BANK OF CANADA
BANQUE DU CANADA

Working Paper/Document de travail
2012-36

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by TengTeng Xu

www.bank-banque-canada.ca

Bank of Canada Working Paper 2012-36

November 2012

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TengTeng Xu

International Economic Analysis Department
Bank of Canada
Ottawa, Ontario, Canada K1A 0G9
txu@bankofcanada.ca

ISSN 1701-9397

Acknowledgements

I am grateful to Professor M. Hashem Pesaran for his valuable guidance and useful discussions. I would also like to thank Pierre Guerin, Richard Louth, Kamiar Mohaddes, Alessandro Rebucci, Til Schuermann, Vanessa Smith and seminar participants at the 1st Cambridge Finance-Wharton Seminar Day, Royal Economic Society Easter School, 10th Econometric Society World Congress, European Central Bank, Bank of England and Bank of Canada for helpful comments. I gratefully acknowledge financial support from the Overseas Research Scholarship, the Smithers & Co. Foundation and the Cambridge Overseas Trust.

Abstract

This paper examines the role of bank credit in modeling and forecasting business cycle fluctuations, and investigates the international transmission of US credit shocks, using a global vector autoregressive (GVAR) framework and associated country-specific error correction models. The paper constructs and compiles a dataset on bank credit for 33 advanced and emerging market economies from 1979Q1 to 2009Q4. The empirical results suggest that the incorporation of credit provides significant improvement in modeling and forecasting output growth, changes in inflation and long run interest rates, for countries with developed banking sector. Impulse response analysis provide strong evidence of the international spillover of US credit shocks to the UK, the Euro area, Japan and other industrialized economies, and the propagation to the real economy.

JEL classification: C32, G21, E44, E32
Bank classification: Credit and credit aggregates; Business fluctuations and cycles; Econometric and statistical methods; International financial markets

Résumé

L'auteure examine le rôle du crédit bancaire dans la modélisation et la prévision des fluctuations économiques. À l'aide d'un modèle mondial de type GVAR (pour *Global Vector Autoregressive*) dans lequel chaque économie est décrite par un modèle à correction d'erreurs qui lui est propre, elle étudie la transmission aux autres pays des chocs de crédit provenant des États-Unis. L'auteure construit un ensemble de données sur le crédit bancaire pour 33 économies avancées et émergentes sur la période allant du premier trimestre de 1979 au quatrième trimestre de 2009. D'après les résultats empiriques, la prise en compte du crédit renforce sensiblement la modélisation et la prévision de la croissance de la production tout comme celles des variations de l'inflation et des taux d'intérêt à long terme dans le cas des pays ayant un secteur bancaire développé. L'analyse des fonctions de réponse fait clairement ressortir que les chocs américains de crédit se répercutent sur le Royaume-Uni, les pays de la zone euro, le Japon et les autres économies industrialisées et qu'ils se propagent à l'économie réelle.

Classification JEL : C32, G21, E44, E32
Classification de la Banque : Crédit et agrégats du crédit; Cycles et fluctuations économiques; Méthodes économétriques et statistiques; Marchés financiers internationaux

1 Introduction

The recent financial crisis and the subsequent economic recessions have raised important issues on the role of credit in international business cycles: how important is credit in modeling and forecasting business cycle dynamics and how are credit shocks transmitted across country borders? This paper tries to address these questions by examining the role of bank credit in 26 major advanced and emerging market economies and studying the international transmission of a shock to US real credit to global financial markets and the real economy.

Over the past 30 years, credit has experienced steady growth in most advanced countries and emerging economies (see Figure 1). At the same time, the globalization of the banking sector, the increase in cross-border ownership of assets, and the rapid development in securitization and financial engineering has increased the inter-dependency of banking and credit markets across country borders. While credit enjoyed considerable attention in monetary policy making in the 1950s and 1960s, its importance was replaced by a focus on money in the 1970s and part of the 1980s (see for example Borio and Lowe, 2004), before this financial crisis ignited fresh debate on this issue.

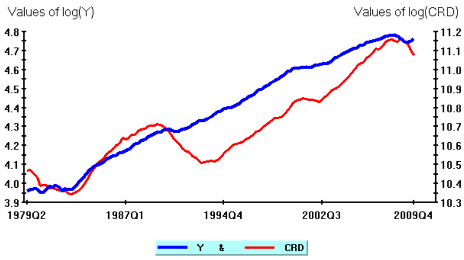
The theoretical literature on credit market frictions has highlighted the importance of credit, in modeling the inter-linkages between financial market and the real economy, see for example Kiyotaki and Moore (1997), Bernanke, Gertler, and Gilchrist (1999) and Gertler and Kiyotaki (2010). The open economy extension of this literature has shown that credit market frictions can play an important role in transmitting shocks across countries, through balance sheet linkages among investors and financial institutions, see for example Devereux and Yetman (2010).

On the empirical side, many have studied the relationship between finance and development and found better functioning financial intermediaries accelerate economic growth, see for example Levine (2005) and Levine, Loayza, and Beck (2000). Several authors have examined the link between credit and business cycles, for example on the empirical evidence of the credit channel of monetary policy (Braun and Larrain, 2005 and Iacoviello and Minetti, 2008), the role of global banks in the transmission of liquidity shocks (Cetorelli and Goldberg, 2008, 2010), and the impact of a US credit shock on global growth using factor models (Helbling, Huidrom, Kose, and Otrok, 2011). However, little empirical work has been done in quantifying the importance of credit in modeling and forecasting business cycle dynamics, and in analysing the international transmission of credit shocks in a global framework, incorporating both emerging market and advanced economies.

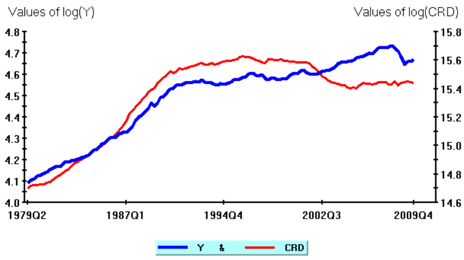
This paper aims to fill in the gap and the contribution in relation to the literature is three fold: first, the paper constructs and compiles a dataset on bank credit for 33 advanced and emerging market countries from 1979Q1 to 2009Q4, accounting for changes

Figure 1: Bank Credit to the Private Sector and Output

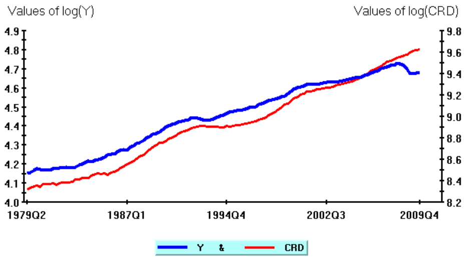
(log of real credit and log of real GDP in levels)



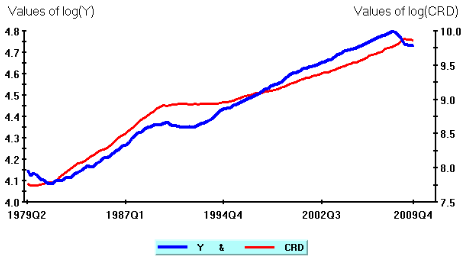
(a) United States



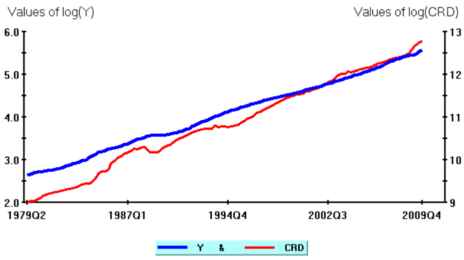
(b) Japan



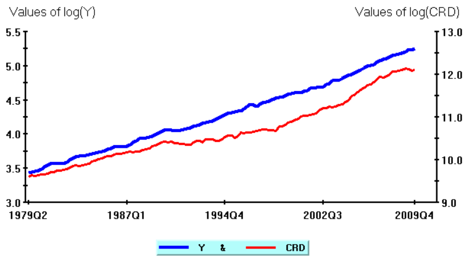
(c) Euro Area



(d) UK



(e) China



(f) India

in the definition of credit and banking institutions in these countries through time. Second, to my knowledge, it is the first comprehensive cross country study, analysing and quantifying the role of credit in business cycle dynamics, for 26 major advanced and emerging economies covering 90% of world GDP. In particular, it examines the importance of credit in modeling and forecasting output, inflation, interest rates, equity prices, as well as exchange rates, using country-specific VARX* models (augmented VAR with foreign variables). Third, it provides detailed analysis of the channels through which a negative shock to US real credit is transmitted across country borders and to the real economy, capturing the impact on output, inflation and interest rates on a country by country basis, using a global vector autoregressive (GVAR) framework. It is important to highlight that the focus of our analysis is to study the transmission of US credit shock across countries, rather than identifying the source of the credit shock explicitly, whether it is due to supply or demand factors.[1]

Among the different measures of credit, we focus on bank credit (loans and advances) to the private sector, following the empirical literature on finance and development where credit to the private sector is considered one of the most important banking development indicators. The GVAR and associated country-specific models are first estimated over the period 1979Q2 to 2006Q4 for 26 advanced and emerging market economies (where eight euro zone countries are treated as a single economy), to examine the importance of credit in modeling business cycle dynamics and to investigate the international transmission of credit shocks. The country-specific models are then used to perform forecasts between 2007Q1 and 2009Q4, to study the role of credit in forecasting the evolution of financial and real variables.

The key findings of the paper are as follows: first, the incorporation of credit provides significant improvement in modelling and forecasting some of the key business cycle variables, for countries with developed banking sector. In particular, the credit model outperforms the AR benchmark, as well as an otherwise identical model except for the exclusion of credit, in modeling and forecasting output growth, changes in inflation and long run interest rates in advanced economies. This result highlights the importance of credit variables in explaining business cycle fluctuations and the value of incorporating credit variables in economic modelling. Second, the results provide strong evidence of the international transmission of credit shocks and the propagation to the real economy. In particular, a negative shock to US real credit is transmitted to credit in the euro area, UK, Japan and some emerging market economies with a high degree of financial openness, with the impact on the UK particularly profound, possibly due to the strong linkages in the banking sectors between the UK and the US. The US credit shock is associated with falling output in the US, UK and the euro area, for 12 to 18 months, and accompanied by a decline in short term interest rates in the US, UK and the euro area, suggesting a possible loosening of monetary policy in association with contraction in credit, as observed in the policy coordination in the aftermath of the recent credit crunch.[2] The rapid transmission of US credit shock and the profound impact on the real economy highlight the important role of credit in international business cycles, and calls for greater attention to be paid to credit measures in economic modelling and policy making.

[1] We do, however, identify the US credit shock by conditioning US credit on contemporaneous values of foreign credit, which renders the cross country dependence of shocks weak, and allows us to interpret the US credit shock with little concerns about the reverse spillover effects from one country to the other.

[2] The results are found to be robust when different weighting schemes are used to construct the country-specific foreign variables and when the sample period includes the recent crisis from 2007Q1 to 2009Q4.

The plan of the paper is as follows: Section 2 briefly reviews the literature on the role of credit. Section 3 presents the dataset, the GVAR methodology and the model specification. Section 4 studies the role of credit in modelling and forecasting business cycle dynamics in 26 country-specific models. Section 5 presents results on the international transmission of credit shocks, studying the degree of comovements in credit compared with other business cycle variables, the contemporaneous effect of foreign credit on domestic credit, and the generalized impulse responses of a shock to US real credit. Section 6 offers some concluding remarks.

2 Literature Review and Motivation

In this literature review, we start with a brief overview on the theoretical literature on financial frictions and their impact on the real economy, which motivates the empirical studies carried out in this paper. We then focus on recent empirical development on the role of credit in business cycles and and discuss the contribution of our paper in relation to the literature.

In the past decades or so, there has been rapid development in the theoretical literature on the macroeconomic implications of financial imperfections, see for example Carlstrom and Fuerst (1997), Kiyotaki and Moore (1997), Bernanke, Gertler, and Gilchrist (1999) and Iacoviello (2005). By introducing credit market frictions (asymmetry of information, agency costs or collateral constraints) in dynamic general equilibrium models, research on the credit channel of monetary policy and credit cycles show that these financial frictions act as a financial accelerator that leads to an amplification of business cycle and highlight the mechanisms through which the credit market conditions are likely to impact the real economy.[3]

Financial market imperfections arise from several sources: first, the asymmetry of information between lenders and borrowers (see for example Bernanke and Gertler, 1995, Bernanke, Gertler, and Gilchrist, 1999 and Gilchrist, 2004), which induces the lenders to engage in costly monitoring activities.[4] The extra cost of monitoring by lenders gives rise to the external finance premium of firms, which reflects the existence of a wedge between a firm's own opportunity cost of funds and the cost of external finance (borrowing from the banking sector). Financial frictions could also stem from the lending collateral constraints faced by borrowers (see for example Kiyotaki and

[3] According to Bernanke and Gertler (1995), the credit channel is not considered as a distinct, free-standing alternative to the traditional monetary transmission mechanism, but rather a set of factors that amplify and propagate conventional interest rate effects of monetary policy. Financial frictions are essential in propagating financial shocks to the real economy. Modigliani and Miller (1958) theorem implies that, without financial frictions, leverage or financial structure is irrelevant to real economic outcomes.

[4] For example, costly state verification, first introduced in Townsend (1979) and further developed in Bernanke, Gertler, and Gilchrist (1999).

Moore, 1997 and Gertler and Kiyotaki, 2010). Credit constraints arise because lenders cannot force borrowers to repay their debts unless the debts are secured by some form of collateral. Borrowers' credit limits are affected by the prices of the collateralized assets, and these asset prices are in turn influenced by the size of the credit limits, which affects investment and demand for assets in the economy. In addition to the *demand* for credit from firms, Chen (2001) and Meh and Moran (2004) argue that banks themselves are also subject to frictions in raising loanable funds and show that the *supply* side of the credit market also contributes to shock propagation, affecting output dynamics in the economy.[5]

Several studies apply models of financial frictions to an open economy to explore the role of financial markets in the international transmission mechanism. Devereux and Yetman (2010) study the international transmission of shocks due to interdependent portfolio holdings among leverage-constrained investors and highlight the importance of balance sheet linkages among investors and financial institutions across countries. Using a two country model, they find that when leverage constraints are binding, a fall in asset values in one country forces a large and immediate process of balance sheet contractions for both domestic and foreign investors. The final result is a magnified impact of the initial shock, a large fall in investment and output, and highly correlated business cycle across countries during the downturn. Other notable papers on financial frictions in an open economy include Gilchrist (2004), who focuses on the asymmetries between lending conditions across economies, using the external finance premium model developed in Bernanke, Gertler, and Gilchrist (1999). Gilchrist (2004) predicts that highly leverage countries (where the share of investment financed through external funds is high) are more vulnerable to external shocks, owing to their effect on foreign asset valuations and thus on borrower net worth. Another important area of theoretical literature examines the spillover of shocks in an open economy through trade linkages. Trade linkages play an important role since the slowdown in output (as a result of a credit shock) is largely transmitted through trade across country borders. Backus, Kehoe, and Kydland (1994) and Kose and Yi (2006) model a particular type of trade linkage between countries, where final goods are produced by combining domestic and foreign intermediate goods. In their framework, an increase in final demand leads to an increase in demand for foreign intermediates, which results in a transmission of shocks to the foreign country.

On the empirical side of the literature, many have studied the linkages between finance and development, see for example the survey papers by Levine, Loayza, and Beck (2000) and Levine (2005). The finance and development literature provides strong

[5]Other work that focus on the role of the banking sector include Christiano, Motto, and Rostagno (2008), Freixas and Rochet (2008), Goodhart, Sunirand, and Tsomocos (2004), Goodhart, Sunirand, and Tsomocos (2005) and de Walque, Pierrard, and Rouabah (2009), with the latter three studying the role of banking sector in financial stability.

evidence that countries with more fully developed financial systems tend to grow faster, in particular those with large, privately owned banks that channel credit to private enterprises and liquid stock exchanges. For example, using cross-country studies, Levine and Zervos (1998) find that the initial level of banking development are positively and significantly correlated with future rates of economic growth, capital accumulation and productivity growth over the next 18 years, even after controlling for schooling, inflation, government spending and political stability. To assess whether the finance-growth relationship is driven by simultaneity bias, Beck, Levine, and Loayza (2000) use cross country instrumental variables to extract the exogenous component of financial development and find a strong connection between the exogenous component of financial intermediary development and long-run economic growth. In light of the econometric problems induced by unobserved country specific effects and joint endogeneity of the explanatory variables in cross country growth regressions, Levine, Loayza, and Beck (2000) use GMM dynamic panel estimators to examine the relationship between the level of the development of financial intermediaries and economic growth. They focus on three measures of financial intermediation, including the overall size of the financial intermediation sector, the relative importance of commercial banking institutions in conducting intermediation (compared with the central bank), and the extent of which financial institutions funnel credit to private sector activities. Their findings confirm that the exogenous component of financial intermediary development is positively and robustly linked with economic growth and in particular better functioning financial intermediaries accelerate economic growth. The finance and development literature also provides evidence that better functioning financial systems ease the external financing constraints that impede firms and industrial expansions. Using industry-level data, Rajan and Zingales (1998) study the mechanisms through which financial development may influence economic growth and argue that better-developed financial systems ameliorate market frictions that make it difficult for firms to obtain external finance.[6]

The analysis in our paper is closely related to two strands of the empirical literature on the linkages between credit and business cycles. First, our work contributes to the existing literature on the impact of credit on real activities. Goodhart and Hofmann (2008) assess the linkages between credit, money, house prices and economic activity in 17 industrialized countries over the last three decades based on a fixed-effects panel VAR, and suggest that shocks to credit have significant repercussions on economic activity. On the role of credit standards, Lown and Morgan (2006) find that shocks to credit standards in the US are significantly correlated with innovations in commercial loans at banks and in real output, using VAR analysis on a measure of bank lending

[6] Other related literature on finance and development include Neusser and Kugler (1998), Christopoulos and Tsionas (2004) and Baltagi, Demetriades, and Law (2009), with the final paper addressing the relationship between financial development and openness.

standards collected by the Federal Reserve. In particular, credit standards are found to be significant in the structural equations of some categories of inventory investment, a GDP component closely associated with bank lending. In a related study, Bayoumi and Melander (2008) estimate the effects of a negative shock to bank's capital asset ratio on lending standards, which in turn affects consumer credit, corporate loans and the corresponding components of private spending and output. They find that an exogenous fall in bank capital/asset ratio by one percent point reduces real GDP by some one and a half percent through its effects on credit availability. Development in the theoretical literature on the credit channel of monetary policy has also sparked interests in examining the empirical evidence of credit channels, see for example Braun and Larrain (2005) and Iacoviello and Minetti (2008). Using micro data on manufacturing industries in more than 100 countries during the last 40 years, Braun and Larrain (2005) find strong support for the existence of the credit channel and show that industries that are more dependent on external finance are hit harder during recessions and countries with poor accounting standards (a proxy for information asymmetries and financial frictions) and highly dependent industries experience more severe impact during economic downturns. On the role of corporate credit market, Meeks (2012) investigates the macroeconomic effects of shocks to corporate credit markets in the US, by studying the influences of expected default on corporate bond spreads. He finds that adverse credit shocks have contributed to declining output in every post-1982 recession, and can account for three-fifths of the decline in output during the 2007-9 contraction.

