BANK OF ENGLAND

Working Paper No. 410
Are EME indicators of vulnerability to financial crises decoupling from global factors?

Guillermo Felices and Tomasz Wieladek

February 2011

BANK OF ENGLAND

Working Paper No. 410
Are EME indicators of vulnerability to financial crises decoupling from global factors?

Guillermo Felices[(1)] and Tomasz Wieladek[(2)]

Abstract

This paper assesses the extent to which common factors underlie indicators of vulnerability to financial crises in emerging market economies and whether this link is changing over time. We use a Bayesian dynamic common factor model to estimate their common component in a sample of up to 41 countries including both developed as well as emerging economies. This permits us to interpret the component in common to both of them as a global factor. We introduce time-variation into the model to investigate whether indicators are decoupling from global factors over time. While decoupling can be observed in a few cases, the exposure to global factors in most countries tends to fluctuate around the mean. Broadly speaking then, the answer is no.

Key words: Financial crises, Bayesian dynamic common factor models, decoupling.

JEL classification: C11, C22, F34.

(1) Global Macro Trading Strategy, Citi. Email: guillermo.felices@citi.com.
(2) International Finance Division, Bank of England. Email: tomasz.wieladek@bankofengland.co.uk

The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England. We would like to thank Martin Brooke, Fabio Canova, Francis X Diebold, Phil Evans, Glenn Hoggarth, Chris Kubelec, Haroon Mumtaz, Chris Peacock, Charles Wyplosz, as well as all of the participants at the International Conference on Factor Structures for Panel and Multivariate Time Series Data in Maastricht and INFINITI 2009 conference in Dublin for helpful comments and advice. All errors remain our own. This paper was finalised on 25 October 2010.

The Bank of England's working paper series is externally refereed.

Information on the Bank's working paper series can be found at
www.bankofengland.co.uk/publications/workingpapers/index.htm

Publications Group, Bank of England, Threadneedle Street, London, EC2R 8AH
Telephone +44 (0)20 7601 4030 Fax +44 (0)20 7601 3298 email mapublications@bankofengland.co.uk

© Bank of England 2011
ISSN 1749-9135 (on-line)

Contents

Summary 3

1 Introduction 5

2 Methodology 8

2.1 The empirical model 9

2.2 Identification 11

2.3 Matching theory with the model 12

3 Implementation and data 13

3.1 Implementation 13

3.2 Data 17

4 Results 18

5 Robustness and caveats 28

5.1 What is the common factor? 28

5.2 Caveats of the analysis 29

6 Conclusion 30

Appendix A : Gibbs sampling 32

References 34

Summary

Traditional indicators of vulnerability to financial crises in emerging market economies (EMEs) suggest a substantial reduction in vulnerability in recent years. Ratios associated with the onset of a crisis - such as reserves relative to short-term debt, total external debt relative to GDP and the current account balance relative to GDP - have improved significantly compared to their levels of the 1990s and at the turn of the millennium.

A careful look at the data reveals that the improvement witnessed prior to the onset of the current crisis seemed to be present across all regions, despite a great variety in economic policies and levels of development. Therefore some of the improvements in vulnerability indicators seen in EMEs in the past decade may have been driven by the contemporaneous benign global conditions experienced by the world economy.

But the improvement observed in the last decade led several economists to believe that this time was different. The improvement in these indicators of external vulnerability, it is argued, may partly reflect the reforms in macroeconomic policies and institutional frameworks following the financial crises of the past two decades, such as the broad movement towards inflation targeting, flexible exchange rate regimes, the rapid growth of local currency bond markets, the diversification of the investor base, as well as better management of the composition of government debt by individual countries.

Investors and policymakers find it very difficult to disentangle whether these improvements were due to good luck or good policy. Better policies may lead to a permanent improvement in the resilience to adverse external economic shocks. If most of the improvement was driven by global factors on the other hand, vulnerabilities could re-emerge as global factors revert. Some questions then deserve careful attention. To what extent are the indicators of EMEs' external vulnerability driven by external factors? Is this link weakening or strengthening over time?

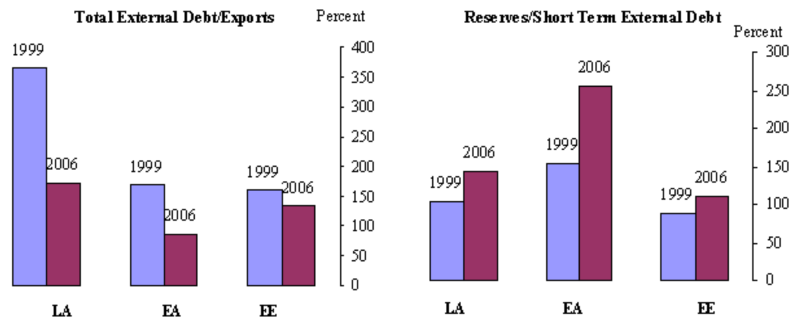
In this study we attempt to answer these important questions. Economic reforms and globalisation can change the exposure of vulnerability indicators to global factors. On the contrary, robust macroeconomic policy frameworks, such as 'leaning against the wind', could

lead to a ‘decoupling’ from the global factor. We examine both international reserve growth and real exchange rate appreciation for decoupling, as previous studies found these to be the two most useful vulnerability indicators in predicting financial crisis across different countries and crisis episodes. Our results suggest that, on average, 60% of fluctuations in a given country’s vulnerability indicators can be explained by global factors. Furthermore, we do not find strong evidence of decoupling in most EMEs during the past decade, implying that most of the improvement in vulnerability indicators has been driven by global factors.

1 Introduction

Traditional indicators of vulnerability to financial crises in emerging market economies (EMEs) have undergone a remarkable transformation in recent years. Ratios associated with the onset of a crisis such as reserves over external short-term debt or total external debt in terms of exports, have improved significantly within a short period of time. Figure 1 reveals that this trend seems to be present across all regions, despite their heterogeneity in economic policies and levels of development.

Figure 1: Financial crises indicators over time



Frankel and Saravelos (2010) survey 80 early warnings system studies and find that various indicators of international reserve adequacy, such as the twelve-month change or the ratio to short-term external debt, to imports of goods and services or M2, and real exchange rate appreciation are 'the two leading indicators that have proven the most useful in explaining crisis incidence across different countries and crises in the past'. Given their importance in predicting crises we therefore focus on these two variables in this study. The availability of comparable data of denominators in measures of international reserve adequacy at monthly horizon constrains our analysis to focus on the twelve-month growth rate of international reserves.

As most EMEs are considered small open economies, both of these variables are to some extent driven by external economic developments. An early study by Calvo, Leiderman and Reinhart (1993) found that a substantial fraction of reserves and real exchange rates in Latin America (LA) prior to the crises of the 1990s was driven by one common factor. This conclusion is confirmed by vector autoregression (VAR) studies. Hoffmaister and Roldos (1997) find that external factors can contribute up to 30% of the variation of domestic macroeconomic variables in East Asia (EA) and LA.[1] Using different identification schemes, regional studies by Canova (2005) on LA, Mackowiak (2006) on Emerging Europe (EE) and Rueffer, Sanchez and Shen (2007) on EA show that external factors contribute about 50% to the variation of domestic macroeconomic aggregates. The conclusions from these studies suggest external factors are important drivers of international reserves, real foreign exchange rates and business cycles in EMEs.

But the speed and size of the recent improvement has led some economists to believe that this time it is different. The change in indicators, it is argued, may reflect economic reforms following the financial crises of the past two decades. For example, the transition towards a flexible exchange rate regime may reduce the automatic movement of international reserves associated with fixed exchange rate regimes during periods of persistent capital inflows. Similarly, an exchange rate peg only leaves the price level as the only margin of adjustment during periods of capital inflows, leading to persistent real exchange rate appreciation. With a flexible exchange rate regime on the other hand, nominal exchange rate appreciation can partially offset domestic inflationary pressure during episodes of capital inflows, therefore weakening the link between real exchange rate appreciation and capital inflows. Reforms of the monetary system may therefore reduce the effect of international factors on, and thus increase the country-specific contribution to, vulnerability indicators permanently. In this case vulnerability indicators will become less dependent on global factors over time. In other words, reforms may lead to decoupling from global factors.

