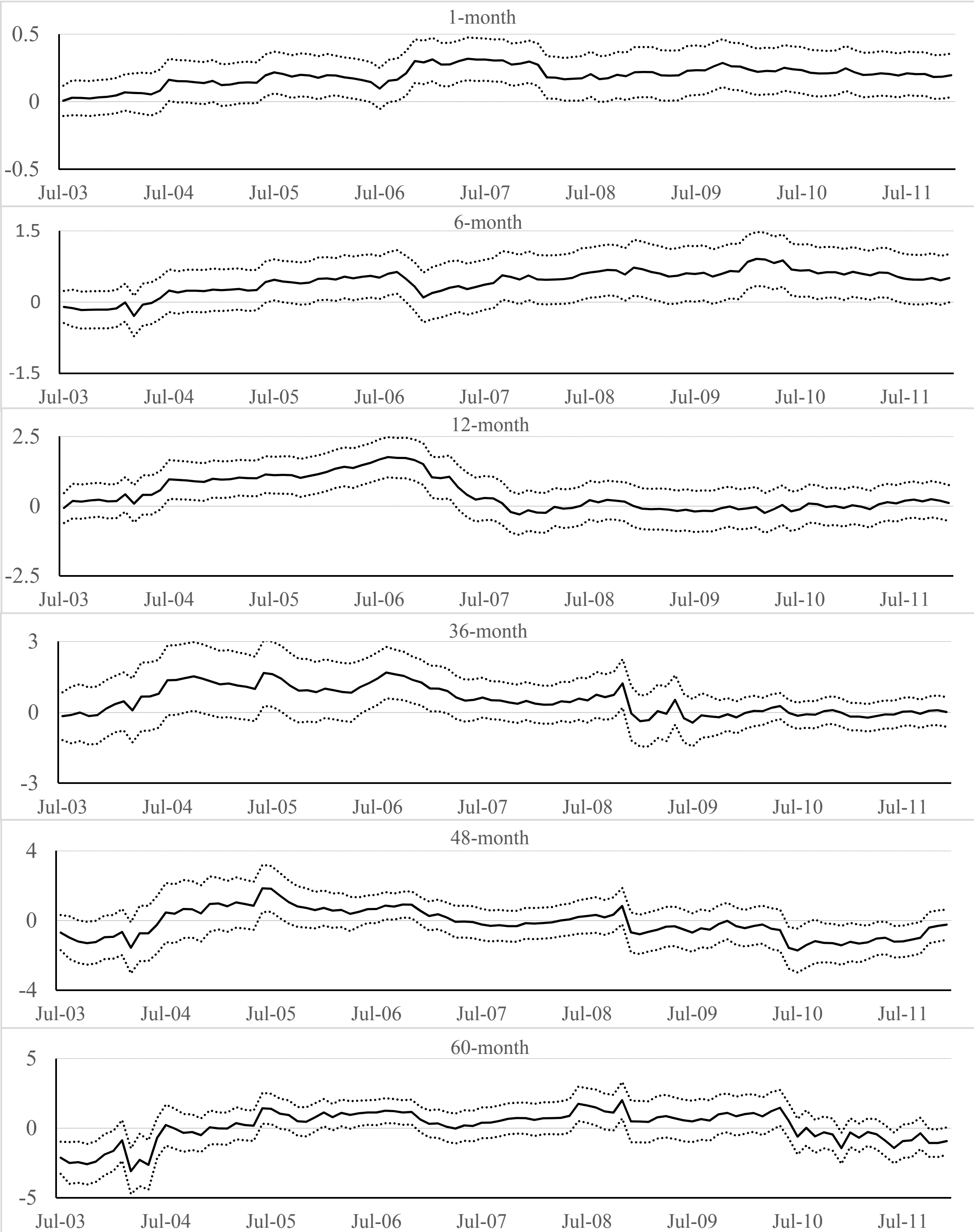
Notes: US-TWI is nominal US trade weighted dollar to major currencies and the Chinese yuan exchange rate in terms of US dollar from 1996.01 - 2013.12.

Figure 2. US-TWI exchange rate and the differential variables between 1996.01 - 2013.12.