The existing empirical literature on the linkages between credit and real activities has largely focused on the impact of credit on output dynamics, while little has been done in analysing the effect of credit on inflation, short term and long run interest rates in the economy, nor in quantifying the importance of credit in modelling and forecasting business cycle dynamics, both of which we aim to address in our paper.

Secondly, our paper is closely related to the latest research on the international transmission of credit shocks. For example, Galesi and Agherri (2009) examine the transmission of regional financial shocks in Europe using a Global VAR framework. The model is estimated for 26 European economies and the US and they find that asset prices are the main channel through which financial shocks are transmitted internationally, at least in the short run, whereas the contribution of other variables, including the cost and quantity of credit only become important over longer horizons. Their analysis focuses on regional spillovers in Europe, in particular between advanced and emerging European economies, while we are more interested in the interactions in the world economy, where emerging Asia and oil-producing countries are increasingly playing an important role. Helbling, Huidrom, Kose, and Otrok (2011) examine the impact of global credit shocks on global business cycles, using global factors of credit, GDP, inflation and interest rates, constructed with data from G-7 countries. They also study the impact of a US credit shock using a FAVAR (factor augmented VAR) model on US GDP and the global factor of GDP and find that the US credit market shocks have a significant impact on the evolution of global growth during the recent financial crisis. While this paper sheds some light on the impact of a US credit shock on the global factor of GDP, it has not examined the mechanism through which US credit shock is transmitted to individual emerging economies and advanced countries, accounting for the differences in responses among countries. Finally, Cetorelli and Goldberg (2008, 2010) show that global banks played a significant role in the transmission of liquidity shocks through a contraction in the cross border lending. However, this line of research has not considered the impact of liquidity shocks on the real economy and the resulting propagation into the real sector.

As can be seen, the existing literature on the international transmission of credit shocks has largely focused on G7 and European economies, while little has been done in studying the transmission of US credit shocks to emerging market economies. Our paper aims to fill in the gap and offers a comprehensive analysis of the channels through which a US credit shock is transmitted to advanced economies as well as emerging Asia, Latin America and oil-producing countries and study the subsequent impact on the real economy including output, inflation and interest rates on a country by country basis.

3 Dataset and Methodology

3.1 Dataset

The dataset used in this paper covers 33 countries, where 8 of the 11 countries that originally joined the euro on 1 January 1999 (Austria, Belgium, Finland, France, Germany, Italy, Netherlands and Spain) are aggregated using the average Purchasing Power Parity GDP weights, computed over the 2001-2003 period (Table 1).

The choice of the credit measure used in this paper "bank credit (loans and advances) to the private sector" is guided by the existing literature, data availability and the consideration of international comparability across country series. First, banking sector refers to deposit money banks, which comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits. They often engage in core banking services that extend loans to the non-financial corporations, which ultimately determine the level of investment and output in the economy. Second, we focus on credit to the private sector, following the empirical literature on finance and development, where credit to the private sector is considered the most important banking development indicator, since it proxies the extent to which new firms have opportunities to obtain bank finance and this in turn could influence short term fluctuations in the level of output and economic growth in the economy.[7] Third, we choose to use the *level* of 'claims on private sector from deposit money banks' rather than its *ratio* to GDP, as seen in the finance and development literature.[8] The reason is that our objective is not to study the extent of financial intermediation in the economy but the overall level of bank credit that is available to the private sector.

Table 1: Countries/Regions Included in the Analysis

Industrialized economies		**Emerging economies**	
United States	**Euro Area**	China	Brazil
United Kingdom	Germany	India	Mexico
Japan	France	Singapore	Argentina
Korea	Italy	Malaysia	Chile
Canada	Spain	Philippines	Peru
Australia	Netherlands	Thailand	
New Zealand	Belgium	Indonesia	Turkey
Sweden	Austria		South Africa
Switzerland	Finland		Saudi Arabia
Norway			

Our main sources for the credit data are the IMF International Finance Statistics (IFS), Datastream and Haver Analytics, with the IFS series 'Claims on Private Sector from Deposit Money Banks' (22d) being the primary data source. For the rest of the variables considered in our analysis, namely output, inflation, interest rates, equity prices, exchange rate and oil prices, the data are drawn from the rejoinder of Pesaran, Schuermann, and Smith (2009) as well as Cesa-Bianchi, Pesaran, Rebucci, and Xu (2011).[9]

Many of the IMF credit series displayed large level shifts due to changes in the definition and re-classifications of the banking institutions. Following Goodhart and Hofmann (2008) and Stock and Watson (2003), we adjust for these level shifts by replacing the quarterly growth rate in the period when the shift occurs with the median of the growth rate of the two periods prior and after the level shift. The level of the series is then adjusted by backdating the series based on the adjusted growth rates. The nominal credit series are deflated by the CPI to obtain the real credit series, which are seasonally adjusted where necessary, according to the combined test for the presence

[7]See for example Levine, Loayza, and Beck (2000) and Baltagi, Demetriades, and Law (2008).

[8]For example, King and Levine (1993a,b) use the ratio of gross claims on the private sector to GDP in their study. Levine and Zervos (1998) and Levine (1998) use the ratio of deposit money bank credit to the private sector to GDP over the period 1976 to 1993. Levine, Loayza, and Beck (2000) use a measure of private credit as an indicator of financial intermediary development from 1960 to 1995, where Private credit equals the ratio of credits by financial intermediaries to the private sector to GDP.

[9]The dataset used in this paper was collected in two stages: first we compiled a dataset to cover the period from 1979Q1 to 2006Q4; it was later extended to 2009Q4, to include the recent financial crisis. See Data Appendix A for a detailed description on the dataset.

of identifiable seasonality.[10]

In order to verify to what degree the credit series have univariate integration properties, we perform the unit root tests over the sample period for the levels and first differences of the logarithm of real credit (after seasonality adjustment) for the 33 countries considered in our analysis. ADF tests and the weighted symmetric estimation of the ADF type regressions (introduced by Park and Fuller, 1995) in general support the view that credit variables are integrated of order one. The test results also support the unit root properties of the other variables considered in our analysis and we consider the key variables including credit as I(1) in our empirical analysis hereafter, since it allows the empirical model to adequately represent the statistical features of the series over the sample period and provides the scope for studying long run structural relationships in the model.[11]

3.2 Methodology

To study the role of credit in modeling business cycle dynamics and the spillover of credit shocks across country borders and to the real economy, we use a global VAR framework, pioneered in Pesaran, Schuermann, and Weiner (2004) (hereafter PSW) and further developed in Pesaran and Smith (2006), Dees, di Mauro, Pesaran, and Smith (2007) (hereafter DdPS), Dees, Holly, Pesaran, and Smith (2007) (hereafter DHPS). The GVAR model is a multi-country framework which allows for the analysis of the international transmission mechanics and the interdependencies among countries.

Suppose there are $N+1$ countries (or regions) in the global economy, indexed by $i = 0, 1, ..., N$, where country 0 is treated as the reference country (which we take as the US in this case). The individual country VARX$^*(p_i, q_i)$ model for the ith economy can be written as:

$$\Phi_i(L, p_i)\mathbf{x}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \Upsilon_i(L, q_i)\mathbf{d}_t + \Lambda_i(L, q_i)\mathbf{x}^*_{it} + \mathbf{u}_{it}, \tag{1}$$

for $i = 0, 1, ..., N$, where $\mathbf{x}_{it}$ is the $k_i \times 1$ vector of domestic variables (including, for example, real GDP, inflation, interest rates and real credit), $\mathbf{x}^*_{it}$ is the $k^*_i \times 1$ vector of country-specific foreign variables, $\mathbf{d}_t$ denotes the $m_d \times 1$ matrix of observed global factors, which could include international variables such as world R&D expenditure, oil or other commodity prices, $\mathbf{a}_{i0}$ and $\mathbf{a}_{i1}$ are the coefficients of the deterministics, here intercepts and linear trends, and $\mathbf{u}_{it}$ is the idiosyncratic country specific shock. Further, we have $\Phi_i(L, p_i) = \sum_{l=0}^{p_i} \Phi_{il}L^l$, $\Upsilon_i(L, q_i) = \sum_{m=0}^{q_i} \Upsilon_{im}L^m$, $\Lambda_i(L, q_i) = \sum_{n=0}^{q_i} \Upsilon_{in}L^n$, where L is the lag operator and p_i and q_i are the lag order of the domestic and foreign

[10] A detailed discussion on the choice of credit variable, a comparison between the IFS and Datastream data source, adjustment for level shifts and seasonality can be found in Appendix A.

[11] Detailed results on unit root testing are provided in the supplement and are available upon request.

variables for the ith country.

Country specific VARX* models are vector autoregression models augmented with country-specific foreign variables $\mathbf{x}_{it}^*$, constructed using trade weights w_{ij}, $j = 0, 1, ..., N$, that capture the importance of country j for country i's economy

$$\mathbf{x}_{it}^* = \sum_{j=0}^{N} w_{ij}\mathbf{x}_{jt}, \tag{2}$$

where $w_{ii} = 0$ and $\sum_{j=0}^{N} w_{ij} = 1, \forall i, j = 0, 1, ..., N$. The weights w_{ij} are estimated by bilateral trade data drawn from the IMF Direction of Trade Statistics, where w_{ij} captures the importance of country j for country i's economy in the share of exports and imports. We first use fixed weights based on the average trade flows computed over the three years 2001 to 2003, we later allow time-varying trade weights in our analysis.

Trade weights are considered our preferred measure of weights in the GVAR for three main reasons. Firstly, trade is found to be the most important determinants of cross country linkages and international business cycle synchronization. Baxter and Kouparitsas (2005) study the determinants of international business cycle comovements and conclude that bilateral trade is the most important source of inter-country business cycle linkages. Imbs (2004) provides further evidence on the effect of trade on business cycle synchronization and concludes that while specialization patterns have a sizable effect on business cycles, trade continues to play an important role in this process. Focusing on global linkages in financial markets, Forbes and Chinn (2004) also show that direct trade appears to be one of the most important determinants of cross-country linkages.

Secondly, time series on bilateral trade data are also more readily available for developing or emerging market economies, as compared to data on bilateral financial flows. For example, the International banking statistics published by the BIS and the Bilateral FDI data published by the OECD do not provide data on bilateral financial flows between developing countries.[12] The lack of available bilateral financial flow data among emerging economies means that these financial weights are not likely to fully capture the interlinkages between the 15 developing countries modeled in the GVAR and to reveal the full extent of globalization. For example, should we use financial weights as the aggregation weights, a weight of zero will be assigned to the bilateral

[12] International banking statistics from the Bank for International Settlements (BIS) measure consolidated foreign claims of reporting banks on individual countries (through both direct lending and local banking systems). The countries that report the consolidated banking statistics to the BIS comprise the largest international banking centers. For the 33 countries considered in the GVAR, only 20 were among the reporting countries. The OECD International Direct Investment Database (Source OECD) publish data on bilateral FDI flows (inflows and outflows) among OECD and non-OECD countries over the period from 1985 to 2006, in particular FDI outflows from OECD countries to all countries, as well as FDI outflows from non OECD countries to OECD countries, but not FDI outflows from non OECD to non OECD countries.

linkage between China and Brazil due to data availability, which does not reflect the important trade linkages between these two countries (according to IMF Direction of Trade Statistics, China accounts for around 10% of total trade in Brazil in 2005).[13]

Furthermore, due to the generally high cross country correlation of variables such as output or real equity prices, mis-specification of the weights may not have strong implication for the measurement of foreign variables. Asymptotic results suggest that the type of aggregate weights used would not be important if there was a strong common factor among the country series. Finally, it is important to note that international financial linkages have already been captured in our modeling framework, through the inclusion of country specific foreign financial variables, such as equity, credit and long run interest rates.

For each country model, we start from a conditional vector error correction model for the endogenous variables[14]

$$\Delta \mathbf{x}_{it} = \mathbf{c}_{i0} - \alpha_i \beta_i' [\mathbf{z}_{i,t-1} - \gamma_i (t-1)] + \Lambda_{i0} \Delta \mathbf{x}_{it}^* + \sum_{j=1}^{m_i - 1} \Psi_{ij} \Delta \mathbf{z}_{i,t-j} + \mathbf{v}_{it}, \quad (3)$$

and a marginal model for the exogenous variables

$$\Delta \mathbf{x}_{it}^* = \sum_{j=1}^{m_i - 1} \Gamma_{x^* ij} \Delta \mathbf{z}_{i,t-j} + a_{x^* i0} + \mathbf{u}_{x^* it} \quad (4)$$

where $\mathbf{z}_{it} = (\mathbf{x}_{it}', \mathbf{x}_{it}^{*'})'$, $m_i = max(p_i, q_i)$, the matrices $\Gamma_{x^* ij}$ capture the short run responses between foreign and domestic variables, $\mathbf{v}_{it}$ and $\mathbf{u}_{x^* it}$ are residuals in the conditional and marginal models, respectively. α_i is a $k_i \times r_i$ matrix of rank r_i, β_i is a $(k_i + k_i^*) \times r_i$ matrix of rank r_i (the number of cointegration relationships in the system). Notice that the coefficient of the linear trend in the error correction form is restricted $(\alpha_i \beta_i' \gamma_i)$, to avoid the possibility of quadratic trend in $\mathbf{x}_{it}$ and to ensure that the deterministic trend property of the country-specific models remains invariant to the cointegrating rank assumptions, see Pesaran, Shin, and Smith (2000). To construct forecasts using the VARX* models, we combine the conditional and the marginal models

[13] Several studies have explored the possibility of using different weights to construct country-specific foreign variables, for example, Hiebert and Vansteenkiste (2007) use weights based on the geographical distances among region, Vansteenkiste (2007) adopts weights based on sectorial input-output tables across industries and Galesi and Agherri (2009) construct financial weights based on the consolidated foreign claims of reporting banks on individual countries in the BIS International banking statistics. However, these studies mainly focus on linkages between developed economies or between developed and developing economies, a weight of zero is imposed for bilateral financial flows among developing countries where data is not available.

[14] Detailed derivations of the conditional model and the marginal model are not presented here due to space considerations. For more details, see Garratt, Lee, Pesaran, and Shin (2006) and Pesaran and Pesaran (2009). To simplify the exposition here, we abstract from common observed variables in the conditional and marginal models.

as set out in equations (3) and (4).[15]

After estimating each country VARX* model, all the $k = \sum_{i=0}^{N} k_i$ endogenous variables are collected in the $k \times 1$ global vector $\mathbf{x}_t = (\mathbf{x}'_{0t}, \mathbf{x}'_{1t}, ..., \mathbf{x}'_{Nt})'$ and solved simultaneously using link matrix defined in terms of the country specific weights. Again denote $\mathbf{z}_{it} = (\mathbf{x}'_t, \mathbf{x}'^*_t)'$ a vector of domestic and foreign variables, then the individual VARX*(p_i, q_i) model in Equation (1) can be written as

$$\mathbf{A}_i(L, p_i, q_i)\mathbf{z}_{it} = \varphi_{it}, i = 0, 1, 2, ..., N, \tag{5}$$

where

$$\mathbf{A}_i(L, p_i, q_i) = [\Phi_i(L, p_i), -\Lambda_i(L, p_i)],$$

$$\varphi_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \Upsilon_i(L, q_i)\mathbf{d}_t + \mathbf{u}_{it}.$$

The vector $\mathbf{z}_{it}$ can be written as

$$\mathbf{z}_{it} = \mathbf{W}_i\mathbf{x}_t, i = 0, 1, 2, ..., N, \tag{6}$$

where $\mathbf{W}_i$ is a link matrix of dimension $(k_i + k_i^*) \times k$, constructed based on country specific weights. Substitute (6) into (5), we have

$$\mathbf{A}_i(L, p_i, q_i)\mathbf{W}_i\mathbf{x}_t = \varphi_{it}, i = 0, 1, 2, ..., N. \tag{7}$$

The vector of endogenous variables of the global economy, $\mathbf{x}_t$, can now be obtained by stacking the country specific models (7) as

$$G(L, p)\mathbf{x}_t = \varphi_t, \tag{8}$$

where

$$\mathbf{G}(L, p) = \begin{pmatrix} \mathbf{A}_0(L, p)\mathbf{W}_0 \\ \mathbf{A}_1(L, p)\mathbf{W}_1 \\ \vdots \\ \mathbf{A}_N(L, p)\mathbf{W}_N \end{pmatrix}, \varphi_t = \begin{pmatrix} \varphi_{0t} \\ \varphi_{1t} \\ \vdots \\ \varphi_{Nt} \end{pmatrix},$$

and $p = max(p_0, p_1, ..., p_N, q_0, q_1, ..., q_N)$. The model in (8) is a high dimensional VAR model which can be solved recursively, and used for generalized impulse response analysis.

[15] For other examples of forecasts with the VARX* model, see Assenmacher-Wesche and Pesaran (2008).

3.3 Model specification

We include real output (y_{it}), the rate of inflation ($\pi_{it} = p_{it} - p_{i,t-1}$), the real exchange rate ($e_{it} - p_{it}$), real equity prices (q_{it}), real credit (crd_{it}), the short term interest rate (ρ_{it}^S) and the long rate of interest (ρ_{it}^L) in the country-specific models, where available. More specifically

$$y_{it} = ln(GDP_{it}/CPI_{it}), p_{it} = ln(CPI_{it}), e_{it} = ln(E_{it}),$$

$$crd_{it} = ln(CRD_{it}/CPI_{it}), q_{it} = ln(EQ_{it}/CPI_{it}),$$

$$\rho_{it}^S = 0.25 \times ln(1 + R_{it}^S/100), \rho_{it}^L = 0.25 \times ln(1 + R_{it}^L/100),$$

where GDP_{it} is the nominal Gross Domestic Product, CPI_{it} the consumer price index, EQ_{it} the nominal equity price index, CRD_{it} the nominal credit, E_{it} the exchange rate in terms of US dollars, R_{it}^S is the short term interest rate, and R_{it}^L the long rate of interest, for country i during the period t.