Instead of decoupling, the outcomes of reforms of a country's monetary system may result in greater comovement with the external economic environment. Improvements in policies and greater monetary credibility can attract international investors, increasing a country's exposure to shocks originating from international financial markets. Imbs (2004) finds that financial integration tends to increase business cycle synchronisation. Similarly, economic reforms can pave the way for a greater degree of trade integration, which may also result in greater business

[1] Subsequently, a number of other empirical studies came to a similar conclusion.

cycle synchronisation (Frankel and Rose (1998)). Any decoupling benefits of reforms could therefore be offset by economic integration.

Economists and policymakers find it difficult – albeit important – to assess whether EMEs are actually decoupling from global factors. Even following economic reforms, it is hard to be confident whether decoupling has occurred. The question we thus seek to answer is to which extent EME indicators of vulnerability to financial crises are driven by external factors and whether this relationship has been weakening or strengthening in recent times?

Previous work on decoupling has used a variety of ways to test this hypothesis. Kose, Otrok and Prasad (2008) apply a Bayesian dynamic common factor model to annual growth rates of consumption, investment and GDP to quantify global business cycle fluctuations. They compare the contribution of their estimated global common factor to EMEs during the pre-globalisation period (1960-1985) and the globalisation period (1985-2005). They find that the variance decomposition of the global factor in EMEs declines in the latter and interpret this as decoupling. Walti (2009) filters annual GDP data with a Hodrick-Prescott filter. Using a concordance measure of synchronisation among countries, he does not find any evidence of decoupling of EMEs from industrial country business cycles. Finally, Dooley and Hutchinson (2009) analyse EMEs' credit default swap (CDS) spreads and US financial markets with a rolling coefficients VAR. They find that while EMEs decoupled from US financial markets during the first phase of the sub-prime crisis, they recoupled following the failure of Lehman Brothers during September 2008.

Our approach differs from previous studies in two respects. To our knowledge, this is the first study to focus on the improvement in indicators of vulnerability to financial crises, as opposed to GDP growth rates or CDS spreads. We follow Kose, Otrok and Prasad (2008) and use a dynamic common factor model to quantify the effect of a common driver on country-specific indicators. Second, previous work has estimated empirical models across different time periods or used rolling regressions to identify decoupling in the data. Unfortunately, this approach cannot differentiate whether changes in coefficients are due to a cyclical or permanent change in correlations. In our approach, we follow Del Negro and Otrok (2008) and introduce time-variation into the coefficients relating the common factor to vulnerability indicators. This feature of our model permits us to analyse changes in indicators' exposure to common factors as a result of permanent structural changes rather than cyclical fluctuations. To facilitate the interpretation of our extracted common component as global, we include several industrial countries into the sample as well. Our model will therefore permit for a rigorous test of whether EMEs have become permanently more or less resilient to fluctuations in global economic environment following the financial crises of the 1990s. In other words, this will allow us to assess whether EMEs have started to decouple from or converge with global factors in recent years.

We find that one common factor explains on average 60% of the variation in vulnerability indicators. In some countries the exposure to this common factor shows a persistent decline throughout our sample period. We interpret this gradual decline as evidence of decoupling. But most countries in this study lack a systematic pattern of continuously falling exposure of vulnerability indicators to the common factor. This evidence leads us to conclude against the presence of decoupling in the majority of EMEs.

Nevertheless the interpretation of the common factor, estimated from a one-factor model, as global could be invalid if there is an EME-specific factor. To control for this and check for the robustness of our results we also estimate a model on a sample that is restricted to EMEs only. Since the common factor seems to have a similar shape and pattern in both cases, our baseline model does not appear to be misspecified.

The rest of the paper is organised as follows. Section 2 outlines the methodology and the empirical model. Section 3 describes the implementation of the model and the data. Section 4 presents the results, while Section 5 provides a robustness check and a discussion of potential caveats. Finally, Section 6 concludes.

2 Methodology

In this study we employ a Bayesian dynamic common factor model to quantify the contribution of one common factor to country-specific vulnerability indicators and to analyse how this contribution has evolved over time. In previous applications such methods have been employed to study and separate the international business cycle from domestic investment, consumption and output data across countries and to quantify the contribution of the world factor (world business cycle) to their variation. Applied to the question at hand, there may for instance be a factor which is common to reserve growth across all countries. Potentially, this factor could be interpreted as a global factor,[2] since the sample consists of both EMEs and industrialised countries.

2.1 The empirical model

One conventional assumption in dynamic common factor models is that the relationship between the individual country and the common factor is time-invariant (see Kose, Otrok and Whiteman (2003)). We argue that for the case of EMEs this seems unreasonable, given domestic reforms following crises, institutional changes and globalisation. The model we propose to implement then, is the following:

$$Y_t = H_t W_t + \varepsilon_t \quad \varepsilon_t \sim NID(0, R) \tag{1}$$

$$H_t = H_{t-1} + \upsilon_t \quad \upsilon_t \sim NID(O, Q) \tag{2}$$

$$W_t = \phi W_{t-1} + \eta_t \quad \eta_t \sim NID(0, G) \tag{3}$$

$$E[\varepsilon_{it}\, \varepsilon_{jt}] = 0, \; E[\eta_{it}\, \eta_{jt}] = 0 \; \forall \; i \neq j \tag{4}$$

Y_t is a vector of vulnerability indicators, such as reserve growth, in n countries. W_t is the common factor which drives time series in all n countries. H_t is a vector of factor loadings, γ_{it}, which are the coefficients relating the common factor to a fundamental in a particular country i. R is the covariance matrix of the idiosyncratic component, Q the covariance matrix governing the shocks to time-variation and G the variance of the common factor.

[2] The idea of interpreting a statistical factor which is common to time series across countries as a global factor is not new. In their seminal work, Calvo, Leiderman and Reinhart (1993) extract a principal component from the foreign exchange reserve series in ten Latin American countries and find a strong correlation with US interest rates.

Since our sample includes both developed and EMEs, one could possibly interpret W_t as a global factor. We assume that $E[\varepsilon_{it}\ \varepsilon_{jt}] = 0$ in order to minimise the amount of parameters which we need to estimate. This assumption is also necessary in order to ensure that W_t captures external factors, while ε_{it} captures the idiosyncratic component of each series. Nevertheless, this assumption may introduce an additional source of misspecification. In particular, permitting for $E[\varepsilon_{it}\ \varepsilon_{jt}] \neq 0$ is a popular empirical testing strategy for contagion in high-frequency financial data (Dungey and Tambakis (2005)). To avoid this problem, we estimate our model across a time period when contagion appeared to be mostly absent, namely from January 1999 until June 2007, the beginning of the sub-prime crisis.[3]

Following Del Negro and Otrok (2008), we embed a second Kalman filter into our empirical model in order to allow for time-variation in each γ_{it} individually. Similar to Cogley and Sargent (2001) we model time-variation as smoothly changing coefficients across periods, since we only want to capture permanent structural changes.

In previous work, variance decompositions were used to infer how much the common factor contributes to the variation of an individual time series. For instance, Kose, Otrok and Prasad (2008) use variance decompositions to show that the exposure of EMEs to a global common factor has declined over time. The variance of a given fundamental in country i is given by

$$var(Y_{it}) = \gamma_{it}^2 var(W_t) + R_i$$

The share of the variance attributed to the common factor can then be computed as:

$$\frac{\gamma_{it}^2 var(W_t)}{\gamma_{it}^2 var(W_t) + R_i}$$

The variance decomposition can be interpreted as the R^2 the world common factor W_t can explain in a specific country's time series. In our case the factor loading, γ_{it} is time-varying, which permits us to trace the evolution of the variance decomposition over time.

[3] In 2003, Kaminsky *et al* (2003) argue that the last emerging market crisis which may have been considered contagious was in the later part of 1998. During the remaining time period, emerging market financial crises seemed to be absent.

2.2 *Identification*

From a purely statistical point of view the above model is subject to three distinct identification problems. Neither the time-varying factor loadings, the scales or the signs of the factor and the factor loadings are identified.

We assume that the shocks to the time-varying coefficients are independent of each other, namely $E[\eta_{it}\ \eta_{jt}] = 0\ \forall\ i \neq j$. As both the factor and the factor loadings are varying over time in our model, $E[\eta_{it}\ \eta_{jt}] = 0\ \forall\ i \neq j$ is necessary in order to identify the factor separately from the time-varying factor loadings. In terms of the implementation, this requires the application of the Kalman filter to each factor loading coefficient by coefficient.[4] As a result the matrix Q is diagonal.