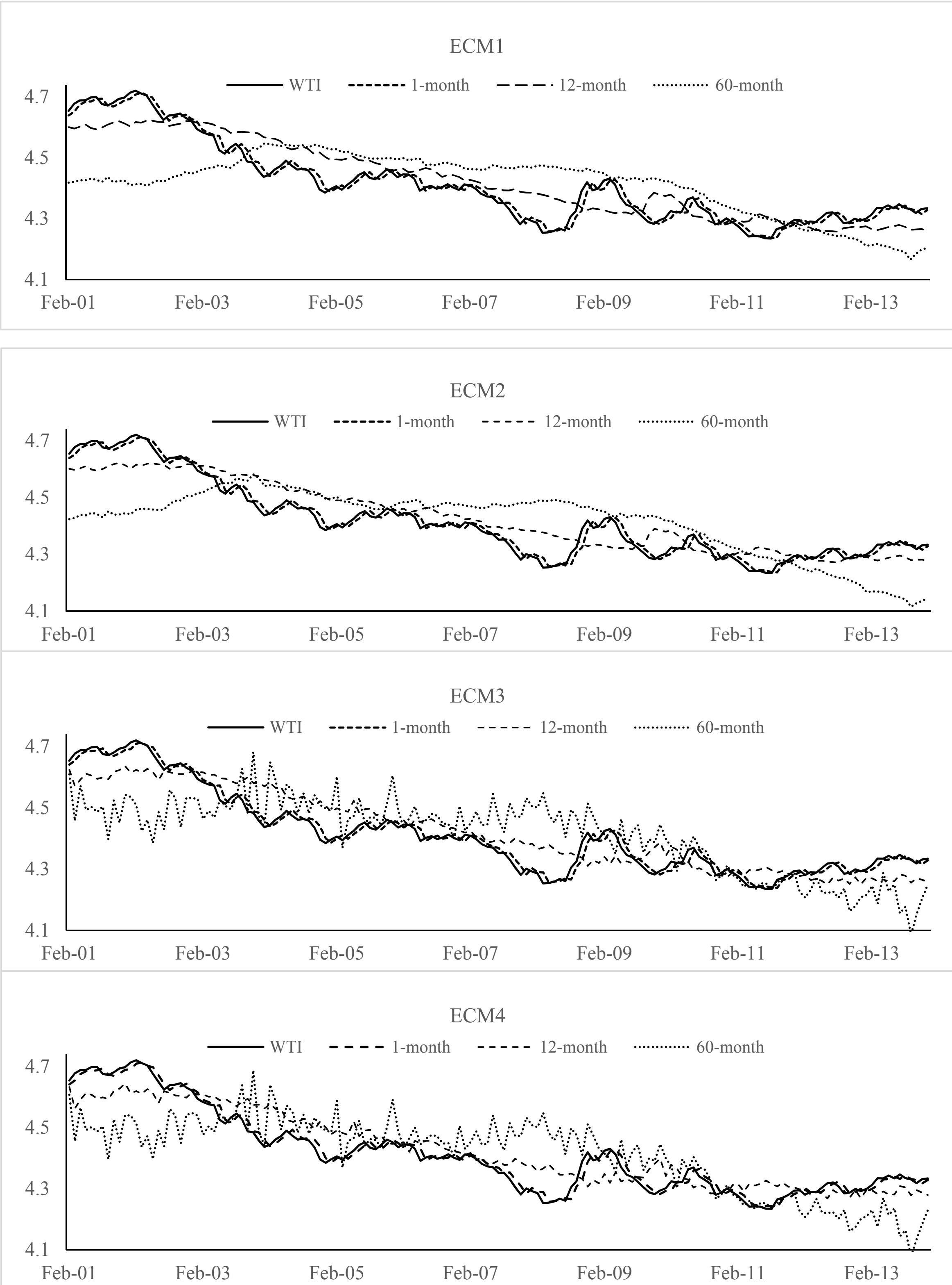
Notes: Variables shown are the logarithm of nominal US-TWI (US trade weighted dollar) and the differential of the logarithm of a US variable and either China or the rest of the world (non-US).

Figure 3. Coefficient estimates of US-China M2 differentials in forecasting the h-month-ahead rate of growth of US-TWI exchange rate



Notes: The coefficient estimates of US-China M2 differentials in forecasting the h-month-ahead rate of growth of US-TWI exchange rate with one-standard error bands are reported. A rolling sample with a 114-month window for the forecast starting in July 2005 is utilized.

Figure 4. Fitted values of TWI using ECMs at different forecasting horizons



Notes: The figures show the fitted values of ln(TWI) using various ECMs shown in Table 4 at 1, 12, and 60 month forecasting horizons over 2001:02 - 2013:12. Ln(TWI) is the natural logarithm of nominal US TWI, ECM1 is the ECM without contemporaneous short-run dynamic variables, ECM2 is the ECM with VIX as a contemporaneous short-run dynamic variable, ECM3 is the ECM with contemporaneous short-run dynamic variables, and ECM4 is the ECM with VIX and contemporaneous short-run dynamic variables.