With the exception of the US model, all country specific models include y_{it}, π_{it}, ρ_{it}^S, ρ_{it}^L, q_{it}, crd_{it} and $e_{it} - p_{it}$ as domestic variables, where available, and their foreign counterparts $y_{it}^*, \pi_{it}^*, q_{it}^*, \rho_{it}^{*S}, \rho_{it}^{*L}, crd_{it}^*$ as country-specific foreign variables, excluding exchange rate, which is already determined in the model, and including the log of oil prices (p_t^o), as given in Table 2.

Table 2: Model Specifications

Country	Domestic variables	Foreign variables
US	y_{it}, Δp_{it}, ρ_{it}^S, ρ_{it}^L, q_{it}, crd_{it}, p_t^o	y_{it}^*, Δp_{it}^*, $\rho_{it}^{S^*}$, $e_{it}^* - p_{it}^*$
Rest of the world	$y_{it}, \Delta p_{it}, \rho_{it}^S, \rho_{it}^L, q_{it}, crd_{it}$, $e_{it} - p_{it}$ where available	$y_{it}^*, \Delta p_{it}^*, \rho_{it}^{S^*}, \rho_{it}^{L^*}, q_{it}^*, crd_{it}^*$, p_t^o

An important condition in the GVAR framework is the weak exogeneity of foreign variables, which implies that there is no *long run* feedback from $\mathbf{x}_{it}$ to $\mathbf{x}_{it}^*$, without necessarily ruling out lagged *short run* feedback between $\mathbf{x}_{it}$ and $\mathbf{x}_{it}^*$. That is, domestic economic conditions cannot affect the 'the rest of the world' in the long run, though there can be short run interactions between the two sets of variables. In effect, each country is treated as a small open economy in the framework except for the US.

The US is considered the dominant economy in the model, and the specification for the US model differs accordingly. Oil prices are included as an endogenous variable in the US model, to allow for macro variables to influence the evolution of oil prices. Given the importance of US financial variables in the global economy, US-specific foreign financial variables $q_{US,t}^*, \rho_{US,t}^{*L}, crd_{US,t}^*$ were not included in the US model as they were not long run forcing (weakly exogenous) with respect to US domestic financial variables.

The US-specific foreign output, inflation, short term interest rate and exchange rate variables y^*_{it}, π^*_{it}, $\rho^{*S}_{US,t}$ and $e^*_{US,t} - p^*_{US,t}$ were included in the US model in order to capture the possible second round effects of external shocks on the US, and as they do satisfy the weak exogeneity assumption.

The weak exogeneity assumption is tested by examining the joint significance of the error correction terms of the individual country vector error correction models in the marginal error correcting model of $\mathbf{x}^*_{it}$, along the lines described in Johansen (1992) and Harbo, Johansen, Nielsen, and Rahbek (1998). In particular, for each lth element of $\mathbf{x}^*_{it}$ the following regression is carried out:

$$\Delta \mathbf{x}^*_{it,l} = \mu_{il} + \sum_{j=1}^{r_i} \gamma_{ij,l} ECM^j_{i,t-1} + \sum_{k=1}^{s_i} \varphi_{ik,l} \Delta \mathbf{x}_{i,t-k} + \sum_{m=1}^{n_i} \vartheta_{im,l} \Delta \tilde{\mathbf{x}}^*_{i,t-m} + \varepsilon_{it,l}, \quad (9)$$

where $ECM^j_{i,t-1}$, $j = 1, 2, ..., r_i$, are the estimated error correction terms corresponding to the r_i cointegrating relations found for the ith country model and $\Delta \tilde{\mathbf{x}}^*_{i,t}= (\Delta \mathbf{x}'^*_{i,t}, \Delta(e^*_{it} - p^*_{it}), \Delta p^0_t)'$. The test for weak exogeneity is an F-test of the joint hypothesis that $\gamma_{ij,l} = 0, j = 1, 2, ...r_i$, in the above regression.[16] We find that the weak exogeneity hypothesis could not be rejected for the majority of the variables being considered, especially for core economies such as the US, the euro area, UK and China.[17]

4 The Role of Credit in Modeling and Forecasting Business Cycle Dynamics

In this section, we study and quantify the importance of credit in modeling business cycle fluctuations, by estimating country specific VARX* models for 26 advanced and emerging economies from 1979Q2 to 2006Q4, taking into account of the long run relationships between financial and real variables and between domestic and country specific foreign variables. In order to evaluate the in-sample performance of the credit models (i.e. error correction models with real credit), we compare their in sample fit with two benchmark models. The first of which captures an otherwise identical error correction model except for the exclusion of the variable real credit (crd_t), while the second benchmark is estimated as an AR(p) specification applied to the first difference of each of the country specific endogenous variables in turn, with the appropriate lag order p selected by the Akaike information Criteria.[18] We then use the estimated error correction models to perform out of sample forecasts from 2007Q1 to 200Q4, and

[16] In the case of the US, the term $\Delta(e^*_{it} - p^*_{it})$ is implicitly included in $\mathbf{x}^*_{i,t}$. Note that we take the lag orders s_i to be the same as the orders p_i of the underlying country-specific VARX* models and the lag orders n_i to be two.

[17] See Table B2 in the appendix for test results for the weak exogeneity hypothesis.

[18] The *a priori* maximum lag order for the autoregressive process is set as four.

evaluate the forecasting performance against the two benchmarks models.

4.1 Credit in modeling business cycles (1979Q2 to 2006Q4)

4.1.1 Results from the in-sample fit of models with credit

The country specific models are estimated by first selecting the appropriate lag order and the number of cointegration relationships in each of the country specific models. Once the appropriate lag order and number of cointegration relationship are specified, the next stage in the estimation is to exactly identify the long run by imposing restrictions that are in accordance with those suggested by economic theory.[19]

For the United States, we follow a VARX*(2,1) specification with two cointegration relationships. The short run dynamics of the US model are characterized by the seven error correction specifications given in Table 3. The credit variable is significant in explaining output and credit growth and changes in the short term interest rate. The estimates of the error correction coefficients show that the long run relations make an important contribution in several equations and that the error correction terms provide for a complex and statistically significant set of interactions and feedbacks across output, inflation and credit equations. The results in Table 3 also show that the core model fits the historical data well, especially for the US output, inflation, short term interest rate and credit equation. In comparison the benchmark models, we find that, the inclusion of credit improves the fit for the output and oil price equation. In particular, the adjusted R^2 rises from 0.488 to 0.571 in the output equation with the inclusion of credit. The core model with credit outperforms the AR benchmark in the case of all variables except for oil prices and the credit variable.

For the euro area, where Austria, Belgium, Finland, France, Germany, Italy, Netherlands and Spain are aggregated as a single economy, we also consider a VARX*(2,1) specification. The results suggest that the core model with credit fits historical data well, especially for the output, inflation, equity and long run interest rate equation in the euro area (Table 4). Bank credit plays a particular important role in explaining real activities in the euro area, as loans (bank finance) are by far the most important source of debt financing of non-financial corporations in the euro area, in comparison to the US (see for example, Ehrmann, Gambacorta, Martinez-Pages, Sevestre, and Worms, 2001). The explanatory power of the equity equation for the euro area seems unreasonably high in first instance ($\bar{R}^2$=0.83), after re-estimating the model with different subset of the variables, we identify that it is foreign equity that contributes most to the $\bar{R}^2$ for the equity equation, which is in line with the high level of international spillover

[19] Detailed test statistics and discussions on selecting lag orders and cointegration relations are provided in the supplement and are available upon request. The results for 26 country-specific models are given in Table B1 in the Appendix.

Table 3: In Sample Fit and Diagnostics for the US Core Model, US VARX*(2,1) model

Equation	Δy_t	$\Delta(\Delta p_t)$	Δq_t	$\Delta \rho_t^S$	$\Delta \rho_t^L$	Δcrd_t	Δp_t^o
Δy_{t-1}	-0.112	$-0.185^{\dagger}$	2.005	-0.004	-0.011	-0.084	-1.445
	(0.093)	(0.082)	(1.240)	(0.033)	(0.023)	(0.188)	(2.579)
$\Delta(\Delta p_{t-1})$	0.072	$0.267^{\dagger}$	-1.806	$-0.133^{\dagger}$	-0.019	0.246	0.984
	(0.126)	(0.111)	(1.689)	(0.045)		(0.256)	(3.514)
Δq_{t-1}	0.013	$0.019^{\dagger}$	0.137	0.006^{*}	$0.004^{\dagger}$	-0.032^{*}	0.355
	(0.008)	(0.007)	(0.110)	(0.003)	(0.002)	(0.017)	0.229
$\Delta \rho_{t-1}^S$	$1.626^{\dagger}$	0.253	-1.585	-0.041	-0.145	-0.423	-13.215
	(0.387)	(0.341)	(5.181)	(0.139)	(0.097)	(0.786)	(10.781)
$\Delta \rho_{t-1}^L$	-0.951^{*}	$1.246^{\dagger}$	-11.197	0.253	$0.272^{\dagger}$	-1.809^{*}	$31.051^{\dagger}$
	(0.522)	(0.460)	(6.980)	(0.188)	(0.131)	(1.059)	(14.523)
Δcrd_{t-1}	$0.143^{\dagger}$	-0.058	0.407	0.026^{*}	-0.006	$0.702^{\dagger}$	1.645
	(0.043)	(0.038)	(0.576)	(0.015)	(0.011)	(0.087)	(1.199)
Δp_{t-1}^o	-0.004	-0.002	0.003	$0.003^{\dagger}$	0.0008	0.009	0.111
	(0.004)	(0.003)	(0.053)	(0.001)	(0.001)	(0.008)	(0.110)
Δy_t^*	$0.712^{\dagger}$	0.125	-2.454	$0.142^{\dagger}$	$0.139^{\dagger}$	$0.591^{\dagger}$	5.558
	(0.127)	(0.112)	(1.699)	(0.046)	(0.032)	(0.258)	(3.535)
$\Delta(\Delta p_t^*)$	0.189^{*}	$0.213^{\dagger}$	1.307	-0.018	0.028	-0.358^{*}	-1.163
	(0.097)	(0.086)	(1.301)	(0.035)	(0.024)	(0.197)	(2.707)
$\Delta \rho_t^{S^*}$	0.218	-0.027	-3.201^{*}	0.036	-0.038	0.290	6.512^{*}
	(0.132)	(0.116)	(1.760)	(0.047)	(0.033)	(0.267)	(3.663)
$\Delta(e_t^* - q_t^*)$	-0.014	-0.006	-0.327	0.006	$0.013^{\dagger}$	-0.014	-0.895
	(0.022)	(0.019)	(0.291)	(0.008)	(0.005)	(0.044)	(0.605)
$\widehat{\xi}_{1,t}$	$-0.032^{\dagger}$	-0.006	0.050	0.002	0.004	0.017^{*}	-0.009
	(0.005)	(0.004)	(0.062)	(0.002)	(0.001)	(0.009)	(0.130)
$\widehat{\xi}_{2,t}$	0.007	$-0.029^{\dagger}$	0.020	0.0008	0.0004	-0.002	0.039
	(0.005)	(0.004)	(0.062)	(0.002)	(0.001)	(0.009)	(0.130)
c	$0.354^{\dagger}$	$-0.480^{\dagger}$	0.018	-0.003	-0.035	0.087	0.730
	(0.091)	(0.080)	(1.220)	(0.033)	(0.023)	(0.185)	(2.538)
$\bar{R}^2$	**0.571**	0.439	0.055	0.282	0.279	0.522	**0.093**
Benchmark1 $\bar{R}^2$	0.488	0.490	0.063	0.309	0.343		0.084
Benchmark2 $\bar{R}^2$	0.115	0.326	0.027	0.126	0.046	0.564	0.100
$\hat{\sigma}$	0.005	0.004	0.062	0.002	0.001	0.009	0.130
$\chi_{SC}^2[4]$	1.451	$11.757^{\dagger}$	$10.100^{\dagger}$	$14.606^{\dagger}$	3.293	$20.924^{\dagger}$	$18.580^{\dagger}$
$\chi_{FF}^2[1]$	1.706	0.909	0.046	0.943	0.530	3.480^{*}	$4.247^{\dagger}$
$\chi_N^2[2]$	1.403	$10.911^{\dagger}$	$140.498^{\dagger}$	$126.993^{\dagger}$	$17.238^{\dagger}$	$10.784^{\dagger}$	$49.257^{\dagger}$
$\chi_H^2[1]$	0.216	0.097	1.144	$15.485^{\dagger}$	2.139	$10.899^{\dagger}$	0.225

Note: Standard errors are given in parentheses. '†' indicates significance at 5% level, and '*' indicates significance at 10% level. The diagnostics are chi-squared statistics for serial correlation (SC), functional form (FF), normality (N) and heteroscedasticity (H). Benchmark 1 captures a model with the same number of cointegration relationships and lag order, but excluding the variable real credit (crd_t) from the country-specific models. Benchmark 2 is estimated as an AR(p) specifications applied to the first difference of each of the seven core endogenous variables in turn, where the appropriate lag order p is selected using AIC (the a priori maximum lag order for the autoregressive process is set as four).

in the equity market. The diagnostics statistics of the equations are generally satisfactory as far as the tests of serial correlation, functional form and heteroscedasticity are concerned. The assumption of normally distributed errors is rejected in the short term interest rate equation, which is understandable if we consider the major hikes in oil prices experienced during the estimation period and special events that have affected the euro area such as German unification and the introduction of the euro in 1999.

Table 4: In Sample Fit and Diagnostics for the EU Core Model, EU VARX*(2,1) model

Equation	Δy_t	$\Delta(\Delta p_t)$	Δq_t	$\Delta(e_t - p_t)$	$\Delta\rho_t^S$	$\Delta\rho_t^L$	Δcrd_t
$\bar{R}^2$	**0.498**	**0.580**	0.834	**0.276**	**0.562**	0.705	0.456
Benchmark1 $\bar{R}^2$	0.458	0.471	0.858	0.139	0.550	0.728	
Benchmark2 $\bar{R}^2$	0.100	0.227	0.085	0.045	0.229	0.294	0.260
$\hat{\sigma}$	0.003	0.002	0.032	0.040	0.0008	0.0005	0.007
$\chi^2_{SC}[4]$	3.513	13.249	2.615	10.866†	5.248	1.772	1.230
$\chi^2_{FF}[1]$	1.302	0.311	0.099	0.008	0.403	3.282*	1.555
$\chi^2_{N}[2]$	0.067	0.357	1.363	0.176	159.021†	3.457	0.005
$\chi^2_{H}[1]$	3.676*	0.816	0.116	1.871	1.192	1.012	0.310

Note: Standard errors are given in parentheses. '†' indicates significance at 5% level, and '*' indicates significance at 10% level. The diagnostics are chi-squared statistics for serial correlation (SC), functional form (FF), normality (N) and heteroscedasticity (H). Benchmark 1 captures a model with the same number of cointegration relationships and lag order, but excluding the variable real credit (crd_t) from the country-specific models. Benchmark 2 is estimated as an AR(p) specifications applied to the first difference of each of the seven core endogenous variables in turn, where the appropriate lag order p is selected using AIC (the a priori maximum lag order for the autoregressive process is set as four).

The country specific models for the rest of the world is estimated following the same procedure as that for the US and the euro area. For industrialized economies with more developed banking sector, we find that the inclusion of credit tends to improve the in sample fit of the output, inflation and long run interest rate equations. For output, the inclusion of credit improves the fit of the model for 8 out of 11 countries; for inflation, 9 out of 11 countries; and for the long run interest rate, 8 out of 11 countries (Table 5).

While for emerging economics, the results are more mixed, we find an improvement in the fit of the output equation for 7 out of 15 countries, for inflation in 9 out of 15 countries, and for long run interest rate, the only emerging economies with this variable is South Africa and we do find an improvement there. The effectiveness of the credit variables depends on the development of the banking sector and institutional features such as the size and maturity of capital markets. In Asia, the credit variable improves the fit for the inflation and the real exchange rate equation for China and India. While for the other Asian economies considered in the GVAR, including Thailand, Singapore, Malaysia, the credit model outperforms the benchmark in fitting the equity equation, possibly a result of the relatively developed banking sector and equity markets in these countries. For the five Latin American economies, Argentina, Brazil, Chile, Peru and Mexico, the inclusion of credit improves the fit of the output and short term interest rate equation for Argentina, Mexico and Peru, but performs less well for variables in the Chile model, which could be a result of the differences in the transmission channels of monetary policy and the size of capital markets in Latin American economies.[20]

[20] The detailed results on the in-sample fit of country specific models can be found in Appendix C1.

Table 5: Summary of In Sample Results for Country-Specific Models

	Industrialized economies		Emerging economies	
No. of Countries	improvement upon B1	available series	improvement upon B1	available series
y_{it}	8	11	7	15
π_{it}	9	11	9	15
q_{it}	5	11	6	8
$e_{it} - p_{it}$	3	10	8	15
ρ_{it}^{S}	5	11	8	14
ρ_{it}^{L}	8	11	1	1

Note: Among the 26 country-specific models (where 8 European countries are grouped as the euro area), 11 economies are classified as industrialized countries, including the US, Japan, UK, Euro Area, Canada, Australia, New Zealand, Korea, Sweden, Switzerland and Norway. The rest of the economies are classified as emerging economies.

4.1.2 Non-nested testing of the significance of the results

To examine the statistical significance of the improvement with the inclusion of credit (seen from the comparison of $\bar{R}^2$), we carry out non-nested testing procedure to test the core model against the benchmark model without credit (Benchmark 1).[21] Among the different test statistics for the non-nested testing procedure, we focus on the W-test statistics since it is found to be more reliable compared with the other tests, based on a Monte Carlo study of the relative performance of the a number of non-nested tests in small samples (see Godfrey and Pesaran, 1983). In particular, the W-test is better behaved when the regressors include lagged dependent variables, which is applicable to the setting of our model.

The null and alternative hypothesis for the W-test is given by

$$H_0 : y = Xb_0 + u_0, u_0 \sim N(0, \sigma_0^2 I),$$

$$H_1 : y = Zb_1 + u_1, u_1 \sim N(0, \sigma_1^2 I).$$

In the first part of the test, we refer to the credit model as the true model under H_0, and the benchmark model without credit as the true model under the alternative hypothesis H_1. Test results for the credit model against the benchmark model suggest that we cannot reject the hypothesis that the core model with credit is the better model in the majority of the cases, in particular, in 17 out of 26 countries in the output equation, in 20 out of 26 countries in the inflation equation and in 9 out of 12 countries in the long run interest rates equation. In the second part of the test, we examine the

[21] A simple variable exclusion test is not appropriate here, as credit does not enter the error correction terms in the benchmark model. For a formal definition of the concepts of nested and non-nested models, see Pesaran (1987).

opposite hypothesis where the benchmark model is the true model under H_0, and the credit model is the true model under the alternative hypothesis H_1. Test results for the benchmark model against the core model suggest that we can reject the hypothesis that the model without credit is the better model in 9 out of the 26 countries in the output equation, in 12 out of 26 countries in the inflation equation and in 8 out of the 12 countries in the long run interest rates equation.