Similar to most dynamic common factor models, our model is also subject to the problem that the relative scale of the model is indeterminate. One can multiply the factor loadings by a constant d for all i, which gives $\widetilde{H}_t = dH_t$. We can also divide the factor by d, which yields $\widetilde{W}_t = \frac{W_t}{d}$. The scale of the model $H_t W_t$ is thus observational equivalent with the scale of the model $\widetilde{H}_t \widetilde{W}_t$. In order to solve this problem, we take the approach that is applied in previous work and set G, the variance matrix of the error term of the factor to 1.

In addition, the model is subject to the rotational indeterminacy problem (Harvey (1993)). For any $k\ x\ k$ orthogonal matrix F there exists an equivalent specification such that the rotations $H_t^* = FH_t$ and $W_t^* = FW_t$ produce the same distribution for Y_t as in the original model. This implies that the signs of the factor loadings and the common factor are not separately identified. This can be easily seen when setting $F = -1$, as in this case $H_t^* W_t^*$and $H_t W_t$ are observational equivalent. In order to solve this problem we follow Del Negro and Otrok (2008) and impose one of the factor loadings during the first time period to be positive, as this permits the identification of the sign of the factor and thus the rest of the model. Finally, it is important to mention that our results concerning the variance decompositions are not affected by this issue, since all parameters affected by the indeterminacy of signs are squared.

[4]Note that in the case of a single common factor, the application of the Kalman filter coefficient by coefficient is the same as applying it equation by equation.

From an economic point of view, we are interested in capturing global factors which are external to EMEs. To facilitate the interpretation of the common factor as global, we also include several industrialised countries into our sample.

Naturally, one may argue that our estimated common factor may captures reforms of the monetary framework if they occurred at the same time in several countries. On the other hand, this would require that the reforms are not only implemented at the same point in time, but would also have exactly the same effect on vulnerability indicators, which we argue is rather unlikely. Furthermore, the assumption that the time-varying shocks in each equation are independent of each other rules this possibility out explicitly. Aside from statistical reasons, the implementation of reforms and the scope of globalisation will probably differ from country to country. Some countries may not introduce reforms at all, while others may resist full implementation as a result of the political costs associated with their introduction. Countries may also pursue different policies regarding their desired degree of international trade and financial integration.

2.3 Matching theory with the model

In theory, the common factor W_t may represent the global economic environment. The factor loadings H_t on the other hand represent the link between vulnerability indicators and the external factor. We expect economic reforms to affect the factor loadings. Reform of the monetary policy framework and in particular the adoption of a flexible exchange rate regime may make a country's vulnerability indicators less dependent on external factors over time. With an open capital account and a flexible exchange rate, the domestic central bank is not required to accumulate international reserves as a result of capital inflows automatically, therefore breaking the link between global factors and international reserves. The transition from a fixed to a floating exchange rate regime may also sever the link between global factors and real exchange rate appreciation. With a fixed exchange rate regime, persistent capital inflows usually result in inflation, as the price level is the only margin of adjustment, and therefore real exchange rate appreciation. On the contrary, with a flexible exchange rate regime, the nominal exchange rate will appreciate, therefore partially offsetting the inflationary pressure and real exchange rate appreciation. The reaction of real exchange rate appreciation to movements in global factors will therefore become smaller. As a result, we would expect a downward trend in γ_{it} over time as foreign reserve accumulation and real exchange rate appreciation become less dependent on the common factor.

On the other hand, one should keep in mind that financial and trade integration following the establishment of successful economic reforms, and thus greater monetary credibility, may more than offset any decoupling effects associated with them. In this case vulnerability indicators may converge[5] with global factors over time. If these effects dominate, we should therefore observe an upward trend in γ_{it}. Our null-hypothesis is therefore that γ_{it} is either constant or mean reverting over time. To reject this null-hypothesis, we should thus observe either a persistent trend decline (decoupling) or increase (economic integration) in γ_{it}, depending on whether decoupling or economic integration dominates.

To summarise, economic theory supports either direction of γ_{it} over time. The data will reveal whether the trend of γ_{it} is upwards, downwards or mean reverting.

3 Implementation and data

3.1 Implementation

Dynamic factor models can be estimated with maximum likelihood methods (Gregory, Head and Raynauld (1997)). Nevertheless, with a large number of series in the cross-section, the resulting likelihood functions may have odd shapes (Bernanke, Boivin and Eliasz (2005)). To address this problem, Kose, Otrok, and Whiteman (2003) use the methods introduced in Carter and Kohn (1994) and surveyed in Kim and Nelson (1999) to develop a Bayesian Kalman filter procedure, which permits them to estimate large dynamic common factor models easily. We follow the approach presented in Del Negro and Otrok (2008) and allow for time-variation in the factor loadings. The model is estimated with a Bayesian technique, Gibbs sampling. The general idea behind Gibbs sampling is explained in Appendix A.

3.1.1 Starting values and initial conditions

[5] By convergence we mean greater comovement with the common factor.

In any time-varying algorithm, starting values for the time-varying coefficients are necessary. Starting values for the time-varying algorithm are used to draw a new path of time-varying coefficients in every single iteration. To obtain the starting values we estimate a Bayesian dynamic common factor model with fixed factor loadings on a training sample from the beginning of data availability until December 1998. The initial conditions to start the algorithm are estimated using a principal components estimator.[6]

One crucial decision is the prior on Q, the variance-covariance matrix of the disturbance term in the state equation, which governs the amount of time-variation. We follow the approach set out in Cogley and Sargent (2001). They set the prior on Q proportional to the variance-covariance matrix of factor loadings K, obtained by estimating a time-invariant model on the training sample. We thus set $Q = g^2 * K$ where g is a proportionality constant. Intuitively, K can be described as the uncertainty surrounding the factor loadings H. Setting $g = .01$ for instance would impose a prior that time-variation cannot explain more than 1% of the uncertainty around H. Cogley and Sargent (2001) suggest that this value for g is conservative, but realistic to explain permanent structural change in quarterly data. Since we have monthly data, we set $g = .003$.[7]

3.1.2 Estimation

Estimation with Gibbs sampling permits us to break the estimation down into several steps, which reduces the difficulty of implementation drastically. For instance, if the unobserved dynamic common factor in equation **(1)** would be known, then the estimation of the time-varying factor loadings would involve the straightforward implementation of a Kalman filter. Similarly, if the factor loadings are known, then the estimation of the unobserved factor only involves the Kalman filter again, but with known parameters, which means that one can just iterate through the sample in order to estimate the unobserved common factor. Finally, given knowledge of the dynamic common factor, the estimation of the autoregressive parameter in equation **(3)** can be performed through a simple regression of the lagged factor on itself. For this purpose we employ a Gibbs sampling algorithm that approximates the posterior distribution and describe each step of the algorithm below.

[6]The method of initialising the dynamic common factor model with the principal component follows the approach presented in Bernanke, Boivin and Eliasz (2005) and Mumtaz and Surico (2008).

[7]Greater values of g do not affect the results qualitatively.

Step 1 - Estimation of the time-varying coefficients conditional on all other parameters

Conditional on a draw of W_t, we draw the factor loadings H_t and the covariance matrix R. With knowledge of all the other parameters we can use the Bayesian variant of the Kalman filter[8] in order to estimate each factor loading γ_{it} separately. The posterior densities which we use to simulate time-variation equation by equation are given by

$$\gamma_{i,T} \mid Y_T, W_T, R, Q \sim N(\gamma_{i,T|T,W_T,R,Q}, P_{T|T,W_T,R,Q}) \quad \textbf{(5)}$$

$$\gamma_{i,t} \mid Y_t, W_t, R, Q \sim N(\gamma_{i,t|t,W_t,R,Q}, P_{t|t,W_t,R,Q}) \quad \textbf{(6)}$$

We first iterate the Kalman filter forward through the sample, in order to calculate $\gamma_{i,T|T,W_T,R,Q} = E(\gamma_{i,T} \mid Y_T, W_T, R, Q)$ and the associated variance-covariance matrix $P_{i,T|T,W_T,R,Q} = Cov(\gamma_{i,T} \mid Y_T, W_T, R, Q)$ at the end of the sample, namely time period T. The calculation of these parameters permits sampling from the posterior distribution in **(5)**. We then use the last observation as an initial condition and iterate the Kalman filter backwards through the sample and sample $\gamma_{i,t}$ from **(6)** at each point in time.