Table 1. The mean square forecast error (MSFE) of the estimation for different models at different forecasting horizons

Horizon (month)	1	3	6	12	18	24	30	36	42	48	54	60
$MSFE^{Sticky}/MSFE^{RW}$	1.016	1.019	0.998	1.009	0.963	0.894	0.826	0.731	0.671	0.686	0.648	0.624
DM-Statistics	0.77	0.53	0.83	0.43	0.67	1.26	1.46*	1.30	1.44*	1.57*	2.20**	3.00***
$MSFE^{Flexible\text{-}1}/MSFE^{RW}$	1.014	1.014	1.004	1.010	0.984	0.950	0.894	0.832	0.801	0.779	0.730	0.689
DM-Statistics	0.71	0.52	0.59	0.28	0.35	0.49	0.59	0.60	0.64	0.75	1.04	1.50*
$MSFE^{Flexible\text{-}2}/MSFE^{RW}$	1.009	1.010	1.007	1.006	0.979	0.945	0.889	0.828	0.797	0.774	0.725	0.685
DM-Statistics	0.70	0.50	0.39	0.27	0.35	0.49	0.58	0.60	0.64	0.75	1.04	1.51*

Notes: The DM-statistics is proposed by Diebold and Mariano (1995). The ***, **, and * denote the significant levels at 1%, 5%, and 15% respectively.

Table 2. Estimates of forecasting the 60-month-ahead rate of growth of US-TWI exchange rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-0.142 ***	-0.118 ***	-0.118 ***	-0.146 ***	-0.086	-0.116 ***	-0.120 ***
	(9.36)	(8.03)	(8.05)	(8.00)	(3.99)	(8.63)	(9.19)
Price Level$_t^{US\text{-}ROW}$	-0.356 ***			-0.342 ***	-0.350 ***	-0.366 ***	-0.357 ***
	(4.08)			(3.93)	(4.03)	(4.14)	(4.02)
Interest Rate$_t^{US\text{-}ROW}$	-0.022	-0.007		-0.017	-0.026	-0.022	-0.019
	(0.90)	(0.27)		(0.71)	(1.05)	(0.88)	(0.79)
Industrial Productivity$_t^{US\text{-}ROW}$	0.576	1.088	1.097	0.689	1.101	0.681	0.731
	(0.43)	(0.77)	(0.78)	(0.51)	(0.81)	(0.50)	(0.53)
$M2_t^{China}$				1.731 **			
				(1.96)			
$M2_t^{US}$					-6.558 **		
					(1.97)		
$M2_t^{(ROW\text{-}China)}$						-0.936	
						(1.29)	
$M2_t^{US\text{-}China}$	-2.257 ***	-2.330 **	-2.322 **				
	(2.59)	(2.55)	(2.55)				
$M2_t^{US\text{-}(ROW\text{-}China)}$	0.859	0.435	0.423				
	(1.20)	(0.58)	(0.57)				
$M2_t^{US\text{-}ROW}$							0.508
							(0.64)
DM-Statistic	3.00***	1.50*	1.51*	2.64***	2.46**	2.48**	2.36**
Adj. R^2	0.114	0.022	0.028	0.099	0.099	0.086	0.078

Notes: The ***, **, and * denote the significant levels at 1%, 5%, and 15% respectively. The coefficient of price level differentials is scaled (i.e., divided) by 100 for the exposition purpose.

Table 3. The mean square forecast error (MSFE) of the ECM estimation at different forecasting horizons

Horizon (month)	1	3	6	12	18	24	30	36	42	48	54	60
$MSFE^{Sticky}/MSFE^{RW}$	0.992	0.926	0.846	0.730	0.659	0.585	0.609	0.684	0.691	0.655	0.614	0.574
DM-Statistic	1.04	1.21	1.40	1.39*	1.45*	1.43	1.12	0.81	0.87	1.19	1.67*	3.01***
EigVal-Statistic (H0: no coint.)	0.17***	0.17***	0.17***	0.19***	0.20***	0.21***	0.21***	0.21***	0.23***	0.23***	0.25***	0.25***

Notes: The DM-statistics is proposed by Diebold and Mariano (1995). The ***, **, and * denote the significant levels at 1%, 5%, and 15% respectively.