The findings from the non-nested tests are broadly in line with the results from the in-sample fit of our models: the inclusion of credit is found to provide significant improvement in the error correction models of output, inflation and long run interest rates, in particular for industrialized economies.[22]

4.2 Credit in forecasting business cycles (2007Q1 to 2009Q4)

Having established the importance of credit in modeling business cycles in sample, we next examine the out of sample forecasting performance of models that incorporate credit variables. We consider unconditional forecasts, which use forecasts of the foreign (exogenous) variables from the marginal model, rather than realized values of exogenous variables. In this way, the forecasts performed are truly out of sample. We also consider dynamic forecasts, which calculate forecasts by using the previously forecasted values of lagged dependent variables.[23] We compare the root mean square forecast error of the core model (with credit) with the forecasting performance of the two benchmark models stated earlier, that is, an otherwise identical error correction model except for the exclusion of credit and an AR benchmark.

Table 6: Summary of Out of Sample Results for Country Specific Models

	Industrialized Economies				Emerging Market Economies			
No. of Countries	improvement upon B1	B2	B1 & B2	available series	improvement upon B1	B2	B1 & B2	available series
y_{it}	9	8	7	11	8	8	5	15
π_{it}	7	7	4	11	7	5	2	15
q_{it}	8	6	5	11	7	5	5	8
$e_{it} - p_{it}$	6	2	2	10	7	6	4	15
ρ^S_{it}	6	2	1	11	7	4	3	14
ρ^L_{it}	5	7	4	11	1	0	0	1

Note: Among the 26 country-specific models (where 8 European countries are grouped as the euro area), 11 economies are classified as industrialized countries, including the US, Japan, UK, Euro Area, Canada, Australia, New Zealand, Korea, Sweden, Switzerland and Norway. The rest of the economies are classified as emerging economies.

The results suggest that the core model with credit outperforms the AR benchmark

[22]Detailed results on non-nested tests and associated statistics can be found in Appendix B3.
[23]The VARX* models in our analysis include lagged dependent variables.

in forecasting output growth, changes in inflation and long run interest rates in advanced economies. In particular, the core model does better in forecasting output growth in 8 out of 11 advanced countries, changes in inflation and long run interest rates in 7 out of 11 advanced countries. In emerging market economies, the core model outperforms the AR benchmark in forecasting output growth in more than fifty per cent of the cases, but it performs less well in forecasting other variables (Table 6).

In comparison to the benchmark model without credit, we find that the core model with credit tend to perform better in forecasting most of the business cycle variables in advanced economies, while the evidence is again more mixed in emerging market economies. The forecasting exercises also show that the incorporation of credit is most useful in forecasting output growth in advanced economies, as the core model tends to outperform both benchmarks.

5 The International Spillover of Credit Shocks

What are the channels through which credit shocks are transmitted across country borders and what are their impacts on the real economy? We first study some stylized facts on the cross country correlation of credit and other business cycle variables. We then examine the contemporaneous effects of foreign variables on domestic counterparts, for example, the effect of a foreign credit shock on domestic credit *on impact*. Finally we analyze the dynamic properties and the *time profile* of the impact of credit shocks and the international transmission of shocks using the Generalized Impulse Response Function (GIRF). Before presenting the results, it is important to note that the global model is stable, supported by the persistence profiles, the eigenvalues of the system and the responses in the GIRFs.[24] In presenting the results, we focus on the period between 1979Q2 to 2006Q4, before the recent crisis. Our results are found be robust when different weighting schemes are used to construct the country-specific foreign variables and when the sample period includes the recent crisis from 2007Q1 to 2009Q4.

5.1 Pair-wise Cross Country Correlation in Credit

To examine the degree of comovements in credit among the 26 largest advanced and emerging economies, we compute the pair-wise cross country correlations in credit and compare our findings with the degree of comovements in other business cycle variables as a preliminary analysis of the international linkages in credit.

The pair-wise cross country correlations in credit are computed in levels, first differences and HP filtered cyclical components. As seen earlier, unit root tests in general support the view that credit variables are integrated of order one. It is therefore mean-

[24]See Appendix B4 on the stability of the global system and persistence profiles.

Table 7: Average Pairwise Cross-country Correlations, World, 1979Q2 to 2006Q4

Variables	HP filtered cycle components	First differences	Levels	No. of economies
real credit ($\mathbf{crd}_{it}$)	**0.065**	**0.034**	**0.643**	**26**
real output (y_{it})	0.154	0.111	0.939	26
the rate of inflation (π_{it})	0.078	0.058	0.301	26
real equity prices (q_{it})	0.354	0.369	0.695	19
real exchange rate ($e_{it} - p_{it}$)	0.286	0.209	0.530	25
short term interest rate (ρ_{it}^S)	0.169	0.087	0.420	25
long rate of interest (ρ_{it}^L)	0.450	0.321	0.753	12

Note: The average pair-wise cross country correlations are calculated for countries with available series. The number of countries/regions with available series for each variable is given in the fifth column in the above table. The average pairwise correlation for first differences uses one less observation at the beginning of the sample period.

ingful to also consider the cross country correlation in the detrended version of the series (integrated of order zero), using the first difference filter and the HP filter.[25]

In reporting the results, we focus on the correlation in levels and the HP filtered cyclical components, since the HP filter is found to be more effective as a device for extracting the business cycle and high frequency components in quarterly data, while the first difference filter tends to reweights strongly towards high frequencies and down-weights lower frequencies, further, the correlation in first differences yield very similar results in order of magnitude.[26]

Consistent with the business cycle literature, the average cross country correlation in real output is very high in levels, at 0.939, followed by real equity prices and long rate of interest, reflecting the high degree of synchronization in the international equity and bond markets (Table 7). The average cross country correlation in real credit is found to be lower compared with that in real equity prices and long run interest rates, in particular in the HP filtered cyclical component. One explanation for the lower degree of comovements in credit could be that the level of credit extended in an economy is more dependent on the *domestic* economic conditions, while equity and bond markets are more responsive to *international* economic conditions. With the growing influence of global banks and cross border holding of assets, we do observe an increase in the degree of comovements in credit over the past 30 years, by examining the pair-wise cross country correlation coefficient of the credit in three subsamples of nine to ten

[25] The first difference filter extracts the cyclical component y_t^c from a time series y_t, where $y_t^c = (1 - L)y_t$. The HP filter (Hodrick and Prescott, 1980, 1997) extracts the cyclical component y_t^c of the series following $y_t^c = \frac{\lambda(1-L)^2(1-L^{-1})^2}{1+\lambda(1-L)^2(1-L^{-1})^2} y_t$, where L is the lag operator, λ is the smooth parameter, typically set as 1600 for quarterly data.

[26] See for example Baxter and King (1999) and Christiano and Fitzgerald (2003) for an comparison and evaluation of different types of band pass filters.

years between 1979Q1 to 2006Q4.[27]

Table 8: Average Pairwise Cross-country Correlations in Credit, by Subgroups of Countries, 1979Q2 to 2006Q4

crd_{it}	HP filtered cycle components	First differences	Levels
Latin America	0.005	0.002	0.204
Asia	0.017	0.011	0.749
Euro Area	0.096	0.059	0.753
G7	0.095	0.057	0.759
Industrialized countries	0.111	0.063	0.764
Emerging countries	0.016	0.008	0.575
World	**0.068**	**0.038**	**0.678**

Note: According to FTSE classification, with the exception of Singapore, the Industrialized economies countries include USA, Japan, UK, Euro Area (8 countries), Canada, Australia, New Zealand, Korea, Sweden, Switzerland and Norway. The rest are considered as Emerging countries.

The pair-wise cross country correlation coefficient of the credit variable by subgroups of countries exhibits some degree of heterogeneity, as can be seen from Table 8. We observe a higher average correlation in the case of industrialized economies with more mature banking sector, compared to the average correlation coefficient for the emerging economies. In particular, the average cross country correlations in real credit for the euro area and G7 are higher than the world average. In contrast, very low correlation can be found in Latin American and Asia, which could have contributed to the low correlation we observe in the world average. On the individual country level, Argentina and Brazil have a negative correlation in the credit variable with the rest of the world, while China, Germany, Peru and Korea have a negative correlation in the credit variable at business cycle frequencies (HP filtered series) with the rest of the world. In contrast, Switzerland, Belgium, Sweden, US, Canada, Australia and UK are among the countries with the highest correlation in credit with the rest of the world. For the US, we observe a reasonably high correlation in credit with the other industrialized economies (in contrast to a negative correlation with emerging countries at business cycle frequency).[28]

5.2 Contemporaneous effects of foreign credit on domestic credit

To examine the international linkages between domestic credit and foreign credit, in particular the impact of foreign credit on domestic credit, we investigate the *contempo-*

[27] The results on the pairwise cross section correlation by subsamples are not presented here due to space considerations but available upon request.

[28] The average pair-wise cross country correlations between the US and industrialized countries are 0.852 in levels and 0.226 in cyclical components; while those with emerging market economies are 0.597 in levels and -0.004 in cyclical components.

raneous effects of foreign variable on their domestic counterparts, with robust t ratios computed using White's heteroskedasticity-consistent variance estimator. These estimates can be interpreted as impact elasticities of domestic to foreign variables.

Consistent with the findings for the cross-country correlation in the earlier section, we observe positive and significant elasticities in foreign and domestic credit in a large number of industrialized countries, but only one emerging market economy (Brazil), which indicates that credit in countries with mature banking sector are more inter-related with the rest of the world. Specifically, for the UK, the euro area and Switzerland, a 1% change in foreign credit in a given quarter leads to an increase in domestic real credit of 0.48%, 0.23% and 0.38% respectively, within the same quarter. The contemporaneous effect of foreign credit on real credit in China and India is positive but not significant, despite the rapid development of banking sector in the two largest emerging economies, reflecting a much lower degree of openness in the banking sector in comparison to more advanced economies (Table 9).

Table 9: Contemporaneous Effects of Foreign Variables on Their Domestic Counterparts

Country	Domestic variables					
	y_t	Δp_t	q_t	ρ_t^S	ρ_t^L	$\mathbf{crd}_t$
US	0.712	0.213	-	0.036	-	-
	[5.141]	[2.443]	-	[0.806]	-	-
Euro Area	0.517	0.057	1.009	0.068	0.67	**0.225**
	[5.138]	[1.395]	[18.371]	[3.938]	[8.134]	**[2.143]**
UK	0.261	0.371	0.88	0.163	0.757	**0.48**
	[1.634]	[1.988]	[16.435]	[1.379]	[5.305]	**[2.95]**
Japan	0.384	0.061	0.635	-0.047	0.549	**-0.085**
	[2.279]	[0.457]	[5.064]	[-1.105]	[6.532]	**[-0.622]**
Sweden	1.33	0.572	1.174	0.348	0.891	**1.989**
	[4.822]	[2.724]	[13.39]	[2.237]	[7.328]	**[4.123]**
Switzerland	0.622	0.219	0.924	0.163	0.386	**0.377**
	[4.716]	[1.667]	[12.226]	[2.616]	[5.05]	**[2.492]**
China	0.022	0.285	-	0.054	-	**0.06**
	[0.195]	[0.827]	-	[1.604]	-	**[0.157]**
Brazil	0.649	0.62	-	1.045	-	**2.605**
	[1.737]	[0.501]	-	[0.526]	-	**[3.138]**
India	-0.226	0.506	0.757	0.009	-	**0.464**
	[-0.861]	[1.479]	[4.22]	[0.24]	-	**[0.85]**
Singapore	1.162	0.464	1.27	0.377	-	**-0.01**
	[5.609]	[3.031]	[11.811]	[1.942]	-	**[-0.061]**

Note: White heteroskedastic-robust t-ratios are given in square brackets.

In addition, results suggest high elasticity of foreign and domestic long run interest rates (statistically significant), implying relatively strong co-movements between the international bond markets. Contemporaneous financial linkages in the equity market are found to be strong and significant, in particular, we observe above unit elasticity in the euro area, Sweden and Singapore, which indicates a high degree of synchronization in the international equity markets.

5.3 The international transmission of credit shocks

To study the international transmission of credit shocks, we investigate the implication of a one standard error negative shock to US real credit, using the Generalized Impulse Response Function (GIRF) (see Koop, Pesaran, and Potter, 1996 and Pesaran and Shin, 1996).[29] In contrast to the Orthogonalized Impulse Responses (OIR) proposed by Sims (1980), GIRF is invariant to the ordering of the variables and the countries in the GVAR model, which offers more flexibility in the modeling strategy without making any *a priori* assumption on the sequence of impacts. GIRF is particular applicable to our global framework, which contains 160 real and financial variables covering 26 advanced and emerging economies in the world. It would be very difficult to impose a sensible ordering among the 160 variables based on existing economic theory, especially given that the mechanism through which shocks are transmitted is likely to have evolved during the long sample period from 1979Q2 to 2006Q4. Note that GIRF and OIR coincide if the error variance matrix is diagonal, in the case of a non-diagonal error variance matrix, the two impulse responses are the same only for shocks to the first equation in the VAR (see Pesaran and Shin, 1996 for a formal proof).

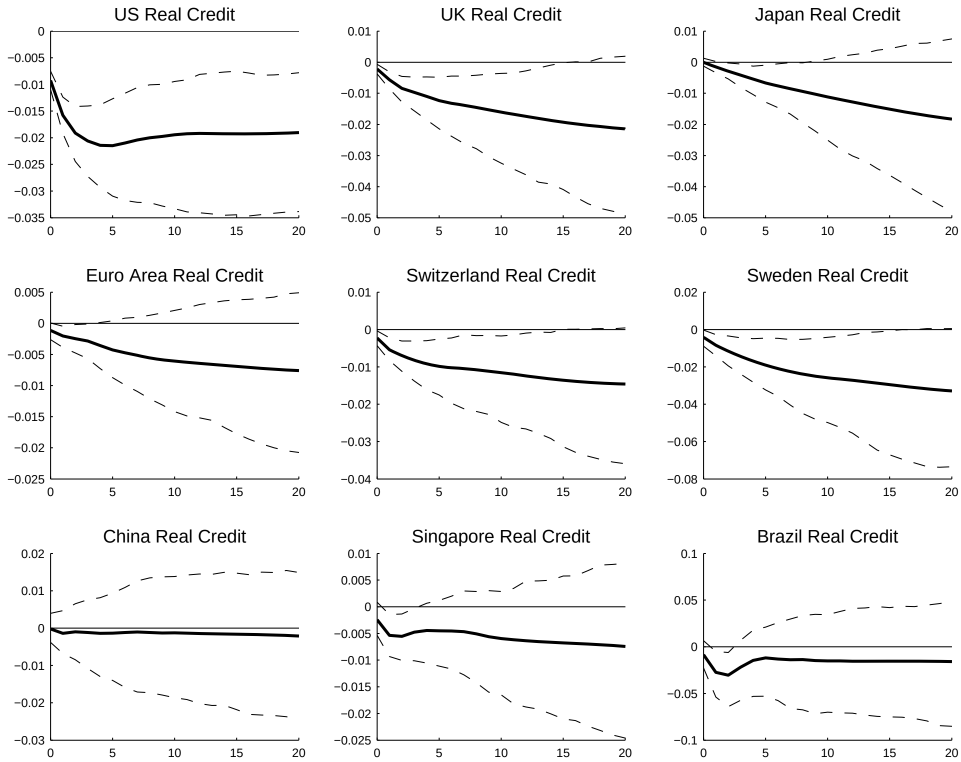
As noted earlier, we do not attempt to interpret the credit shock structurally, that is, to distinguish between the demand or supply sources of these shocks. Instead, we interpret the credit shock as a displacement (decline) in the level of credit, either due to demand or supply factors, and examine the channels through which a credit shock originated in the US is transmitted to the rest of the world. Note that in the GVAR model, once x_{it} is conditioned on x^*_{it}, the estimated country specific credit shocks have little or no correlation across countries.[30] This makes it possible to consider GIRFs to a US credit or equity shocks with little concerns about the reverse spillover effects from one country to the other.

A one standard error negative shock to US real credit is equivalent to a fall of around 0.9-1% per quarter. The real credit shock results in a permanent fall in US real credit of around 2% at two year horizon, reflecting the persistence of the credit series. The impulse response function suggests strong evidence of international spillover of credit shocks, which is consistent with our earlier finding of a significant contemporaneous impact of foreign credit on domestic credit, especially for advanced economies.

[29] We also consider the impact a one standard error negative shock to US real equity prices and a one standard error positive shock to oil prices. Due to space considerations, they are not presented here, but are available upon request.

[30] The average pairwise cross-country correlations of the VARX* residuals are 0.006 for real credit, 0.004 for real output, 0.005 for inflation rate, -0.001 for real equity prices, 0.140 for real exchange rate, 0.006 for short term interest rates and 0.011 for long term interest rates.