Subsequently, we construct the vector of innovations associated with each time-varying parameter and draw the associated variance-covariance matrix of the innovations υ_{it} from the following inverse gamma distribution as in Del Negro and Otrok (2008).

$$\sigma^2_{1\upsilon} \sim IG(\frac{\delta_1}{2}, \frac{z_1}{2}) \quad \textbf{(7)}$$

where $z1 = T_1 + T$ and $\delta_1 = g^2 * K + (\gamma_{it} - \gamma_{it-1})'(\gamma_{it} - \gamma_{it-1})$. T_1 is set to n, as in Cogley and Sargent (2001) where n is the number of time-varying coefficients. T is the number of observations in the time-varying sample and g a proportionality constant. K is the variance-covariance matrix of the factor loadings estimated on the training sample.

[8] See Carter and Kohn (1994) for derivation and further description.

Step 2 - Estimation of the dynamic common factor conditional on all other parameters

We can now obtain an estimate of W_t with the Bayesian Kalman filter. We assume W_t to be latent and unobservable. We draw W_t conditional on all other parameters from

$$W_T \quad | \quad Y_T, H_T, R, Q \sim N(W_{T|T,H_T,R,Q}, P_{T|T,H_T,R,Q}) \qquad \textbf{(8)}$$

$$W_t \quad | \quad Y_t, H_t, R, Q \sim N(W_{t|t,W_{t+1},H_t,R,Q}, P_{t|t,W_{t+1},H_t,R,Q}) \qquad \textbf{(9)}$$

In order to estimate W_t, we proceed as in step 1. We first iterate the Kalman filter forward through the sample, in order to calculate $W_{T|T,H_T,R,Q} = E(W_T \mid Y_T, H_T, R, Q)$ and the associated variance-covariance matrix $P_{T|T,H_T,R,Q} = Cov(W_T \mid Y_T, H_T, R, Q)$ at the end of the sample. The calculation of these parameters permits sampling from the posterior distribution in **(8)**. We then use the last observation as a an initial condition and iterate the Kalman filter backwards through the sample and draw W_t from **(9)** at each point in time.

Step 3 - Estimation of ϕ and R conditional on all other parameters

The AR coefficient ϕ is obtained through a standard regression of W_t on its own lagged value and the coefficients are sampled from a normal distribution. We only retain draws with roots inside the unit circle. G is set to 1 in order to identify the scale of the model. The posterior density in this case is:

$$\phi \mid 1, Y \sim N(\phi_1, \Sigma_1)$$

where $\phi_1 = (w_t' w_t)^{-1} w_t' w_{t-1}$and $\Sigma_1 = (w_t' w_t)^{-1}$, where $w_t = [W_1 \; W_2 \dots W_T]$. We draw the individual covariances of each error term ε_{it} from an inverse gamma distribution.

$$\sigma_{i\varepsilon}^2 \sim IG(\frac{\delta_0}{2}, \frac{T}{2}) \qquad \textbf{(10)}$$

where $\delta_0 = (Y_{it} - W_t \gamma_{it})'(Y_{it} - W_t \gamma_{it})$ and T is the number of observations during the period of time-variation. The prior on $\sigma^2_{i\varepsilon}$ is therefore non-informative.

Step 4 - Go to step 1

3.1.3 Testing for convergence

We replicate the above algorithm 10,000 times with Gibbs sampling and discard the first 9,000 replications as burn-in. We then obtain the parameter estimates of the posterior distribution from the last 1,000 replications by taking the median and constructing 68% confidence levels around it. We follow previous work and try various length of the iterative process. The results do not change, whether we replicate the model 100,000 times and retain 10,000 draws or replicate it 10,000 times and retain the final 1,000 draws for inference.

Two possible test for convergence in our case are the two-sided Kolmogorov-Smirnov and Cramer-von-Mises test. These tests permit the statistical assessment of whether the underlying distribution behind two random samples is the same. We split the retained 1,000 draws in two samples and test whether they differ. Since we could never reject the null hypothesis that both samples come from the same distribution, we conclude that our procedure always seems to converge.

3.2 Data

We obtain data on all of the vulnerability indicators at a monthly frequency. Our data come from the IMF International Financial Statistics (IFS) database and the Bank of International Settlements database on real effective exchange rates. We have tried to maximise the time horizon of the series as well as the number of countries included in the analysis. Thus, some series start as early as January 1994, while others start as late as March 1995. The sample ends in June 2007, before the onset of the sub-prime crisis. This is to avoid periods of contagion, as our econometric model would be misspecified otherwise.

In order to obtain reserve growth, we take year-on-year changes in monthly data from the IFS. Real effective exchange rate appreciation is constructed through year-on-year changes from the BIS data. All variables are tested for stationarity[9] and the null-hypothesis of a unit-root could be rejected at the 5% level. Conforming with previous work, we demean each series and divide each observation by the standard deviation for the whole sample in order to normalise the variance to unity. This normalisation will ensure that all of the series receive equal weight and that the results are not dominated by the most volatile series.

In order to faciliate the interpretation of the estimated common factor as global, both emerging market and industrialised economies are included in the sample. Our definition of an emerging market economy is consistent with the definition of the IMF (2006).[10] Some countries matured from emerging to advanced economies during our sample period. In this case we still count them as EMEs. The date when we start time-variation, January 1999, coincides with the introduction of the euro. The introduction of the euro may change reserve and real exchange rate dynamics across member countries significantly. Since the study in this paper is concerned with decoupling of emerging markets, we exclude euro-area countries from our developed country sample, to avoid any potential biases. The selection of the remaining industrialised countries is based on data availability. As a result up to 31 EMEs and 10 industrialised countries are included.

4 Results

We present all of our results below. To answer the main question of this paper, namely whether EMEs are decoupling, we first look at the evolution of time-varying coefficients. Our model is parametrised to pick up permanent structural changes. We therefore interpret a slow and gradual trend towards zero in the time-varying coefficients as decoupling and an increase away from zero as convergence.

[9] We use both the augmented Dickey-Fuller unit-root test, as well as the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) stationarity test.

[10] The IMF changed its definition from emerging to advanced economies for some countries during our sample period. Since this maturing process could be interpreted as decoupling, we apply the term emerging market to these countries.