Table 4. Estimates of ECMs that forecast the 60-month-ahead rate of growth of US-TWI exchange rate

	(1)		(2)		(3)		(4)	
Constant	-0.097	***	0.258	**	-0.137	***	-0.033	
	(9.01)		(2.07)		(10.22)		(0.24)	
Price $Level_t^{US\text{-}ROW}$					-0.359	***	-0.332	***
					(4.68)		(3.91)	
Interest $Rate_t^{US\text{-}ROW}$					-0.035	*	-0.033	*
					(1.62)		(1.53)	
Industrial $Productivity_t^{US\text{-}ROW}$					0.764		0.645	
					(0.65)		(0.54)	
$M2_t^{US\text{-}China}$					-1.784	**	-1.814	**
					(2.32)		(2.35)	
$M2_t^{US\text{-}(ROW\text{-}China)}$					1.783	***	1.666	**
					(2.77)		(2.51)	
VIX			0.386	**			0.112	
			(2.86)				0.78	
EC Term	-1.082	***	-1.082	***	-1.142	***	-1.134	***
	(6.00)		(6.14)		(6.65)		(6.59)	
DM-Statistic	3.01***		2.66***		7.08***		16.33***	
Adj. R^2	0.19		0.22		0.31		0.31	

Notes: The DM-statistics is proposed by Diebold and Mariano (1995). The ***, **, and * denote the significant levels at 1%, 5%, and 15% respectively. The coefficient of price level differentials is scaled (i.e., divided) by 100 for the exposition purpose.

Table 5. The mean square forecast error (MSFE) of the estimation using MA(12) data for different models at different forecasting horizons

Horizon (month)	1	3	6	12	18	24	30	36	42	48	54	55
$MSFE^{Sticky}/MSFE^{RW}$	0.900	0.917	0.940	0.943	0.841	0.648	0.467	0.349	0.278	0.266	0.296	0.301
DM-Statistics	2.65***	1.22	0.90	0.79	1.11	1.92*	2.16**	2.04**	2.31**	3.01***	5.79***	7.88***
$MSFE^{Flexible\text{-}1}/MSFE^{RW}$	0.899	0.918	0.943	0.952	0.864	0.701	0.537	0.436	0.374	0.321	0.330	0.333
DM-Statistics	2.62***	1.21	0.85	0.55	0.72	1.17	1.52*	1.54*	1.70*	2.22**	3.79***	4.58***
$MSFE^{Flexible\text{-}2}/MSFE^{RW}$	0.896	0.913	0.939	0.948	0.860	0.698	0.536	0.439	0.377	0.322	0.328	0.331
DM-Statistics	2.70***	1.20	0.79	0.55	0.72	1.15	1.53*	1.56*	1.68*	2.24**	3.90***	4.74***

Notes: All the variables in the underlying regressions are 12-month moving average of monthly data (MA(12)) . The DM-statistics is proposed by Diebold and Mariano (1995). The ***, **, and * denote the significant levels at 1%, 5%, and 15% respectively.

Tasmanian School of Business and Economics

2015-01 Surfing through the GFC: Systemic Risk in Australia, **Mardi Dungey**, Matteo Luciani, **Marius Matei**, and David Veredas

2015-02 Intra– and Inter-Village Conflict in Rural Coastal Communities in Indonesia: The Case of the Kei Islands, **Satoshi Yamazaki**, Budy Resosudarmo, Wardis Girsang, and **Eriko Hoshino**

2015-03 Turn-Taking in Finitely Repeated Symmetric Games: Experimental Evidence, **Hugh Sibly**, **John Tisdell**, and Shuan Evans

2015-04 High Frequency Characterization of Indian Banking Stocks, **Mohammad Abu Sayeed**, **Mardi Dungey**, and **Wenying Yao**

2015-05 The Role of Intra-day Volatility Pattern in Jump Detection: Empirical Evidence on How Financial Markets Respond to Macroeconomic News Announcements, **Wenying Yao** and **Jing Tian**

2015-06 Understanding the Deviations of the Taylor Rule: A New Methodology with an Application to Australia**,** Kerry Hudson and **Joaquin Vespignani**

2015-07 A New Monthly Indicator of Global Real Economic Activity, Francesco Ravazzolo and **Jaquin Vespignani**

2015-08 The Macroeconomic Effects of Oil Price Shocks on ASEAN-5 Economies, **Mala Raghavan**

2016-01 Global Uncertainty and the Global Economy: Decomposing the Impact of Uncertainty Shocks, Wensheng Kang, Ronald A Ratti and **Joaquin Vespignani**

2016-02 The Implications of Liquidity Expansion in China for the US Dollar, Wensheng Kang, Ronald A Ratti and **Joaquin Vespignani**

2016-03 The Impact of Oil Price Shocks on the US Stock Market: A Note on the Roles of US and non-US Oil Production, Wensheng Kang, Ronald A Ratti and **Joaquin Vespignani**

UNIVERSITY of TASMANIA
AUSTRALIA