Figure 2: GIRFs of a one standard deviation negative shock to US real credit (bootstrap mean estimates with 90% error bounds)

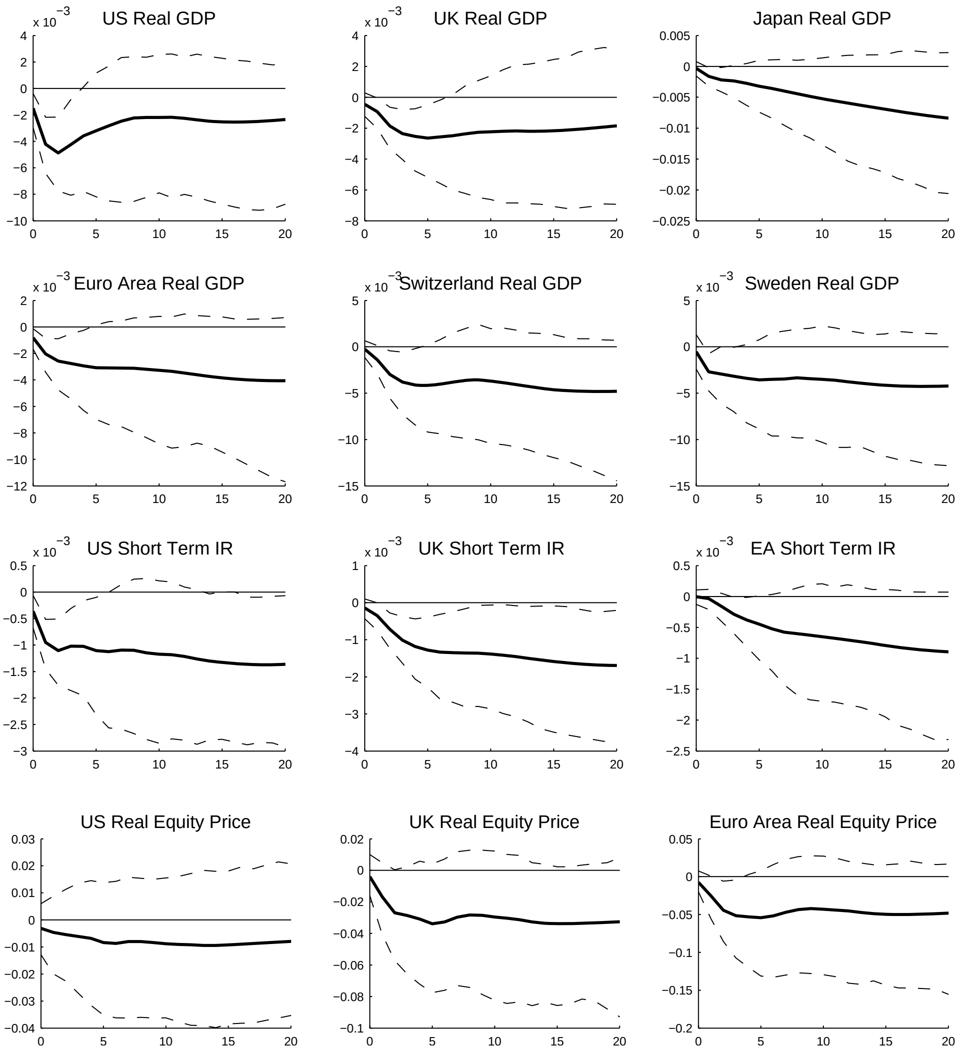


The GIRFs show that the transmission of the real credit shock to the euro area, UK and Japan real credit takes place rather quickly, with the impact on UK real credit especially strong at around 1.5% after one year, possibly due to the strong linkages in the banking sector between the US and the UK. We also observe the spillover of credit shock to emerging market economies, such as Singapore and Brazil, where the negative impact on the real credit variable is significant in the first three or four quarters, however the negative impact on China real credit is not statistically significant. One possible explanation is the greater openness of the banking sector and capital markets in Singapore and Brazil in comparison to China. A greater presence of global banks in Singapore and Brazil also makes their domestic banking sector more susceptible to credit shocks originated in the US (see Figure 2).

The real credit shock is transmitted to the real economy, as seen by a decline in US real GDP of around 0.15% on impact, by 0.5% at the end of two quarters, although the process starts to reverse after one year. The impact on the euro area, UK and Japan real GDP is negative and significant, at around 0.2% to 0.3% on average (see Figure 3). As predicted by economic theory, a decline in credit (either through a fall in demand or a shortage in credit availability) is accompanied by a fall in firm investments and a reduction in output in the economy. The subsequent spillover in the real economy could be a result of the strong trade linkages between US, the euro area, UK and Japan.

The negative shock to US real credit is accompanied by decreases in short term

Figure 3: GIRFs of a one standard deviation negative shock to US real credit–cont. (bootstrap mean estimates with 90% error bounds)



interest rates in the US, UK, the euro area and several other advanced economies, suggesting a possible loosening of monetary policy in association with the fall in the availability of credit, as observed in the policy coordination in the aftermath of the recent credit crunch. The impact of the real credit shock is also reflected in a significant fall in the UK and European equity markets at around 3 to 4%, possibility reflecting a fall in investor confidence and a deterioration in the economic fundamentals in the economy.

5.4 Robustness of the GVAR results

5.4.1 Estimation with time-varying weights

The results presented so far are based on country specific foreign variables constructed using three year average trade weights between 2001 and 2003. To check the robustness of our results to the choice of trade weight, we also estimate the GVAR model using time-varying weights, constructed as rolling three year moving averages of the annual trade weights. First, we study the relationship of the two measures, $\mathbf{x}_{it}^{*}$ (based on fixed weights) and $\mathbf{x}_{it}^{**}$ (based on time-varying weights). We find that the correlation coefficients of the levels of the variables being very close to unity, while the correlations in terms of first differences are not as high, particularly in the case of inflation rates and credit.[31] Given the high correlations in the levels of the series, we conjecture that the main conclusions of the paper is unlikely to be affected by whether fixed or time-varying trade weights are used. We find that this is indeed the case.

By re-estimating the GVAR model using time-varying weights, we find that the same number of lag orders p_i and q_i are chosen for the individual VARX$^*(p_i, q_i)$ model and we obtain similar number of cointegration relationships. Compared with Table B1, we estimate a time-varying GVAR model with the same number of cointegration relationships for all countries, except for Argentina, Brazil, Indonesia, Turkey, where the number of cointegrating relationships was decreased by one, and for Chile, Malaysia, Philippines, Singapore, India, Saudi Arabia and Switzerland, where the number of cointegrating relations was increased by one.[32]

With regard to the impact effects of the foreign variables, we obtain similar results, especially in the case of real output, real equity prices, short term and long term interest rates. The results from the Generalized Impulse Response Functions (GIRF) for a one standard error negative shock to US real credit are also found to be similar, except for a few cases on the significance of the responses. For example, a negative shock to US credit now has significant (negative) impact on US and Japan equity when re-estimating with time-varying weights.

5.4.2 Estimation with data up to 2009Q4

To further investigate the robustness of our results, we re-estimate the GVAR model from 1979Q2 to 2009Q4, to include the most recent financial crisis. We find that similar number of lag orders and cointegration relationships are chosen for the individual VARX$^*(p_i, q_i)$ models. In particular, we estimate a GVAR model with the same number of lag orders for all countries except for Japan, Switzerland and the UK, and the same number of cointegrating relationships for all countries, except for China, Japan, Peru, Mexico, New Zealand, Malaysia, Singapore, Thailand, India, Turkey, Norway and the United States, where the number of cointegrating relations was increased or decreased by one with the longer sample period.

The results from the GIRFs for a one standard error negative shock to US real credit

[31] Due to space consideration, the correlation coefficients of country-specific foreign variables using fixed and time-varying trade weights are not presented here, but are available upon request.

[32] For Mexico, the number of cointegrating relationships decreases by two.

are found to be similar, in both magnitude and significance. In particular, we find strong evidence of the international transmission of credit shocks to advanced economies, and to the real economy (output and short term interest rates). One difference is that, with the inclusion of the latest financial crisis, a negative shock to US real credit also has a significant impact on long run interest rates in the US and the UK, which were not found to be significant in the shorter sample period. One possible explanation is that, given the severity of the 2007-2009 credit crunch, credit market conditions were informative on the fundamentals and growth prospects of the economy and reflected the private sector's expectation of aggressive monetary policy easing.

6 Conclusion

This paper investigates the role of bank credit in modelling and forecasting business cycle dynamics by estimating VARX* models for 26 major advanced and emerging market economies, and studies the channels through which a negative shock to US credit is transmitted across country borders and to the real economy using a global VAR framework.

We find robust results from the country specific VARX* models that the incorporation of credit provides statistically significant improvement in modelling output growth, changes in inflation and long run interest rates for countries with developed banking sector. Results from the forecasting exercises suggest that the incorporation of credit tends to perform better compared with an AR benchmark, especially for forecasting output growth, changes in inflation and long run interest rates for advanced economies, while the evidence is more mixed for emerging market economies. Our results confirm the theoretical predictions that credit market conditions could lead to direct impact on the real economy and highlight the importance of bank credit in forecasting the dynamics of business cycle fluctuations and the value of incorporating credit in economic modeling.

The impulse responses of a negative shock to US credit shed light on interesting insights of the international transmission of credit shocks. First, we find strong evidence of international spillover of US credit shocks to the euro area, UK and Japan, with the impact on the UK particularly profound, possibly due to the strong linkages in the banking sectors between the UK and the US. Second, the model predicts the spillover of credit shock to the US real economy and its subsequent international propagation in the real sector. Indeed, the interactions between financial market and the real economy is not simply a one way process. A shock to US credit is accompanied by falling output in the US, UK and the euro area for 12 to 18 months, as shown in our analysis. Third, the US credit shock is associated with a fall in short term interest rates in several economies including the US, UK and the euro area, suggesting a possible loosening of monetary policy in response to the contraction in credit availability, as observed in the policy coordination in the aftermath of the recent credit crunch. Furthermore, US credit shock is accompanied by a significant fall in the UK and European equity markets. Our results are consistent with the theoretical insights that credit markets play an important role in the international transmission of shocks, resulting a magnified impact of the initial shock and highly correlated business cycles across countries during the downturn. The rapid international transmission of credit shocks and profound impact on the international financial markets and the global real economy highlights the important role of credit in international business cycles and calls for greater attention to credit measures in economic policy making.

A Data Appendix

The dataset used in this paper was collected in two stages: first we compiled a dataset to cover the period from 1979Q1 to 2006Q4; it was later extended to 2009Q4, to include the recent financial crisis. The credit variable in our analysis measures bank credit to the private sector. Our main sources for the credit data are the IMF International Finance Statistics (IFS), Datastream and Haver Analytics.[33] For the rest of the variables considered in our analysis, namely output, inflation, interest rates, equity prices, exchange rate and oil prices, the data source is the rejoinder of Pesaran, Schuermann, and Smith (2009) for the period between 1979Q1 and 2006Q4, and Cesa-Bianchi, Pesaran, Rebucci, and Xu (2011) for extending the dataset to 2009Q4.

A1 Data source: 1979Q1 to 2006Q4

The data source for credit data between 1979Q1 and 2006Q4 is IFS and Datasteam. In terms of country coverage and time coverage, the IFS statistics is more complete for the 33 countries considered in our analysis (among which 8 countries are later grouped together as the Eurozone), compared with Datastream. To draw meaningful comparison between the 33 countries, maintain the consistency of the definition of the credit series and reduce errors due to assessing data from different statistical sources, we have decided to use the IMF IFS database as our primary source for the credit data and Datastream as a secondary source.[34]

The source of credit data for all 33 countries, except UK, Australia and Canada, was the series 'Claims on Private Sector from Deposit Money Banks' (22d) from the IFS Money and Banking Statistics, measured in national currency in current prices. The data source for the UK and Australia was the National Statistics from Datastream and for Canada was the OECD data from Datastream.

A1.1 Choice of the credit variable (IFS series)

The choice of the appropriate credit variable is guided by existing literature, data availability and the consideration of international comparability between country series.

There are a few important decisions to be made with regard to our chosen measure of bank credit to the private sector. First, the definition of the banking sector. We choose to follow the definition of 'deposit money banks' in the IFS Money and Banking Statistics. Deposit money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits. They often engage in core banking services that extend loans to the non-financial corporations, which ultimately determine the level of investment and output in the economy, as shown in the theoretical literature on credit.

[33] Several studies in the finance and development literature, see for example Baltagi, Demetriades, and Law (2008), used the World Development Indicators (WDI) (published by the World Bank) as the source for credit data (private credit as a percentage of GDP). The credit data in WDI is also taken from the IMF International Finance Statistics, for example, the indicator "Claims on private sector" in WDI is taken from IFS line 32d, which includes gross credit from the financial system (monetary authority and deposit money banks) to the private sector. Credit data from Datastream and Haver Analytics are drawn from National Sources and the OECD Main Economics Indicators.

[34] Further, the OECD data on credit to the private sector was discontinued at the beginning of 2007. For the purpose of updating the database in the future, we have decided not to use the OECD credit series unless necessary.

In addition to 'deposit money banks', IFS also publish data on 'other banking institutions', which comprise institutions that do not accept transferable deposits but that perform financial intermediation by accepting other types of deposits or by issuing securities.[35] We have decided not to include 'other banking institutions' in our definition of banking sector for two reasons. First, 'other banking institutions' often focus on consumer mortgages loans business and security investment, rather than core lending services to the private sector that is of interest to our analysis. For example, in the US, mortgages make up close to 70 percent of the credit market instruments held by savings institutions (part of 'other banking institutions').[36] Further, the data on 'other banking institutions' is missing for 15 out of 33 countries considered in the GVAR.[37] Where available, the measure 'claims on private sector from other banking institutions' (42d) does not have complete time coverage for the period 1979Q1 to 2006Q4.

We also note that our interests lie in the role of the commercial banking sector rather than the central bank in the provision of credit, as a result, we do not include monetary authority in our definition of the banking sector and the measure of 'claims on private sector in the monetary survey' (32d) is not appropriate in our study (where monetary survey consolidates the account of the Central Bank and deposit money banks).

Second, our credit measure (claims on private sector from deposit money banks) isolates credit issued to the private sector, as opposed to credit issued to governments, government agencies, and public enterprises, following the empirical literature on finance and development. In the development literature, credit to the private sector (as expressed as percentages of GDP) is considered the most important banking development indicator, since it proxies the extent to which new firms have opportunities to obtain bank finance and it closely accords to the McKinnon-Shaw school's inside money model which asserts that it is the supply of credit to the private sector that determines both the level and component of investment. This in turn could influence the level of output and economic growth and better economic prospects could lead to increased flow of bank credit to the private sector, see for example Masih (2001).

One potential limitation of the measure 'claims on the private sector from deposit money banks' is that the private sector is composed of both individuals and non-financial corporations in the IFS statistics (no separate series are available), while our preferred credit measure is bank lending to non-financial corporations. Although some national sources publish separate series for bank credit to individuals and non-financial corporations (see for example the Fed Flow of Funds accounts), this measure can not be found in all the 33 countries considered in our analysis (for example, the Bank of Japan also groups bank credit to individual and non-finance corporations in their money and banking data). In order to maintain the consistency of the definition of 'private sector' in our analysis, we have decided to follow the IFS definition and use the series 'claims on the private sector from deposit money banks' (22d) as our preferred measure for private credit.

In addition, we explored the possibility of using a broader credit measure 'domestic

[35]For example, other banking institutions covers savings and mortgage loan institutions, post-office saving institutions, building and loan associations, finance companies that accept deposits or deposit substitutes, development banks and offshore banking institutions.

[36]See 'Guide to the Flow of Funds account' published by the Federal Reserve Statistical Release at http://www.federalreserve.gov/releases/z1/current/ for more details.

[37] The data category 'other banking institutions' is not available for the following countries: Australia, Austria, Belgium, China, Finland, France, Germany, India, Indonesia, Italy, Japan, Spain, Thailand, Turkey and United Kingdom.

credit' (line 32), which is the sum of the claims on central government, state and local government, non-financial public entreprises, private sector, other bank institutions and non bank financial institutions in the monetary survey. The measure 'domestic credit' captures the net credit available in the economy, with its components measuring the net rather than gross claims on the different sectors, such as net claims on central government. Since we are interested in the level of credit used for investment and production, rather than the transfer of credit between different sectors in the economy, 'domestic credit' is not an appropriate measure for our purpose. Furthermore, the other components 'claims on non-financial public enterprises' and 'claims on other banking institutions' of 'domestic credit' are often very small compared with 'claims on the private sector'.[38]

Third, we choose to use the *level* of 'claims on private sector from deposit money banks' rather than its *ratio* to GDP, as seen in the finance and development literature.[39] The reason is that our objective is not to study the extent of financial intermediation in the economy but the overall level of bank credit that is available to the private sector.

Our preferred Datastream series has a definition that is closest to the IFS series and a similar magnitude. Several studies on the role of credit also adopt the same credit measure, see for example Goodhart and Hofmann (2008) and Levine and Zervos (1998).

A1.2 Data on the Euro Zone

For countries within the Eurozone, two series are available for the measure 'Claims on Private Sector from Deposit Money Banks'. One series is denominated in national currency for the period from 1979Q1 to 1998Q4 (series 22d.zf), before the introduction of the Euro, the other series is denominated in euros from 1999Q1, after the introduction of the euro (series 22d.zw). The latter series is compiled on the base of national residency criteria (as oppose to Euro Area-wide residency criteria), described in the fifth edition of the IMF Balance of Payment Manual.

The former series denoted in national currency is converted into euro using an appropriate exchange rate series between euro and national currency. This exchange rate series is constructed using the ratio of two series, one being the synthetic Eurodollar exchange rate from Datastream, the other the exchange rate of dollar to national currency (consistent with the exchange rate used to derive the euro dollar rate in DdPS).[40]

[38]The measure 'domestic credit' can sometimes be negative (due to negative net claims on central government), while in fact bank credit to the private sector was in steady growth in the economy for the corresponding period, see for example Saudi Arabia from 1979Q1 to 1987Q3.

[39]For example, King and Levine (1993a,b) use the ratio of gross claims on the private sector (line 32d) to GDP in their study. Levine and Zervos (1998) and Levine (1998) use the ratio of deposit money bank credit to the private sector (line 22d) to GDP over the period 1976 to 1993. Levine, Loayza, and Beck (2000) uses a measure of private credit as an indicator of financial intermediary development from 1960 to 1995, where Private credit equals the ratio of credits by financial intermediaries to the private sector (line 22d+42d) to GDP.

[40]The synthetic Euro/US exchange rate in Datastream is constructed as follows: The EMU (European Monetary Unit) in national currencies are weighted by 1996 national GDP levels, and then expressed in Deutschmark terms using the bilateral rates set by the EU (implicitly taken as the best approximation to the fixed bilateral rates that will prevail on December 31, 1998). The individual components are each converted to Deutschmarks at current exchange rates using the Reuters Closing Spot Rates. Finally, by multiplying the series by the fixed Deutschmark/Euro rate, Datastream produces a Deutschemark/Euro exchange rate that reflects both the changing relative strengths of the EMU in countries over time and the presumed fixed local to Euro bilateral rates. By converting the series using the appropriate US/Deutschmark rate, also taken from Reuters, a synthetic Euro/US rate

In DdPS, quarterly averages of daily Datastream GTIS US$ exchange rate data, calculated based on the last Wednesday of each month within the quarter, are used for Brazil (1994Q1-2006Q4), Chile (1994Q1-2006Q4), Peru (1991Q1-2006Q4). For the rest of the countries (1986Q1-2006Q4), the rate of change of the IFS series 'rf.zf' is used to backfill the series to 1979Q1.

A1.3 Datastream credit series

As mentioned earlier, the series on credit to private sector in Datastream are taken from National Sources and the OECD Main Economics Indicators.[41] The credit series for Australia, Canada and the UK are taken from Datastream. A brief description of the series are given below.

For Australia, we use the datastream series (AUBANKLPA) from the Reserve Bank of Australia, which captures loans and advanced by banks, which includes all bank loans and advances to the private sector (including public trading enterprises) on the balance sheet of banks, net of loans to non-bank financial institutions (NBFIs).