Figure 2: Time-varying factor loadings – reserve growth

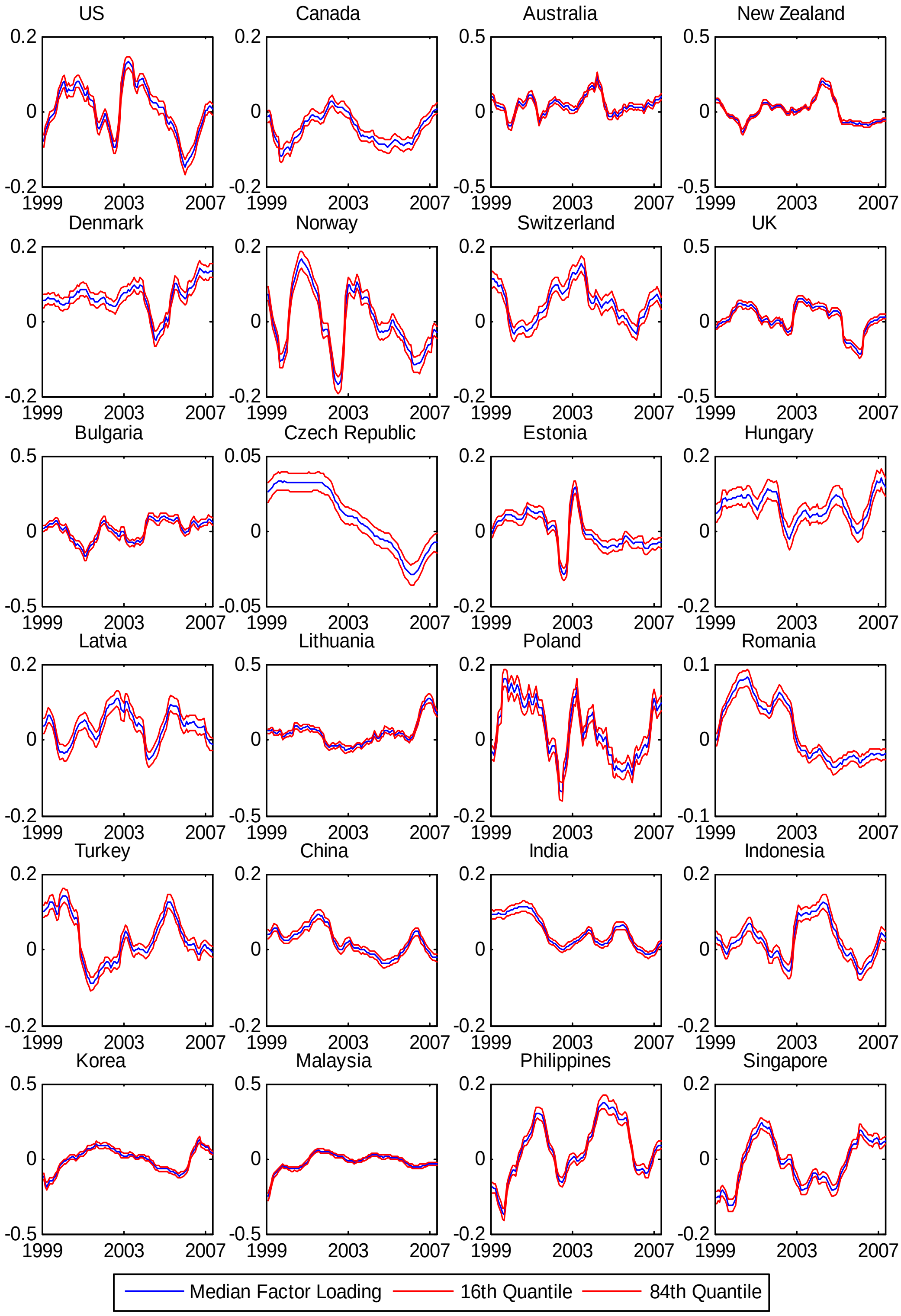


Figure 2: Time-varying factor loadings – reserve growth – continued

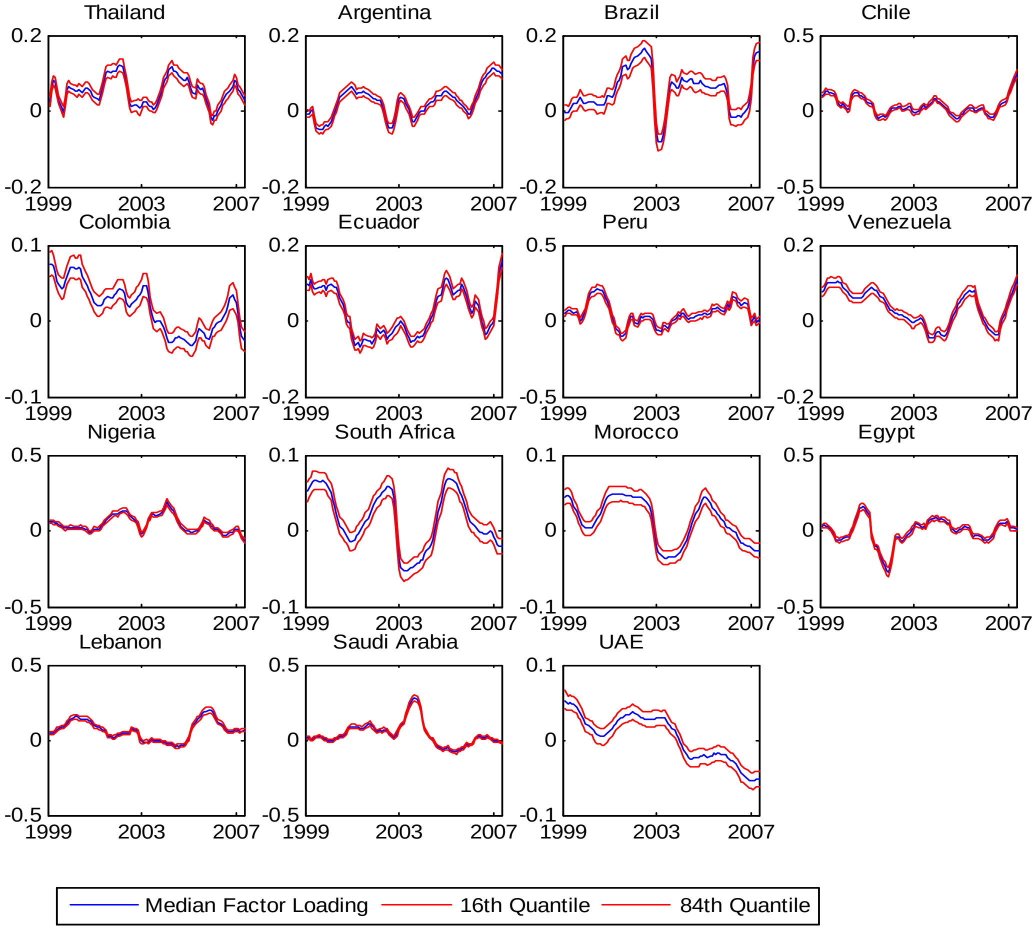


Figure 3: Time-varying factor loadings – real exchange rate appreciation

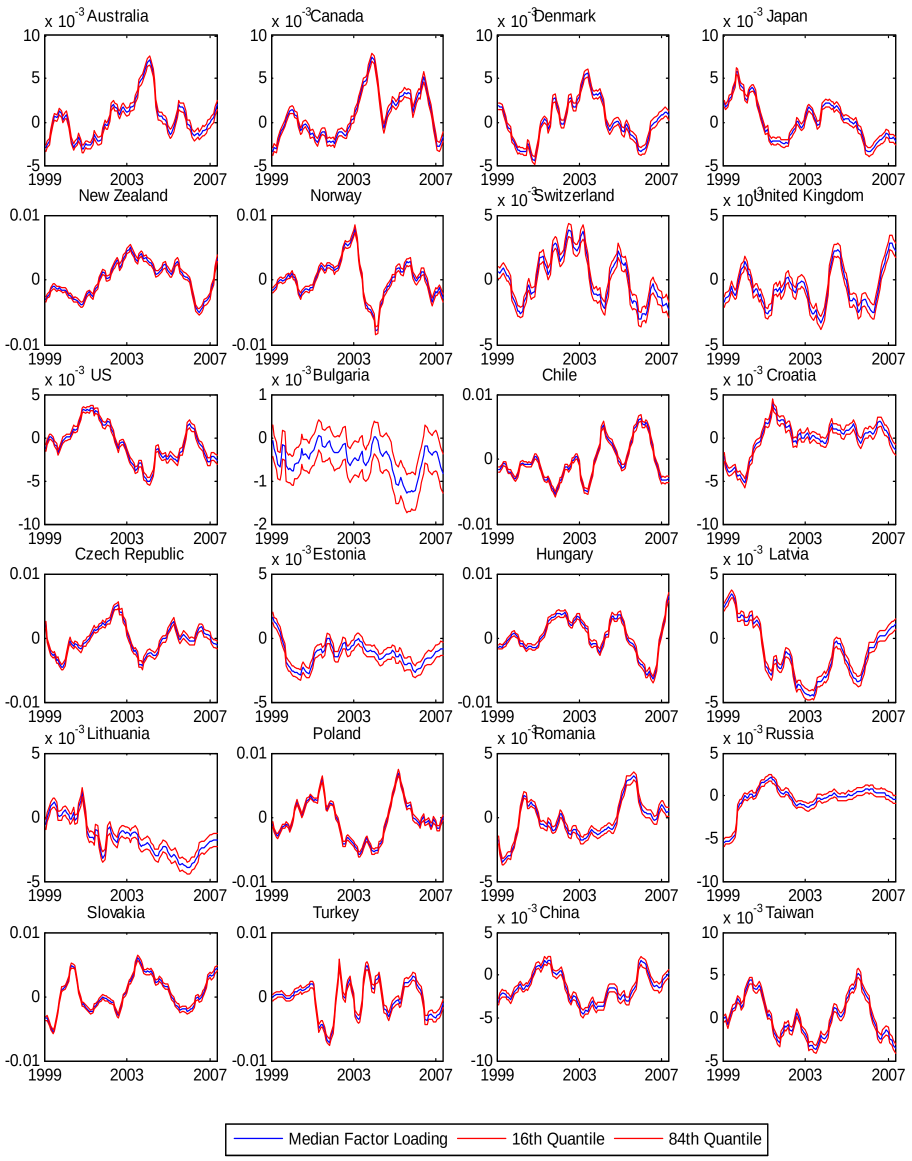
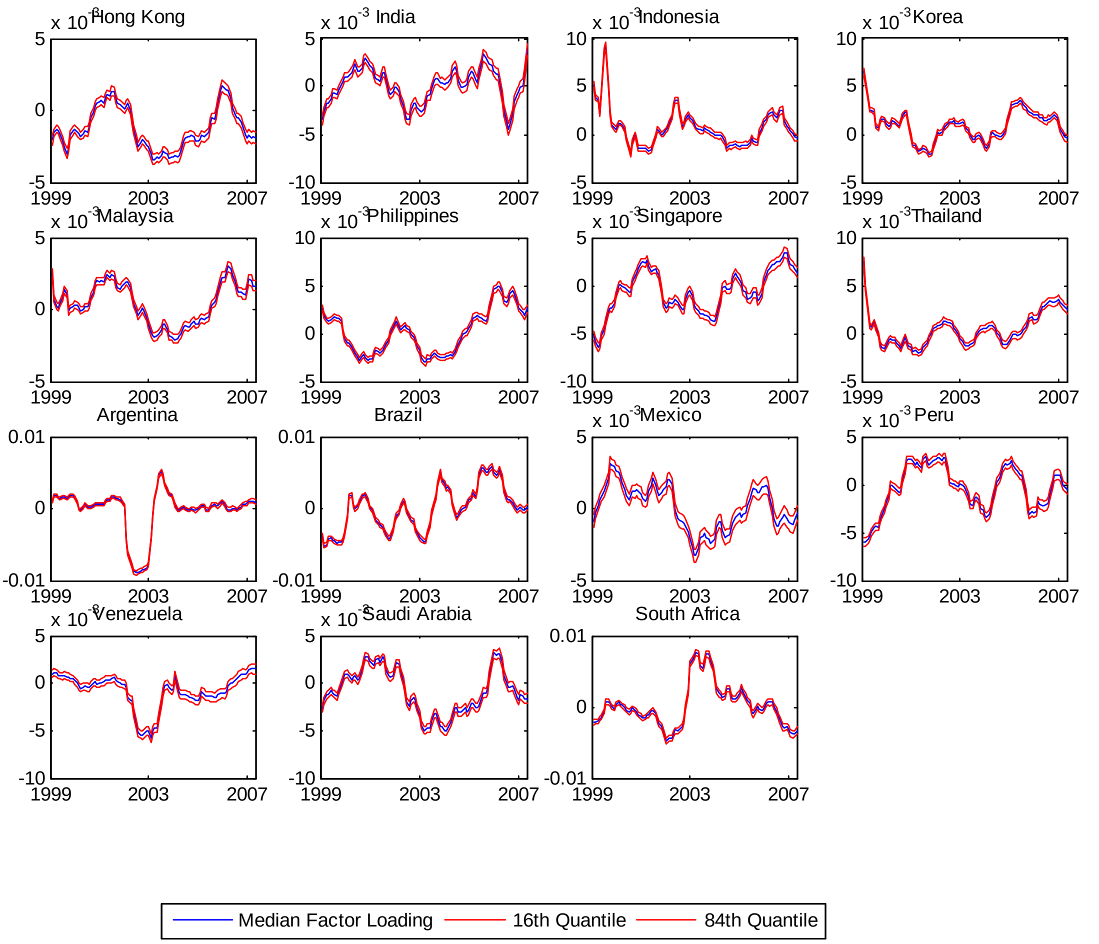


Figure 3: Time-varying factor loadings – real exchange rate appreciation – continued



Figures 2-3 show the evolution of time-varying coefficients by country and variable over time. While some countries show a tendency to decouple or converge, there is no such pattern for most of them. For reserve growth, the evolution of the time-varying coefficients shows a persistent trend towards zero in Colombia, Romania, India and Malaysia. Since this trend is persistent and gradual over time for each of these countries, we interpret this is as clear evidence of decoupling.

For real exchange rate appreciation the coefficients of most countries tends to fluctuate around their respective mean. Since it is difficult to find a systematic pattern of decoupling at individual country level, we conclude that either decoupling or convergence seems to be absent for most countries.

To assess the degree of exposure of individual country vulnerability indicators to the global factor over time, we look at time-varying variance decompositions (see Tables 1-2).[11] Variance decompositions can be interpreted as the exposure of vulnerability indicators to the global factor.[12]

[11] To save space only point estimates are reported.

[12] This approach follows Kose, Otrok and Prasad (2008). They compare variance decompositions between the pre-globalisation and globalisation period in their sample and argue that a lower value of the variance decomposition in the latter suggests the presence of decoupling.

Table 1: Variance decompositions – reserve growth

	1999	2000	2001	2002	2003	2004	2005	2006	2007
United States	0.62	0.90	0.67	0.76	0.95	0.55	0.83	0.88	0.23
Canada	0.76	0.80	0.25	0.28	0.69	0.91	0.91	0.73	0.15
Australia	0.69	0.75	0.61	0.66	0.75	0.77	0.45	0.56	0.92
New Zealand	0.84	0.94	0.78	0.61	0.74	0.97	0.95	0.98	0.95
Denmark	0.78	0.81	0.82	0.74	0.90	0.50	0.70	0.92	0.95
Norway	0.76	0.88	0.73	0.92	0.91	0.51	0.58	0.94	0.64
Switzerland	0.75	0.34	0.41	0.89	0.89	0.70	0.24	0.41	0.69
United Kingdom	0.46	0.94	0.36	0.63	0.96	0.87	0.88	0.59	0.51
Bulgaria	0.52	0.64	0.75	0.39	0.77	0.83	0.70	0.54	0.70
Czech Republic	0.77	0.78	0.78	0.51	0.14	0.09	0.49	0.63	0.21
Estonia	0.62	0.79	0.66	0.75	0.54	0.76	0.66	0.78	0.75
Hungary	0.56	0.58	0.58	0.47	0.49	0.53	0.49	0.52	0.61
Latvia	0.49	0.40	0.37	0.86	0.65	0.43	0.77	0.55	0.16
Lithuania	0.75	0.87	0.78	0.77	0.66	0.55	0.64	0.82	0.98
Poland	0.78	0.94	0.73	0.74	0.74	0.45	0.89	0.55	0.91
Romania	0.78	0.97	0.91	0.83	0.61	0.77	0.81	0.76	0.68
Turkey	0.96	0.85	0.88	0.65	0.33	0.59	0.88	0.26	0.18
China	0.84	0.85	0.96	0.50	0.22	0.64	0.49	0.67	0.58
India	0.98	0.99	0.92	0.36	0.86	0.70	0.90	0.32	0.51
Indonesia	0.31	0.69	0.36	0.61	0.93	0.89	0.36	0.62	0.66

Table 1: Variance decompositions – reserve growth – continued

	1999	2000	2001	2002	2003	2004	2005	2006	2007
Korea	0.93	0.35	0.91	0.83	0.38	0.65	0.95	0.85	0.84
Malaysia	0.95	0.90	0.78	0.59	0.46	0.51	0.40	0.90	0.83
Philippines	0.97	0.79	0.94	0.69	0.50	0.99	0.90	0.76	0.85
Singapore	0.97	0.72	0.92	0.38	0.91	0.92	0.68	0.90	0.85
Thailand	0.73	0.87	0.90	0.64	0.56	0.96	0.77	0.63	0.78
Argentina	0.61	0.69	0.85	0.62	0.44	0.70	0.57	0.81	0.97
Brazil	0.29	0.37	0.85	0.88	0.74	0.86	0.80	0.24	0.95
Chile	0.92	0.82	0.66	0.51	0.66	0.67	0.38	0.69	0.99
Colombia	0.84	0.77	0.53	0.57	0.31	0.51	0.36	0.28	0.42
Ecuador	0.96	0.71	0.88	0.62	0.72	0.70	0.92	0.56	0.94
Peru	0.67	0.97	0.61	0.45	0.53	0.52	0.84	0.92	0.50
Venezuela, Rep. Bol.	0.97	0.93	0.91	0.41	0.53	0.69	0.76	0.63	0.97
Nigeria	0.74	0.42	0.82	0.88	0.90	0.72	0.59	0.44	0.73
South Africa	0.90	0.38	0.36	0.77	0.84	0.58	0.77	0.15	0.46
Morocco	0.58	0.47	0.86	0.69	0.75	0.50	0.56	0.28	0.64
Egypt	0.77	0.84	0.97	0.78	0.86	0.64	0.76	0.83	0.45
Lebanon	0.96	0.99	0.86	0.85	0.34	0.77	0.99	0.97	0.96
Saudi Arabia	0.54	0.72	0.98	0.93	1.00	0.83	0.96	0.68	0.60
United Arab Emirates	0.67	0.16	0.50	0.55	0.32	0.36	0.36	0.66	0.79