For Canada, we use an OECD series (CNOCR016A) "credit to the private sector", which consists of consumer credits, residential mortgage credits, short-term (business loans, chartered bank foreign currency loans, banks' acceptances, commercial paper issued by non-financial corporations) and other (non-residential mortgages, leasing receivables, bonds and debentures, equity and other) business credit.

Finally, for the UK, we take a credit series from the Bank of England that measures bank and building society lending (UKVQJMQ.). This series represents the seasonally adjusted quarterly amounts outstanding of M4 lending (monetary financial institutions' sterling net lending to private sector) made by Banks and Building societies; where the M4 private sector consists of all UK residents other than the public sector and MFIs.[42]

The description of the Datastream series on credit for other countries is not presented here due to space considerations, but available upon request.

A1.4 Comparison between IFS and Datastream credit data

The choice of the appropriate credit series between the IFS and the Datastream series on a country by country basis is guided by two principles. First of all, we use the IFS series when no alternative series is available from Datastream or the available Datastream series have missing observations for more than a year. Second, for countries with full series available in Datastream, we compare the logarithms of the credit data in levels and first differences between IFS and Datastream and choose the series that are more consistent with the credit history of the country.[43] For Australia, Canada and UK, the Datastream series significantly improve upon the IFS credit series, where the spike in the Australia series in 1985 and the movement in the Canada and UK series at the beginning of the 80s can not be explained by the credit history in these economies.

is constructed. Documentation is available on-line at www.datastream.com.

[41] In datastream, the relevant credit series are available for the 33 countries in the GVAR except for Argentina and Saudi Arabia, however, only a number of countries have series for the full period from 1979Q1 to 2006Q4, namely Australia, Canada, France (data is missing from 1979Q1 to 1979Q4), Germany, Japan, Korea, Norway, South Africa, Spain, Turkey, the United Kingdom and the United States. Note also, the OECD credit series were discontinued from 2007Q2.

[42] For details, see http://www.bankofengland.co.uk/mfsd/iadb/notesiadb/M4_counterparts.htm

[43] The countries include Australia, Canada, France, Germany, Japan, Korea, Norway, South Africa, Turkey, the United Kingdom and the United States.

The spikes could be a result of measurement errors or a change in the definition of banking sector (although the level shift due to a change in definition have already been accounted for). We have decided to replace the IFS series with the Datastream series for Australia, Canada and the UK. For the rest of the countries, the Datastream series do not provide an improvement upon the IFS series and we decide the keep the credit series from the IFS database. In particular, the IFS series for the US reflects a more profound credit cycle, which is consistent with the credit history in the US and the changes in commercial credit standards as shown in the Loan Officer Opinion Survey, see for example Lown and Morgan (2006) and Lown, Morgan, and Rohatgi (2000).[44]

A2 Adjustments to credit data

A2.1 Interpolation

The countries with complete data series for 'Claims on private sector from Deposit Money Banks'(22d) are Argentina, Australia, Canada, Chile, India, Japan, Korea, Malaysia, Mexico, New Zealand, Peru, Singapore, Switzerland, Thailand, Turkey, UK and US. Some observations are missing for the following countries (missing data in bracket): 1) EU countries: Austria (1998Q4), Belgium (1998Q4), France (1998Q3 to 1998Q4), Netherlands (1998Q1 to 1998Q4). 2) Ex-EU countries: Brazil (1986Q3 to 1988Q1), China (1979Q1 to 1985Q3), Indonesia (1979Q1 to 1979Q4), Norway (1987Q1 and 1987Q2), Philippines (1983Q3, 1984Q1 to 1984Q3, 1985Q1 to 1985Q3, 1986Q1 to 1986Q3), Saudi Arabia (1983Q1 to 1983Q3), South Africa (1991Q3 and 1991Q4), Sweden (2001Q1 to 2001Q3).

For country series with missing observations, we interpolate the series with missing observations using the growth rate of a comparable series when available. For China, the credit data (Claims on private sector from Deposit Money Banks, 22d) from 1979Q1 to 1985Q3 is constructed by using the growth rate of the series 'Claims on private sector from Deposit Money Banks AND Monetary authority' (32d) (the two series have similar growth rate for overlapping periods). For Austria, missing observations for 1998Q4 was generated using the growth rate of a series from Datastream named 'lending to private sector' (OELNBNK.A). For France, missing observations for 1998Q3 and 1998Q4 were generated based on the growth rate of a Datastream series 'loans to resident private sector' (FRBANKLPA). For the Netherlands, missing observations from 1998Q1 to 1998Q4 were generated using the growth rate of a series 'bank lending to private sector' (NLBANKLPA) from Datastream. For South Africa, missing observations for 1991Q3 and 1991Q4 were generated from the growth rate of a Datastream series 'bank lending to private sector' (SABANKLPB). For Sweden, missing observations for 2001Q1 to 2001Q3 were generated from the growth rate of a comparable credit series on 'bank lending to non financial corporations' (SDBANKLPA) on Datastream. Following Goodhart and Hofmann (2008), missing observations in 1987Q1 to 1987Q2 for Norway were generated from the growth rate of an IMF series for credit extended by non bank financial institutions to the private sector (IFS series 42d).

In the case when comparable series are not available, we use the median growth rate of the adjacent four quarter as a proxy of the growth rate of the missing observations. For Indonesia, the credit data from 1979Q1 to 1979Q4 is constructed by using the

[44] The comparison charts for IFS and Datastream series in levels and first differences are not presented here due to space considerations, but are available upon request.

median growth rate of the next four quarter. For Belgium, Brazil and Saudi Arabia, missing observations (Belgium (1998Q4), Brazil (1986Q3 to 1988Q1) and Saudi Arabia (1983Q1 to 1983Q3)) were generated from the median growth rate of the previous four quarters. In the case of Philippines, the data was missing at multiple dates, missing observations for 1983Q3, 1984Q1 to 1984Q3, 1985Q1 to 1985Q3, 1986Q1 to 1986Q3 were generated from linear interpolation (alternative national sources and international sources also have observations missing for the corresponding periods).

A2.2 Adjusting for level shifts in the credit data

Many of the IMF credit series (claims on the private sector from deposit money banks) displayed large level shifts due to changes in definition and re-classifications of the banking institutions. For example, for countries in the euro area, a new reporting system is adopted after the introduction of the Euro (1999Q1), which consolidates the account of all resident units classified as other monetary financial institutions (other MFIs). A number of countries introduced improved classifications and sectorization of banking institutions, which led to changes in the definition of 'deposit money banks' over the sample period from 1979Q1 to 2006Q4. For example, the coverage of financial institutions in Germany was broadened to include all cooperative banks from 1985. In Singapore, post office savings deposits was classified under 'deposit money banks' from 1998Q4 and thereafter excluded from the category 'other banking institutions'.[45]

Following Stock and Watson (2003) and Goodhart and Hofmann (2008), we adjust for these level shifts by replacing the quarterly growth rate in the period when the shift occurs with the median of the growth rate of the two periods prior and after the level shift. The level of the series is then adjusted by backdating the series based on the adjusted growth rates.

The following level shifts were adjusted for (the dates at which the IMF credit series were butt spliced and the euro was introduced): Argentina 1990Q1, 1994Q1; Australia 1989Q1, 2002Q1; Austria 1984Q1 1995Q4, 1999Q1; Belgium 1992Q4, 1999Q1; Brazil 1986Q1, 1988Q2, 2001Q4; Canada 1981Q4 2001Q4; Chile 1997Q4; China 1993Q1 2002Q1; France 1999Q1; Germany 1985Q4 1990Q2 1999Q1; Indonesia 1992Q4 2001Q4 2004Q2; Italy 1999Q1; Japan 1997Q4 2001Q4; Malaysia 1992Q1 1996Q4 2001Q4 2002Q4; Mexico 1982Q1 1997Q1 2001Q4; Netherlands 1982Q4 1999Q1; New Zealand 1988Q3; South Africa 1992Q1 2001Q4 2002Q2; Saudi Arabia 1983Q4 1992Q4; Spain 1983Q1 1986Q1 1999Q1; Sweden 1983Q1 1996Q1 2001Q4; Switzerland 1982Q3 1984Q4 1996Q4; Thailand 1986Q1 2001Q4 2002Q4; United Kingdom 1981Q4 1986Q3 1992Q3 1999Q3; United States 2001Q4.

Even after all the necessary adjustment on the credit series (to account for changes in the definition of banking sector), we see clear evidence of banking and economic crises from the sudden drop in credit supply. For example, Mexico's economy enjoyed a stage of rapid credit expansion from December 1988 to November 1994, till the Peso crisis took place in December 1994. In addition to a sudden stop of foreign capital, domestic credit

[45] In addition, Austria adopted new sectorization of accounts in 1984Q1, Brazil in 2001Q4, Finland in 1991Q1, Indonesia in 1992Q4, Japan in 1998Q2 and 2001Q4, Malaysia in 2002Q4, Mexico in 2001Q4, Philippines in 1983Q4, South Africa in 2002Q2, Thailand in 2001Q4, Turkey in 2002Q4 and the United States in 2001Q4. The table with detailed definition of banking institutions ('deposit money banks' and 'other banking institutions') and changes in the definition for the 33 countries in the GVAR is not presented here due to space considerations, but available upon request.

Table A1: Occurrence of Banking Crisis in Selected Countries

Country	Dates	Description	Literature
Philippines	1984Q1	Debt crisis	Intal and Llanto (1998)
	1997Q4	Asia Financial Crisis	Chan-Lau and Chen (1998)
Thailand	1998Q1	Asia Financial Crisis	Chan-Lau and Chen (1998)
Indonesia	1998Q3-1999Q2	Asia Financial Crisis	Chan-Lau and Chen (1998)
Malaysia	1983Q3	Debt crisis	Hagen and Ho (2008)
	1999Q1	Asia Financial Crisis	Hagen and Ho (2008)
Mexico	1995Q1	Mexico Peso Crisis	Hagen and Ho (2008)
Argentina	1989-1990	Banking Crisis	Glick and Hutchison (2001)
Brazil	1990	Banking Crisis	Glick and Hutchison (2001)
Austria	1985Q1	Banking Crisis	Hagen and Ho (2008)
Finland	1991Q3	Banking Crisis	Kaminsky and Reinhart (1999)
New Zealand	1983Q1	Banking Crisis	Hagen and Ho (2007)

provision in Mexico contracted in 1995.[46] Countries in Southeast Asia experienced a severe credit crunch during the Asia Financial Crisis in 1997-1998, as observed in the credit series for Philippines (1997Q4), Thailand (1998Q1) and Indonesia (1998Q3-1999Q2). Table A1 reports the date of banking crisis identified by the literature, which could contribute to the unusual movement that we observe in the credit series.

A2.3 Seasonal Adjustments

Seasonality is identified in the credit series in the following countries Australia, Austria, Belgium, China, Finland, France, Germany, India, Italy, Japan, Mexico, Philippines, Saudi Arabia, Spain, Switzerland, Thailand, Turkey and US, according the combined test for the presence of identifiable seasonality.[47]

To seasonally adjust the level of the *log real* credit series (integrated of order one), we first adjust the **change** in the log real credit series using the X-12 quarterly seasonal adjustment method in Eviews, under the additive option. Then we use the first observation of raw series in the level of log real credit (not seasonally adjusted) and the seasonally adjusted series of change in log real credit to accumulate the seasonally adjusted series in the **level** of log real credit.

A3 Extension of the dataset to 2009Q4

A3.1 Credit series

For all countries except for Australia, Canada, Norway, Sweden and the United Kingdom, the credit series are taken from the IFS dataset (series 22d., claims on the private sector). For Australia, we extend the credit data using the Datastream series (AUBANKLPA) from the Reserve Bank of Australia. For Canada, the original OECD series "credit to the private sector" was discontinued in 2007Q3, instead we use a comparable series from the Bank of Canada, "Canada: Business and Household Credit" (Haver mnemonics S156FCB@G10) to extend the series to 2009. For Norway and Sweden, the IFS series 22d were discontinued in 2007Q1 and 2009Q3 respectively. We use a comparable series from the Bank of Norway, "Credit: From Private Banks" (Haver

[46] See for example http://www.cato.org/pubs/journal/cj17n3-14.html

[47] The results of seasonality tests are not presented here due to space considerations, but are available upon request.

mnemonics NONFCPV@NORDIC) to extend the credit data for Norway. In the case of Sweden, a comparable series "MFI Lending to Swedish Non-MFIs" (Haver mnemonics SENFL@NORDIC) from Statistiska Centralbyran/Sveriges Riksbank was used, to extend the credit data for Sweden. For the UK, again we use the Datastream series (UKVQJMQ.) from the Bank of England that measures bank and building society lending.

In order the extend the credit dataset from 2006Q4 to 2009Q4, we first download the nominal credit series from the sources described above, covering 2002Q1 to 2009Q4. We then covert the nominal series to real credit series using CPI data and seasonally adjust the real credit series using X-12 quarterly seasonality adjustment method in Eviews, as described in A2.3. Finally, we use the growth rate of the new seasonally adjusted series from 2002Q1 to 2009Q4, to extend the original credit series from 2007Q1 to 2009Q4.

A3.2 Other variables

For all the other variables included in our analysis, namely output, inflation, equity prices, short run, long run interest rates and oil prices, we extend the existing dataset from 2007Q1 to 2009Q4 using the growth rate of data series from Cesa-Bianchi, Pesaran, Rebucci, and Xu (2011).

B Test Results

B1 Lag order and Cointegration Relationships

Table B1: VARX* Order and Number of Cointegration Relationships in the Country-specific Models

Country	VARX*(p_i, q_i)		No. of	Country	VARX*(p_i, q_i)		No. of
	p_i	q_i	CR		p_i	q_i	CR
China	2	1	2	Malaysia	1	1	1
Euro Area	2	1	3	Philippines	2	1	2
Japan	2	1	4	Singapore	1	1	3
Argentina	2	1	3	Thailand	1	1	**2**
Brazil	2	1	2	India	2	1	1
Chile	2	1	3	South Africa	2	1	3
Mexico	2	1	4	Saudi Arabia	2	1	1
Peru	2	1	3	Turkey	2	1	2
Australia	2	1	**3**	Norway	2	1	4
Canada	2	1	4	Sweden	2	1	**3**
New Zealand	2	1	**3**	Switzerland	2	1	3
Indonesia	2	1	3	UK	2	2	**3**
Korea	2	1	4	US	2	1	**2**

Note: The lag orders of the VARX* models are selected by AIC. The number of cointegration relationships are based on trace statistics with MacKinnon's asymptotic critical values. To resolve the issues of potential overestimation of cointegration relationships with asymptotic critical values, we reduce the number of cointegration relationships for six countries, as marked in bold, to be consistent to economic theory and to maintain the stability in the global model.

B2 Weak Exogeneity Test

Table B2: F-statistics for Testing the Weak Exogeneity of the Country-specific Foreign Variables and Oil Prices

Country		Foreign variables							
		y_t^*	Δp_t^*	q_t^*	$\rho_t^{S^*}$	$\rho_t^{L^*}$	crd_t^*	p_t^o	$e_t^* - p_t^*$
China	F(2,79)	1.953	1.351	0.378	0.126	0.312	1.508	1.517	
Euro Area	F(3,72)	0.187	2.495	1.710	2.726	0.898	1.408	1.305	
Japan	F(4,73)	0.597	0.991	0.71	1.761	1.336	0.233	1.832	
Argentina	F(3,76)	0.653	0.55	0.178	0.85	0.689	1.706	0.619	
Brazil	F(2,79)	0.242	1.957	1.703	2.258	0.843	3.664†	0.582	
Chile	F(3,76)	1.305	0.07	0.325	0.841	1.066	1.907	0.336	
Mexico	F(4,77)	0.717	1.187	0.539	2.411	0.272	1.878	0.258	
Peru	F(3,78)	1.062	1.193	0.731	1.671	0.45	0.369	4.517†	
Australia	F(3,74)	0.254	3.553†	0.029	2.581	2.176	1.174	0.415	
Canada	F(4,73)	0.867	0.741	0.631	0.7	0.822	0.673	0.523	
New Zealand	F(3,74)	0.229	1.198	1.725	0.504	1.007	1.449	1.545	
Indonesia	F(3,78)	0.871	1.633	0.866	0.669	0.062	0.388	0.753	
Korea	F(4,73)	1.508	0.627	0.77	0.897	0.679	2.262	0.896	
Malaysia	F(1,84)	0.031	0.375	0.425	0.03	0.342	0.212	0.01	
Philippines	F(2,77)	0.064	1.031	0.471	0.765	0.189	1.368	1.327	
Singapore	F(3,82)	0.478	0.708	1.135	0.132	0.905	0.404	0.294	
Thailand	F(2,83)	4.166†	1.292	0.542	1.05	1.228	1.835	1.229	
India	F(1,78)	0.039	0.111	1.433	0.028	0.375	0.022	0.011	
South Africa	F(3,74)	1.487	2.532	0.312	1.767	1.736	1.666	0.304	
Saudi Arabia	F(1,82)	0.01	0.019	0.006	1.054	0.199	0.588	0.179	
Turkey	F(2,79)	4.029†	0.233	0.725	2.757	0.403	0.148	0.415	
Norway	F(4,73)	1.249	1.252	0.83	1.057	1.485	0.588	2.168	
Sweden	F(3,74)	0.214	1.419	1.132	0.149	0.688	0.471	0.433	
Switzerland	F(3,74)	0.154	0.2	1.163	0.199	0.59	1.668	2.778	
UK	F(3,74)	0.409	0.774	0.125	0.135	0.056	2.532	0.397	
US	F(2,83)	0.143	1.309		1.247				2.57

Note: These F statistics test zero restrictions on the coefficients of the error correction terms in the error-correction regression for the country-specific foreign variables. '†' indicates significance at 5% level. The lag orders of the VARX* models used for the weak exogeneity tests are set as follows: the lag order for the domestic variable is equal to the that in the GVAR model selected by AIC, the lag order for the foreign variables is set to be two for all countries except the euro zone where we use the lag order 4, since there was serial correlation in several of the regression equations with lower order.

B3 Non-nested Tests

Table B3: W-test for Credit Model (M_1) against Benchmark Model (M_2)

Equation	Δy_t	$\Delta(\Delta p_t)$	Δq_t	$\Delta(e_t - p_t)$	$\Delta\rho_t^S$	$\Delta\rho_t^L$	p_t^o
China	0.285	0.440		-1.860	-2.908*		
Euro Area	-0.171*	1.010	-4.426*	1.444	-0.331	-2.621*	
Japan	0.614	-0.125	0.041	-10.236*	1.419	0.339	
Argentina	0.679	-0.577	-9.393*	-2.268*	-1.676		
Brazil	-3.619*	-0.122		-3.122*	0.800		
Chile	-2.658*	-1.638	1.337	-7.701*	-3.507*		
Mexico	-0.957	-0.002		0.205	-0.987		
Peru	-0.294	-4.094*		-2.418*	-1.761		
Australia	-1.421	0.252	-5.689*	-1.547	-3.033*	1.514	
Canada	-3.289*	-2.279*	-1.430	-0.955	-0.575	-0.751	
New Zealand	-2.481*	-1.363	0.084	-19.230*	-0.956	-1.635	
Indonesia	-4.455*	-0.894		0.673	-2.932*		
Korea	-1.491	0.360	-0.989	0.611	0.269	0.562	
Malaysia	-1.633	-1.789	0.356	0.151	0.256		
Philippines	0.228	-0.785	-0.016	1.077	0.305		
Singapore	1.263	-0.050	-1.561	-1.643	-6.986*		
Thailand	-2.128*	-9.457*	-0.267	-0.404	-2.611*		
India	-1.133	0.837	-2.185*	0.487	-16.743*		
South Africa	-0.882	-0.123	-0.323	-1.369	-1.872*	-1.565	
Saudi Arabia	1.963*	0.510		1.075			
Turkey	-0.054	-2.102*		-5.062*	-1.344		
Norway	-2.049*	-0.147	-0.039	-4.144*	-1.169	1.185	
Sweden	-2.523*	-0.653	1.245	-2.169*	-1.184	0.173	
Switzerland	0.521	-5.466*	-1.240	-0.353	0.832	0.860	
UK	-1.322	0.331	1.861	-12.846*	-1.409	-2.966*	
US	2.179*	-3.355*	-0.055		-5.180*	-4.150*	0.454

Note: H_0: M_1 is the right model; H_1: M_2 is the right model. * indicates significance at 5% level. A negative and significant value indicates that H_0 can be rejected at 5% level.

Table B4: W-test for Benchmark Model (M_2) against Credit Model (M_1)

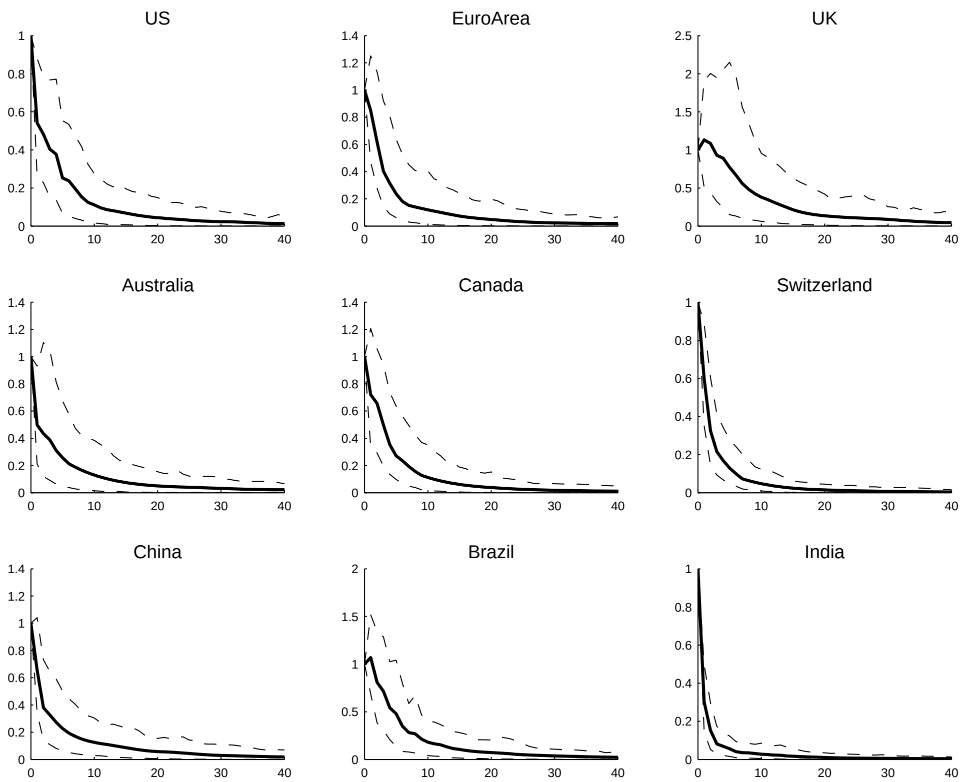
Equation	Δy_t	$\Delta(\Delta p_t)$	Δq_t	$\Delta(e_t - p_t)$	$\Delta\rho_t^S$	$\Delta\rho_t^L$	p_t^o
China	-0.236	-4.292*		-3.689*	1.349		
Euro Area	-2.427*	-4.905*	-0.149	-5.200*	-1.219	0.432	
Japan	-3.168*	-2.787	0.159	0.678	-1.306	-1.185	
Argentina	-0.083	-5.476*	0.514	-0.548	-2.151*		
Brazil	0.301*	-3.980*		-1.232	-4.540*		
Chile	1.119	-0.996	-8.778*	0.317	1.041		
Mexico	-2.702*	-3.609*		-5.256*	-4.972*		
Peru	-2.469*	-0.404		-0.929	-2.507*		
Australia	-2.457*	-2.693*	-1.486	-1.340	-1.809	-4.552*	
Canada	1.052	-2.490*	-1.761	-0.663	-0.473	-7.922*	
New Zealand	-7.495*	-2.020*	-9.624*	1.131	0.304	-2.884*	
Indonesia	0.663	-5.566*		-2.536*	-0.761		
Korea	-2.168*	-0.896	-2.565*	-1.877	0.153	-3.086*	
Malaysia	1.190	-0.480	-0.261	0.367	-2.933*		
Philippines	0.060	0.365	-1.775	-0.090	-2.592*		
Singapore	-1.865	-1.367	-5.918*	0.660	1.531		
Thailand	-1.833	-0.315	-0.379	0.088	-0.260		
India	-0.308	-7.474*	1.064	-3.050*	2.017*		
South Africa	-4.645*	-0.505	-0.996	-1.233	-0.999	-2.729*	
Saudi Arabia	-1.485	-2.311*		-2.060*			
Turkey	-1.454	-0.013		0.181	-4.549*		
Norway	-1.128	-2.265*	-4.554*	-1.452	-1.233	-5.436*	
Sweden	1.291	-1.398	-0.824	-1.061	-1.122	-4.589*	
Switzerland	-0.630	-0.832	1.266	0.162	-1.160	-2.021*	
UK	-1.662	-1.141	-2.293*	-1.870	0.545	1.290	
US	-6.301*	-0.776	0.623		0.640	1.510	-0.339

Note: H_0: M_2 is the right model; H_1: M_1 is the right model. (Note the reverse in the null and alternative hypothesis in comparison to the test of M_1 against M_2). * indicates significance at 5% level. A negative and significant value indicates that H_0 can be rejected at 5% level.

B4 Stability of the global system and persistence profiles

It is important to note that the global model is stable, supported by the persistence profiles, the eigenvalues of the system and the responses in the GIRFs. The persistence profiles refer to the time profiles of the effects of system or variable specific shocks on the cointegration relations in the GVAR model.[48] We use persistence profiles to examine the effect of system-wide shocks on the dynamics of the long-run relations.[49] As shown in DHPS, the value of these profiles is unity on impact, while it should tend to zero as $n \to \infty$, if the vector under investigation is indeed a cointegration vector. The persistence profiles of the system suggests that all cointegrating relationships return to their long run equilibrium within a ten year period after a shock to the system, although the speed of convergence varies greatly depending on countries. The persistence profiles for a selection of the cointegrating vectors are shown in Figure B1.

Figure B1: Persistence Profiles for a Selection of Cointegrating Vectors



The Persistence Profiles together with the Generalized Impulse Response Functions suggest that the model is stable, which is supported by the eigenvalues of the GVAR model. Following PSW, we do not expect the rank of the cointegrating matrix in the global model to exceed 71 (the number of cointegrating relations in all the individual country models). As a result, the global system should have at least 89 (the number of variables-the number of cointegrating relationships=160-71) unit roots. Indeed the global system has 90 eigenvalues that fall on the unit circle, with the remaining eigenvalues having moduli all less than unity.[50]

[48] See Pesaran and Shin (1996) for a discussion on persistence profile applied to cointegrating models.

[49] See DHPS for the detailed mathematical exposition of the persistence profile.

[50] Among the remaining eigenvalues, 164 (82 pairs) are complex, which introduces cyclical features in the impulse responses. The eigenvalues with the largest complex parts are $0.043045 \pm 0.663667i$

C Results from Country Specific Models

C1 In sample fit in country specific models

Table C1: In Sample Fit and Diagnostics for the UK, Japan and China

UK VARX*(2,2)–CV=3							
Equation	Δy_t	$\Delta(\Delta p_t)$	Δq_t	$\Delta(e_t - p_t)$	$\Delta \rho_t^S$	$\Delta \rho_t^L$	Δcrd_t
Core $\bar{R}^2$	**0.597**	**0.678**	**0.775**	0.307	0.169	0.408	0.683
Benchmark1 $\bar{R}^2$	0.578	0.667	0.752	0.445	0.219	0.463	
Benchmark2 $\bar{R}^2$	0.347	0.145	-0.004	0.039	0.032	0.035	
$\hat{\sigma}$	0.004	0.004	0.032	0.040	0.002	0.0009	0.007
$\chi^2_{SC}[4]$	3.402	8.042*	5.133	5.600	2.530	1.665	8.546*
$\chi^2_{FF}[1]$	7.502†	1.476	1.540	1.180	0.733	0.542	2.707
$\chi^2_{N}[2]$	2.944	1.715	28.238†	173.801†	20.288†	3.323	7.597†
$\chi^2_{H}[1]$	1.219	0.032	0.470	0.025	1.672	3.704*	4.816†
Japan VARX*(2,1)–CV=4							
Equation	Δy_t	$\Delta(\Delta p_t)$	Δq_t	$\Delta(e_t - p_t)$	$\Delta \rho_t^S$	$\Delta \rho_t^L$	Δcrd_t
Core $\bar{R}^2$	**0.418**	**0.639**	0.391	0.088	**0.552**	**0.378**	0.715
Benchmark 1 $\bar{R}^2$	**0.338**	**0.601**	0.391	0.304	**0.532**	**0.355**	
Benchmark 2 $\bar{R}^2$	0.155	0.342	0.140	0.074	0.263	-0.004	0.578
$\hat{\sigma}$	0.006	0.003	0.065	0.051	0.001	0.0008	0.007
$\chi^2_{SC}[4]$	6.569	4.221	5.013	16.311†	20.141†	4.695	12.782†
$\chi^2_{FF}[1]$	0.072	5.849†	0.00003	1.822	2.217	2.761*	5.610†
$\chi^2_{N}[2]$	2.660	8.858†	6.578†	2.869	123.202†	1.193	1.889
$\chi^2_{H}[1]$	0.725	2.209	2.364	0.579	13.371†	3.088^{*r}	0.408
China VARX(2,1)–CV=2							
Equation	Δy_t	$\Delta(\Delta p_t)$	Δq_t	$\Delta(e_t - p_t)$	$\Delta \rho_t^S$	$\Delta \rho_t^L$	Δcrd_t
Core $\bar{R}^2$	0.712	0.204		0.273	0.322		0.328
Benchmark1 $\bar{R}^2$	0.713	0.090		0.181		0.372	
Benchmark2 $\bar{R}^2$	0.662	0.090		0.028	0.057		0.104
$\hat{\sigma}$	0.004	0.009		0.041	0.001		0.023
$\chi^2_{SC}[4]$	13.924†	11.382†		4.472	13.892†		7.175
$\chi^2_{FF}[1]$	0.641	6.658†		13.061†	0.053		3.585*
$\chi^2_{N}[2]$	63.050†	22.885†		796.234†	42.870†		103.012†
$\chi^2_{H}[1]$	0.723	0.545		30.108†	24.367†		21.387†

and -0.551615 ± 0.611136i, where $i = \sqrt{-1}$. After the unit roots, the three largest eigenvalues (in moduli) are 0.96499, 0.920200 and 0.913697, implying a rapid rate of convergence of the model after a shock to its long run equilibrium.

Table C2: In Sample Fit and Diagnostics for Other Advanced Economies

Equation	Δy_t	$\Delta(\Delta p_t)$	Δq_t	$\Delta(e_t - p_t)$	$\Delta \rho_t^S$	$\Delta \rho_t^L$	Δcrd_t
Switzerland VARX*(2,1)–CV=3							
$\bar{R}^2$	0.566	0.462	0.772	0.281	0.403	0.510	0.432
Benchmark1 $\bar{R}^2$	0.559	0.551	0.781	0.285	0.387	0.479	
Benchmark2 $\bar{R}^2$	0.069	0.171	0.053	0.019	0.069	0.137	0.235
$\hat{\sigma}$	0.005	0.003	0.036	0.045	0.001	0.0005	0.009
$\chi^2_{SC}[4]$	4.197	7.848*	3.077	2.063	12.693†	13.612†	5.292
$\chi^2_{FF}[1]$	0.810	3.022*	10.284†	0.007	7.110†	0.007	5.398†
$\chi^2_{N}[2]$	1.882	6.992†	3.960	1.493	0.636	0.850	15.076†
$\chi^2_{H}[1]$	0.200	0.085	3.926†	0.015	0.223	0.006	0.199
New Zealand VARX*(2,1)–CV=3							
$\bar{R}^2$	0.346	0.501	0.621	0.153	0.468	0.441	0.388
Benchmark1 $\bar{R}^2$	0.198	0.464	0.470	0.461	0.479	0.427	
Benchmark2 $\bar{R}^2$	0.025	0.157	0.200	0.073	0.014	0.100	0.096
$\hat{\sigma}$	0.008	0.007	0.055	0.046	0.003	0.001	0.034
$\chi^2_{SC}[4]$	15.627†	11.403†	22.272†	3.829	8.912*	18.577†	1.026
$\chi^2_{FF}[1]$	1.198	10.488†	4.318†	0.493	4.784†	9.394†	7.674†
$\chi^2_{N}[2]$	34.011†	29.919†	7.129†	39.930†	24.923†	8.499†	54.568†
$\chi^2_{H}[1]$	0.507	38.008†	0.468	0.263	10.582†	28.390†	5.186†
Korea VARX*(2,1)—CV=4							
$\bar{R}^2$	0.545	0.541	0.414	0.284	0.456	0.284	0.196
Benchmark1 $\bar{R}^2$	0.518	0.529	0.385	0.242	0.461	0.208	
Benchmark2 $\bar{R}^2$	0.047	0.350	0.046	0.130	0.112	0.025	0.053
$\hat{\sigma}$	0.012	0.008	0.106	0.039	0.003	0.002	0.018
$\chi^2_{SC}[4]$	6.807	11.303†	2.420	6.742	7.150	2.012	4.291
$\chi^2_{FF}[1]$	11.844†	5.720†	0.011	9.491†	0.521	0.106	1.596
$\chi^2_{N}[2]$	0.804	4.069	1.233	5074.8†	54.940†	3.004	1.769
$\chi^2_{H}[1]$	6.201†	14.356†	2.716*	1.378†	0.224	0.536	5.288†
Norway VARX*(2,1)—CV=4							
$\bar{R}^2$	0.509	0.623	0.680	0.197	0.474	0.589	0.166
Benchmark1 $\bar{R}^2$	0.516	0.593	0.616	0.222	0.487	0.456	
Benchmark2 $\bar{R}^2$	0.345	0.331	0.036	0.027	-0.0006	0.129	0.166
$\hat{\sigma}$	0.013	0.004	0.064	0.039	0.002	0.001	0.022
$\chi^2_{SC}[4]$	12.628†	2.819	7.357	1.871	0.969	19.922†	3.297
$\chi^2_{FF}[1]$	19.300†	10.737†	1.728	0.0002	11.232†	0.004	0.101
$\chi^2_{N}[2]$	5.009*	54.941†	0.056	0.482	259.598†	0.103	0.623
$\chi^2_{H}[1]$	8.936†	14.786†	2.532	0.185	4.467†	0.422	2.304
Australia VARX*(2,1)—CV=3							
$\bar{R}^2$	0.303	0.543	0.473	0.162	0.277	0.407	0.550
Benchmark1 $\bar{R}^2$	0.274	0.503	0.550	0.134	0.265	0.286	
Benchmark2 $\bar{R}^2$	0.067	0.298	0.005	0.063	0.038	0.046	0.424
$\hat{\sigma}$	0.007	0.006	0.060	0.040	0.002	0.001	0.009
$\chi^2_{SC}[4]$	2.099	1.411	7.929†	9.568†	2.440	3.362	14.655†
$\chi^2_{FF}[1]$	0.604	12.073†	7.666†	0.399	2.809*	0.239	0.008
$\chi^2_{N}[2]$	0.481	13.087†	4.530	1.711	52.665†	10.098†	3.420
$\chi^2_{H}[1]$	0.117	7.705†	33.775†	0.887	0.255	0.283	0.324
Canada VARX*(2,1)–CV=4							
$\bar{R}^2$	0.491	0.555	0.804	0.360	0.666	0.851	0.723
Benchmark1 $\bar{R}^2$	0.546	0.547	0.797	0.363	0.663	0.793	
Benchmark2 $\bar{R}^2$	0.302	0.220	0.080	0.189	0.062	0.006	0.433
$\hat{\sigma}$	0.005	0.004	0.032	0.019	0.001	0.0005	0.005
$\chi^2_{SC}[4]$	8.646*	18.008†	7.428	18.438†	10.256†	6.101	6.182
$\chi^2_{FF}[1]$	0.000001	0.431	2.260	0.208	0.817	4.260†	6.560†
$\chi^2_{N}[2]$	1.498	35.085†	1.738	2.450	10.598†	1.452	1.160
$\chi^2_{H}[1]$	1.073	0.188	0.111	4.345†	1.775	4.704†	0.848
Sweden VARX*(2,1)–CV=3							
$\bar{R}^2$	0.405	0.573	0.688	0.140	0.309	0.675	0.103
Benchmark1 $\bar{R}^2$	0.451	0.558	0.679	0.143	0.312	0.612	
Benchmark2 $\bar{R}^2$	0.174	0.283	0.099	0.080	-0.009	0.236	0.325
$\hat{\sigma}$	0.010	0.005	0.061	0.047	0.002	0.0008	0.025
$\chi^2_{SC}[4]$	7.389	14.328†	12.875†	7.302	7.896*	4.135	27.267†
$\chi^2_{FF}[1]$	1.857	0.135	0.090	8.721†	0.091	3.707*	2.076
$\chi^2_{N}[2]$	0.089	23.221†	1.078	6.455†	40.894†	8.234†	0.327
$\chi^2_{H}[1]$	3.474*	0.296	0.0000004	1.060	0.260	1.173	3.501*