Table 2: Variance decompositions – real exchange rate appreciation

	1999	2000	2001	2002	2003	2004	2005	2006	2007
United States	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54
Canada	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19
Australia	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
Denmark	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Japan	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
New Zealand	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19
Norway	0.38	0.86	0.66	0.85	0.74	0.65	0.79	0.60	0.96
Switzerland	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
United Kingdom	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Bulgaria	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Croatia	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
Czech Republic	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Estonia	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Hungary	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Latvia	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
Lithuania	0.15	0.15	0.15	0.15	0.15	0.15	0.16	0.15	0.16
Poland	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43
Romania	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
Russia	0.96	0.91	0.83	0.61	0.22	0.02	0.12	0.19	0.14
Slovakia	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table 2: Variance decompositions – real exchange rate appreciation – continued

	1999	2000	2001	2002	2003	2004	2005	2006	2007
Turkey	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
China	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66
Taiwan	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Hong Kong SAR	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62
India	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Indonesia	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
Korea	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14
Malaysia	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Philippines	0.77	0.91	0.70	0.22	0.63	0.39	0.86	0.98	0.98
Singapore	0.35	0.35	0.35	0.35	0.35	0.35	0.34	0.34	0.34
Thailand	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
Chile	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Argentina	0.97	0.86	0.84	0.73	0.69	0.44	0.96	0.88	0.73
Brazil	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14
Mexico	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24
Peru	0.51	0.25	0.44	0.94	0.51	0.57	0.78	0.42	0.82
Venezuela	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60
Saudi Arabia	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18

On average the estimated common factor seems to be able to explain approximately 60% of the variation in EME financial crisis vulnerability indicators. For both vulnerability indicators, the estimated common factor has greater explanatory power for emerging markets than for developed countries, which suggests that emerging markets are more dependent on global factors than developed countries.

In conclusion, our results suggest that while decoupling occurs in some countries, this is not the case for the majority. The estimated common factor also seems to explain a significant fraction of variation in most EMEs, confirming the dependency of vulnerability indicators in EMEs on external factors.

5 Robustness and caveats

5.1 What is the common factor?

We refer to our common factor as global throughout the text, but it is not clear whether it indeed reflects global factors. To faciliate the interpretation of the common factor as global, we have included developed countries into our sample.

Figure 6: Common factors

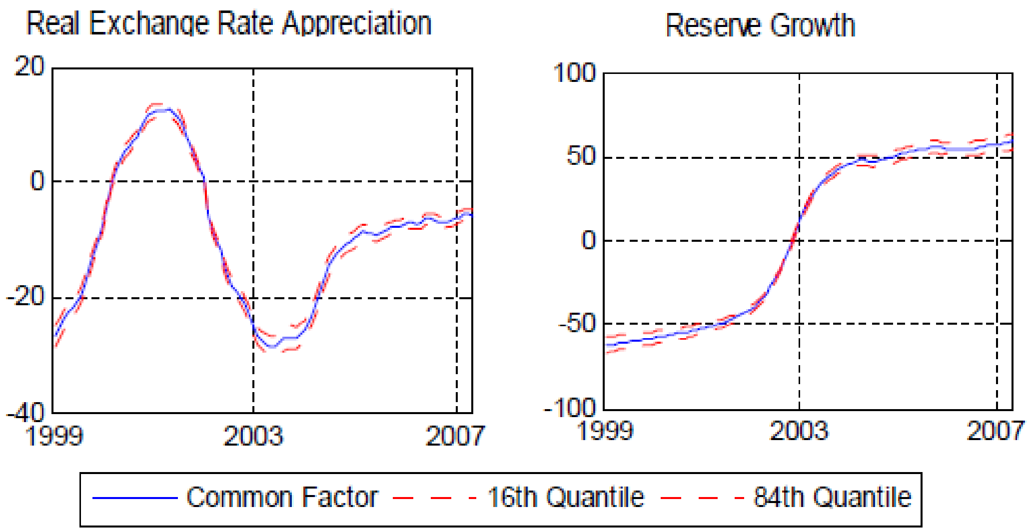


Figure 6 shows the estimated common factors and their respective 16th and 84th quantiles. If the distribution of the common factors were normal, these would correspond to one standard deviation confidence bands. All of the common factors display a positive trend in the period leading up to the sub-prime crisis. If the common factor truly reflects global economic factors, this would suggest that the most recent improvement in vulnerability indicators was indeed driven by external fluctuations.

But this conclusion is made based on a 'global' factor extracted from one factor model. If there is an EME-specific common factor, which behaves very differently from the estimated global factor, then our econometric model would be misspecified and the interpretation of the common factor as global invalid. To assess whether this is the case, we re-estimate the model restricting the sample to EMEs only. If there is an EME-specific common factor, we would expect the common factor estimated from this model to display a different shape and behaviour than the common factor estimated from the whole sample.

Figure 7 - Common factors - robustness check

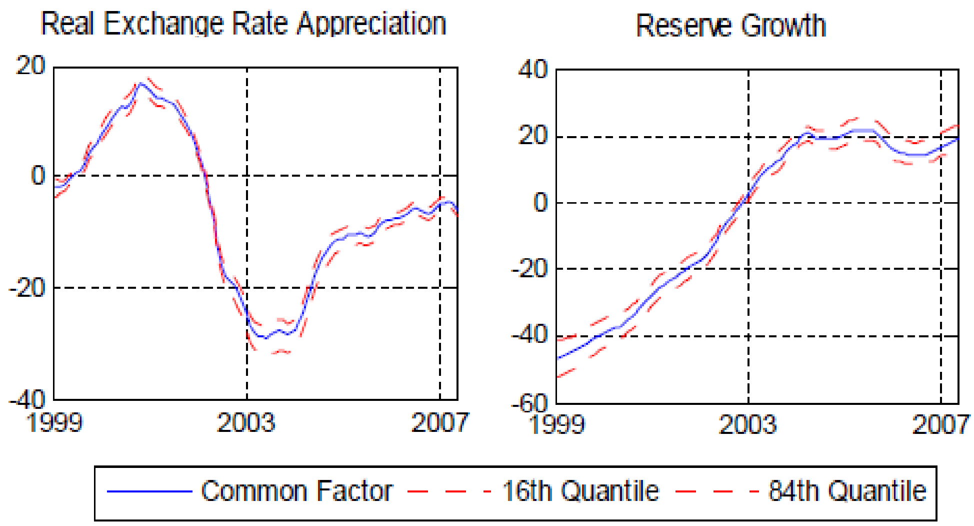


Figure 7 shows the common factors, estimated from a sample of EMEs only, and their respective 16th and 84th quantiles. The general shape of these common factors appears to be fairly similar to those from our baseline model. This suggests that the absence of an EME-specific factor in our baseline model does not affect our inference significantly.

5.2 Caveats of the analysis

Several criticisms of our empirical approach can be made. One could criticise our approach on the basis that monetary reforms are one-off events and thus modelling the time-variation as Markov switching rather than drifting coefficients may be appropriate. On the other hand, reforms take time to have an effect on the relationship between the vulnerability indicators and our estimated global factors. The full effect will probably not be felt instantly, but strengthen over time. Since our data is at monthly frequency, we argue that a drifting coefficients specification may capture these evolving relationships better than Markov switching. Furthermore, our empirical model is simple compared to more general Bayesian models with multiple lags in the common factor, regional factors, time-varying stochastic volatility and serially correlated error terms (Del Negro and Otrok (2008)). This is done for reasons of parsimony as otherwise the model would be overparametrised. To estimate such a model, we would need to impose additional priors on the model parameters. Unlike the case for industrialised countries, we argue that it is difficult to impose credible priors on the data in the case of EMEs. As a result we adopt a non-informative prior, permitting the data to speak for itself.