Table C3: In Sample Fit and Diagnostics, Asia and Turkey

Equation	Δy_t	$\Delta(\Delta p_t)$	Δq_t	$\Delta(e_t - p_t)$	$\Delta\rho_t^S$	Δcrd_t
India VARX*(2,1)–CV=1						
$\bar{R}^2$	0.036	0.377	0.127	0.104	-0.014	0.028
Benchmark1 $\bar{R}^2$	0.049	0.204	0.174	0.023	0.275	
Benchmark2 $\bar{R}^2$	0.104	0.232	0.064	0.062	0.0009	0.003
$\hat{\sigma}$	0.011	0.010	0.128	0.029	0.002	0.027
$\chi^2_{SC}[4]$	9.973†	2.828	1.934	4.644	9.427†	1.276
$\chi^2_{FF}[1]$	3.716*	2.386*	0.158	6.782†	0.013	6.651†
$\chi^2_{N}[2]$	11.343†	84.312†	72.297†	93.608†	261.457†	48.372†
$\chi^2_{H}[1]$	2.109	4.226†	0.834	43.839†	0.655	0.040
Singapore VARX*(1,1)–CV=3						
$\bar{R}^2$	0.418	0.500	0.759	0.290	0.270	0.319
Benchmark1 $\bar{R}^2$	0.388	0.486	0.726	0.323	0.402	
Benchmark2 $\bar{R}^2$	0.089	0.237	0.017	0.017	0.152	0.151
$\hat{\sigma}$	0.013	0.005	0.054	0.019	0.002	0.019
$\chi^2_{SC}[4]$	5.116	24.788†	9.519†	3.038	14.472†	3.462
$\chi^2_{FF}[1]$	0.788	0.021	0.445	0.387	0.087	3.507*
$\chi^2_{N}[2]$	1.875	14.538†	3.652	8.689†	47.695†	86.230†
$\chi^2_{H}[1]$	3.500*	4.649†	4.488†	0.804	0.706	0.027
Malaysia VARX*(1,1)—CV=1						
$\bar{R}^2$	0.335	0.420	0.443	0.067	0.172	0.034
Benchmark1 $\bar{R}^2$	0.348	0.439	0.440	0.071	0.121	
Benchmark2 $\bar{R}^2$	0.126	0.264	-0.007	0.180	0.024	-0.008
$\hat{\sigma}$	0.013	0.004	0.110	0.031	0.001	0.052
$\chi^2_{SC}[4]$	2.972	4.104	6.179	14.487†	5.806	1.965
$\chi^2_{FF}[1]$	9.138†	1.968	1.020	2.670	2.868*	1.597
$\chi^2_{N}[2]$	3.743	0.718	11.066†	2509.2†	130.000†	2754.3†
$\chi^2_{H}[1]$	0.165	9.152†	0.396	0.139	17.956†	0.167
Philippines VARX*(2,1)–CV=2						
$\bar{R}^2$	0.202	0.577	0.405	0.114	0.485	0.558
Benchmark1 $\bar{R}^2$	0.206	0.585	0.381	0.113	0.446	
Benchmark2 $\bar{R}^2$	0.077	0.265	0.102	0.049	0.039	0.487
$\hat{\sigma}$	0.014	0.015	0.135	0.041	0.004	0.032
$\chi^2_{SC}[4]$	6.466	3.303	0.972	1.310	7.177	11.844†
$\chi^2_{FF}[1]$	1.884	3.628*	11.488†	6.448†	0.001	0.040
$\chi^2_{N}[2]$	38.525†	47.575†	102.568†	60.929†	29.434†	0.171
$\chi^2_{H}[1]$	1.166	1.154	34.294†	0.716	13.354†	1.536
Thailand VARX*(1,1)–CV=2						
$\bar{R}^2$	0.526	0.261	0.339	-0.010	0.120	0.669
Benchmark1 $\bar{R}^2$	0.537	0.533	0.337	0.005	0.147	
Benchmark2 $\bar{R}^2$	0.259	0.255	0.018	0.122	-0.007	0.566
$\hat{\sigma}$	0.011	0.009	0.116	0.043	0.004	0.019
$\chi^2_{SC}[4]$	6.536	13.363†	2.825	18.601†	1.780	1.668
$\chi^2_{FF}[1]$	14.075†	6.045†	0.078	15.921†	12.204†	3.076*
$\chi^2_{N}[2]$	31.959†	1.706†	11.880†	599.463†	53.280†	11.088†
$\chi^2_{H}[1]$	0.017	14.586†	0.264	8.383†	2.646	0.778
Indonesia VARX*(2,1)–CV=3						
$\bar{R}^2$	0.386	0.620		0.428	0.251	0.648
Benchmark1 $\bar{R}^2$	0.478	0.491		0.376	0.272	
Benchmark2 $\bar{R}^2$	-0.009	0.073		0.121	0.045	
$\hat{\sigma}$	0.018	0.017		0.080	0.009	0.048
$\chi^2_{SC}[4]$	6.789	12.599†		7.367	6.732	17.053†
$\chi^2_{FF}[1]$	0.583	0.004		18.670†	3.229*	7.190†
$\chi^2_{N}[2]$	91.190†	35.745†		302.722†	1637.0†	31.131†
$\chi^2_{H}[1]$	2.144	19.763†		60.132†	0.005	3.115*
Turkey VARX*(2,1)–CV=2						
$\bar{R}^2$	0.181	0.533		0.111	0.257	0.342
Benchmark1 $\bar{R}^2$	0.144	0.547		0.167	0.160	
Benchmark2 $\bar{R}^2$	0.079	0.250		-0.006	0.002	0.192
$\hat{\sigma}$	0.024	0.031		0.066	0.013	0.056
$\chi^2_{SC}[4]$	9.966†	7.667		4.881	5.757	6.851
$\chi^2_{FF}[1]$	6.370†	2.586		18.413†	0.616	1.547
$\chi^2_{N}[2]$	63.601†	150.085†		22.805†	73.961†	1.547†
$\chi^2_{H}[1]$	0.010	5.562†		6.032†	34.748†	0.131

Table C4: In Sample Fit and Diagnostics, Latin America and Others

Equation	Δy_t	$\Delta(\Delta p_t)$	Δq_t	$\Delta(e_t - p_t)$	$\Delta\rho_t^S$	$\Delta\rho_t^L$	Δcrd_t
Chile VARX*(2,1)–CV=3							
$\bar{R}^2$	0.382	0.427	0.517	0.358	0.396		0.544
Benchmark1 $\bar{R}^2$	0.445	0.430	0.280	0.477	0.482		
Benchmark2 $\bar{R}^2$	0.057	0.246	0.142	0.208	0.201		0.145
$\hat{\sigma}$	0.017	0.014	0.081	0.039	0.014		0.032
$\chi^2_{SC}[4]$	4.280	5.906	2.814	24.839†	1.306		9.227*
$\chi^2_{FF}[1]$	7.759†	0.413	0.770	6.709†	9.196†		5.356†
$\chi^2_{N}[2]$	3.884	99.800†	0.144	193.117†	97.596†		43.258†
$\chi^2_{H}[1]$	2.011	3.467*	1.644	1.700	4.677†		10.932†
Argentina VARX*(2,1)–CV=3							
$\bar{R}^2$	0.437	0.873	0.247	0.297	0.642		0.702
Benchmark1 $\bar{R}^2$	0.433	0.836	0.407	0.309	0.634		
Benchmark2 $\bar{R}^2$	0.325	0.226	-0.004	-0.023	0.372		0.138
$\hat{\sigma}$	0.017	0.104	0.278	0.130	0.119		0.083
$\chi^2_{SC}[4]$	7.045	6.622	9.029*	8.133*	0.722		18.929†
$\chi^2_{FF}[1]$	7.044†	5.314†	2.334	12.647†	2.210		26.464†
$\chi^2_{N}[2]$	10.397†	193.883†	14.989†	70.094†	224.504†		13.875†
$\chi^2_{H}[1]$	0.452	0.181	0.130	15.628†	20.416†		19.153†
Mexico VARX*(2,1)–CV=4							
$\bar{R}^2$	0.464	0.599		0.420	0.496		0.579
Benchmark1 $\bar{R}^2$	0.433	0.541		0.265	0.392		
Benchmark2 $\bar{R}^2$	0.066	0.072		0.018	0.059		0.341
$\hat{\sigma}$	0.011	0.022		0.053	0.011		0.046
$\chi^2_{SC}[4]$	11.136†	4.895		2.211	17.058†		17.494†
$\chi^2_{FF}[1]$	5.033†	14.713†		11.704†	20.309†		0.007
$\chi^2_{N}[2]$	3.279	339.432†		66.326†	39.466†		57.105†
$\chi^2_{H}[1]$	0.469	3.668*		7.009†	50.395†		0.016
Brazil VARX*(2,1)–CV=2							
$\bar{R}^2$	0.241	0.510		0.255	0.374		0.336
Benchmark1 $\bar{R}^2$	0.261	0.428		0.252	0.255		
Benchmark2 $\bar{R}^2$	0.080	0.129		0.018	0.067		0.139
$\hat{\sigma}$	0.016	0.105		0.070	0.157		0.086
$\chi^2_{SC}[4]$	10.014†	9.293*		3.197	5.830		4.098
$\chi^2_{FF}[1]$	4.483†	7.880†		2.669	47.047†		4.643†
$\chi^2_{N}[2]$	1.087	194.215†		128.316†	200.801†		13.660†
$\chi^2_{H}[1]$	0.375	12.790†		7.314†	29.370†		0.109
Peru VARX*(2,1)–CV=3							
$\bar{R}^2$	0.391	0.727		0.213	0.618		0.653
Benchmark1 $\bar{R}^2$	0.342	0.761		0.236	0.601		
Benchmark2 $\bar{R}^2$	0.149	0.105		0.019	0.133		0.280
$\hat{\sigma}$	0.026	0.106		0.090	0.053		0.053
$\chi^2_{SC}[4]$	7.647	13.960†		14.353†	23.086†		6.056
$\chi^2_{FF}[1]$	16.362†	0.092		0.192	45.318†		9.758†
$\chi^2_{N}[2]$	63.379†	253.341†		62.528†	57.004†		6.325†
$\chi^2_{H}[1]$	0.434†	6.418†		1.696	28.406†		39.255†
South Africa VARX*(2,1)—CV=3							
$\bar{R}^2$	0.603	0.566	0.470	0.075	0.397	0.357	0.086
Benchmark1 $\bar{R}^2$	0.520	0.568	0.454	0.046	0.386	0.290	
Benchmark2 $\bar{R}^2$	0.320	0.194	0.050	0.071	0.195	0.032	0.056
$\hat{\sigma}$	0.005	0.007	0.077	0.064	0.002	0.001	0.023
$\chi^2_{SC}[4]$	6.244	13.296†	3.407	6.337	11.272†	14.438†	9.088*
$\chi^2_{FF}[1]$	1.904	1.475	2.933*	1.038	2.602	0.0001	0.002
$\chi^2_{N}[2]$	10.188†	1.654	2.688	22.958†	155.412†	23.875†	12.761†
$\chi^2_{H}[1]$	1.979	0.550	0.096	2.419	0.728	0.990	0.407
Saudi Arabia VARX*(2,1)–CV=1							
$\bar{R}^2$	0.400	0.449		0.162			0.099
Benchmark1 $\bar{R}^2$	0.379	0.413		0.118			
Benchmark2 $\bar{R}^2$	0.547	0.330		0.080			0.141
$\hat{\sigma}$	0.018	0.008		0.009			0.034
$\chi^2_{SC}[4]$	52.656†	9.294*		11.015†			11.486†
$\chi^2_{FF}[1]$	0.679	0.807		6.294†			3.119*
$\chi^2_{N}[2]$	34.716†	622.339†		317.905†			1.566
$\chi^2_{H}[1]$	2.443	0.330		2.422			0.821

C2 Forecast comparison

Table C5: Forecast Comparison, Advanced Economies

	Δy_t	$\Delta(\Delta p_t)$	Δq_t	$\Delta(e_t - p_t)$	$\Delta\rho_t^S$	$\Delta\rho_t^L$	Δcrd_t	Δp_t^o
US								
Core (M1)	103.4%	95.5%	101.1%		118.9%	107.6%	89.7%	99.5%
Benchmark1 (M2)	102.8%	96.6%	100.5%		119.8%	111.8%		99.5%
Euro Area								
Core (M1)	100.6%	101.5%	100.9%	100.4%	99.6%	93.0%	127.1%	
Benchmark1 (M2)	100.9%	104.4%	102.2%	98.9%	101.8%	94.7%		
UK								
Core (M1)	97.5%	103.3%	102.1%	100.4%	102.0%	91.9%	100.8%	
Benchmark1 (M2)	105.5%	104.6%	103.6%	107.0%	111.4%	90.4%		
Japan								
Core (M1)	97.9%	99.7%	99.5%	101.3%	88.0%	127.1%	105.7%	
Benchmark1 (M2)	102.1%	99.6%	98.9%	104.6%	72.9%	107.9%		
Switzerland								
Core (M1)	94.9%	97.8%	98.8%	102.2%	106.8%	93.5%	92.6%	
Benchmark1 (M2)	92.7%	95.3%	99.4%	100.0%	96.8%	89.7%		
New Zealand								
Core (M1)	91.5%	104.1%	97.3%	100.4%	112.2%	96.3%	99.6%	
Benchmark1 (M2)	100.6%	105.5%	102.2%	109.0%	130.6%	108.4%		
Korea								
Core (M1)	102.8%	98.5%	102.1%	100.1%	104.9%	94.0%	99.7%	
Benchmark1 (M2)	102.9%	99.8%	100.7%	100.0%	111.8%	102.3%		
Norway								
Core (M1)	99.6%	94.0%	98.8%	99.3%	100.7%	101.0%	100.2%	
Benchmark1 (M2)	100.4%	94.1%	100.6%	100.1%	98.7%	99.7%		
Australia								
Core (M1)	95.4%	99.4%	100.5%	101.0%	101.0%	99.7%	110.0%	
Benchmark1 (M2)	98.6%	99.1%	102.5%	102.0%	102.5%	99.4%		
Canada								
Core (M1)	97.0%	96.4%	98.5%	99.1%	145.4%	135.6%	87.2%	
Benchmark1 (M2)	111.4%	106.0%	102.3%	99.5%	107.5%	109.6%		
Sweden								
Core (M1)	99.6%	106.0%	99.7%	102.0%	100.1%	87.7%	88.5%	
Benchmark1 (M2)	99.6%	103.9%	100.4%	100.4%	99.2%	95.1%		

Note: For each country, the first line of results denotes the ratio of root mean squared forecast error between the forecasts obtained from the core model with credit (M1) and an AR(p) benchmark (benchmark 2). The second line of results denotes the ratio of root mean squared forecast error between the forecasts obtained from benchmark 1 without credit (M2) and an AR(p) benchmark (benchmark 2). A ratio below one suggests an improvement of forecast performance against an AR model.

Table C6: Forecast Comparison, Emerging Market Economies

	Δy_t	$\Delta(\Delta p_t)$	Δq_t	$\Delta(e_t - p_t)$	$\Delta\rho^S_t$	$\Delta\rho^L_t$	Δcrd_t
China							
Core (M1)	98.1%	102.1%		115.5%	99.2%		103.2%
Benchmark1 (M2)	97.6%	101.4%		122.7%	99.7%		
India							
Core (M1)	94.2%	100.8%	100.0%	98.5%	100.8%		100.0%
Benchmark1 (M2)	99.3%	102.1%	101.5%	101.7%	103.3%		
Singapore							
Core (M1)	102.9%	99.1%	100.6%	96.4%	101.8%		91.9%
Benchmark1 (M2)	101.6%	99.0%	100.2%	97.3%	99.8%		
Malaysia							
Core (M1)	100.3%	99.0%	97.1%	101.7%	100.2%		98.0%
Benchmark1 (M2)	100.3%	99.1%	97.8%	102.1%	100.0%		
Philippines							
Core (M1)	97.4%	99.1%	95.7%	102.4%	111.1%		106.4%
Benchmark1 (M2)	96.5%	99.0%	97.2%	101.3%	101.7%		
Thailand							
Core (M1)	98.0%	99.9%	100.8%	101.6%	97.0%		94.3%
Benchmark1 (M2)	101.6%	99.8%	101.0%	99.1%	104.3%		
Indonesia							
Core (M1)	101.5%	90.1%		102.2%	87.4%		77.6%
Benchmark1 (M2)	101.1%	103.3%		101.4%	87.2%		
Turkey							
Core (M1)	97.2%	105.5%		101.7%	150.4%		106.0%
Benchmark1 (M2)	96.5%	104.3%		98.4%	118.8%		
Chile							
Core (M1)	104.3%	102.4%	99.5%	99.4%	101.1%		130.1%
Benchmark1 (M2)	108.0%	99.6%	99.5%	101.8%	115.5%		
Argentina							
Core (M1)	116.3%	440.4%	99.0%	100.7%	267.4%		79.2%
Benchmark1 (M2)	118.3%	778.2%	100.0%	113.3%	570.0%		
Mexico							
Core (M1)	105.3%	271.9%		111.4%	535.3%		165.7%
Benchmark1 (M2)	96.4%	87.5%		99.4%	223.1%		
Brazil							
Core (M1)	90.8%	781.4%		96.7%	1026.1%		103.5%
Benchmark1 (M2)	96.4%	1387.5%		96.7%	1933.1%		
Peru							
Core (M1)	118.2%	1341.9%		37.5%	1061.0%		148.2%
Benchmark1 (M2)	112.9%	1117.7%		33.5%	913.3%		
South Africa							
Core (M1)	94.9%	102.4%	97.7%	99.4%	94.0%	100.0%	99.5%
Benchmark1 (M2)	100.2%	104.4%	98.5%	100.7%	94.1%	101.0%	
Saudi Arabia							
Core (M1)	96.3%	102.5%		100.5%			108.6%
Benchmark1 (M2)	96.3%	102.9%		99.3%			

Note: For each country, the first line of results denotes the ratio of root mean squared forecast error between the forecasts obtained from the core model with credit (M1) and an AR(p) benchmark (benchmark 2). The second line of results denotes the ratio of root mean squared forecast error between the forecasts obtained from benchmark 1 without credit (M2) and an AR(p) benchmark (benchmark 2). A ratio below one suggests an improvement of forecast performance against an AR model.

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