From an economic perspective, it is not completely clear whether reforms can actually affect the relationship between vulnerability indicators and the global factor in practice. Furthermore, our analysis does not yield any evidence on the scale of reforms necessary to facilitate decoupling. Possibly the largest caveat of our analysis is that we cannot explicitly say what the latent global factor is. If the latent global factor reflects low interest rates in world capital markets, then this condition may certainly be reversible. On the other hand, the integration of India and China into the world economy may lead to a permanent increase in the level of commodity prices.

6 Conclusion

Compared to the 1990s, the past decade seemed to be a time of great moderation for EMEs. This period of stability coincided with abundant liquidity in global financial markets, high commodity prices and a growing world economy. Previous studies confirm EMEs' dependency on these external factors. But the length of macroeconomic stability and the size of the improvement in vulnerability indicators, led some observers to believe that this time it is different. The question we therefore seek to answer in this contribution is not whether EME financial crises are a relic of the past, but whether EMEs are possibly breaking their dependency on external factors. For this purpose we apply a Bayesian dynamic common factor model to two vulnerability indicators of financial crises: real exchange rate appreciation and international reserve growth. Both of these variables have been found to be the most useful predictors of financial crisis by previous work (Frankel and Saravelos (2010)). Since our sample for each indicator consists of up to 41 countries, consisting of both EMEs and advanced economies, we argue that the common factor can be interpreted as a global factor.

We find that one common factor contributes on average up to 60% to the vulnerability indicators' variation. Reforms of the exchange rate regime may lead to decoupling, while subsequent economic integration can result in a greater influence of global factors. Some countries show a gradual and persistent decline in their exposure to global factors, which we interpret as decoupling. But in most countries the exposure tends to either decline and rise or stay constant over time. In light of these findings, we conclude that it is difficult to find evidence of decoupling for most countries.

Our results suggest that while a few countries have become more resilient to a reversal of benign financial global factors, most have not. If this is truly the case, then the boom experienced in most emerging markets following the Asian financial crises should have turned into a bust once global factors reverted. The sudden stops experienced in most EMEs in October 2008 seems to have confirmed this thesis. Our investigation raises several interesting questions for future research. While we quantify the extent to which vulnerability indicators are exposed to global factors, our model does not explicitly say what they are. Future research should therefore focus on teasing out the exact contribution of economic variables such as commodity prices to our estimated common factors. Another interesting, but perhaps technically more challenging, question is to ask why there does not appear to be any decoupling in most countries. It could be that some reforms do not increase resiliency from reversals in global factors, but this remains an open question to be answered in the future.

Appendix A : Gibbs sampling

Gibbs sampling is a numerical method for the approximation of joint and marginal distributions from conditional distributions. The numerical implementation of this algorithm occurs through the iterative simulation of Monte Carlo Markov Chains. Suppose that we are presented with the following joint density $f(x, y_1, y_2, \ldots, y_k)$. We are then interested in the estimation of the parameters, such as the mean and the variance, of the following marginal density:

$$f(x) = \int_{y_k} \cdots \int_{y_1} f(x,\ y_1,\ y_2, \ldots,\ y_k) dy_1 \ldots dy_k$$

The direct approach to obtain the marginal density would be to perform the integration above. In some cases, such as the dynamic common factor model with time-varying coefficients which we employ in this study, this may be analytically infeasible and computationally very burdensome. The Gibbs sampler is a technique which allows us to sample from the marginal density $f(x)$ without having to compute it. All one needs for Gibbs sampling are the conditional distributions, as we show in the example below.

Consider the following bivariate joint density $f(x, y)$. Suppose that the conditional densities $f(x \mid y)$ and $f(x \mid y)$ are known. We can then simulate a 'Gibbs Sequence' of draws $y_0, x_0, y_1, x_1 \ldots y_J, x_J$ from these two conditional densities through the iteration of the following algorithm.

1. Draw x_j from $f(x \mid y_j)$
2. Draw y_j from $f(y \mid x_j)$
3. Return to Step 1

In the first step we can randomly draw x_j conditional on knowing y_j. Since we know the value of x_j by the time the second step is reached, sampling y_j randomly conditional on knowing x_j is straightforward. To start this algorithm we need to specify an initial condition. In particular, we need to specify a value for y_0 in order to draw x_0 conditional on knowing y_0. While the initial condition needs to be set by the researcher, the choice of the initial condition does not affect the outcome in most cases since the first couple of hundred draws are usually discarded.

Geman and Geman (1984) show that the draws x_j, y_j converge at an exponential rate to the true joint and marginal distributions, $f(x, y)$ and $f(x)$, $f(y)$ respectively, as $j \to \infty$. Once j is large enough to ensure convergence, every subsequent iteration will yield draws from the true joint and marginal distribution. The collection of a sufficiently large amount of draws following convergence permit us to calculate parameters of interest such as the mean of the true marginal distribution. If we for instance keep M draws after the Gibbs sampling procedure has converged, then the mean of the marginal distribution for x can be calculated as

$$\frac{\sum_{j=1}^{M} x_j}{M}$$

Since each x_j subsequent to convergence is a draw from the true marginal density, we can also calculate the median[13] and create confidence intervals around any of the parameters of the marginal density which are of interest to us.

Convergence of the Gibbs sampling procedure is an important issue. Kim and Nelson (1999) suggest that if the estimated densities after a certain cut-off point of iterations do not vary much, the procedure has converged.[14]

[13] Since in practice, we choose M to be usually a large number such as 1,000, empirically, the mean and the median will be the same.

[14] One should thus set the number of iterations to be high and try different numbers of iterations in order to verify whether the results change. If they do not, one can conclude that the procedure has converged and report the results.

References

Bernanke, B, Boivin, J and Eliasz, P (2005), 'Measuring monetary policy: a factor augmented vector autoregressive (FAVAR) approach', *Quarterly Journal of Economics*, Vol. 120.

Calvo, G, Leiderman, L and Reinhart, C (1993), 'Capital inflows and real exchange rate appreciation in Latin America: the role of external factors', *IMF Staff Papers*.

Canova, F (2005), 'The transmission of US shocks to Latin America', *Journal of Applied Econometrics*, Vol. 20(2), pages 229-51.

Carter, J and Kohn, R (1994), 'On Gibbs sampling for state space models', *Biometrika,* Vol. 81, pages 541-53.

Cogley, T and Sargent, T (2001), 'Evolving post World War II US inflation dynamics', *NBER Macroeconomics Annual,* Vol. 16, pages 331-73.

Del Negro, M and Otrok, C (2008), 'Dynamic common factor models with time-varying oarameters', University of Virginia, manuscript.

Dooley, M and Hutchinson, M (2009), 'Transmission of the US subprime crisis to emerging markets: evidence on the decoupling-recoupling hypothesis', *NBER Working Paper No. 15120.*

Dungey, M and Tambakis, D (2005), 'Identifying international financial contagion: progress and challenges', Oxford University Press, New York.

Frankel, J and Rose, A (1998), 'The endogeneity of the optimum currency area criteria', *The Economic Journal*, Vol. 108, pages 1,009-25.

Frankel, J and Saravelos, G (2010), 'Are leading indicators of financial crises useful for assessing country vulnerability? Evidence from the 2008-09 global crisis', *NBER Working Paper No. 16047.*

Geman, S and Geman, D (1984), 'Stochastic relaxation, gibbs distribution and the Bayesian restoration of images', *IEEE Trans. Pattern Anal. Mach. Intell*, Vol. 6, pages 721-41.

Gregory, A , Head, A and Raynauld, J (1997), 'Measuring world business cycles', *International Economic Review*, Vol. 38, pages 677-702.

Harvey, A (1993), 'Time series models', MIT Press.

Hoffmaister, A and Roldos, J (1997), 'Are business cycles different in Asia and Latin America?', *IMF Working Paper No. 97/82*.

Imbs, J (2004), 'Trade, finance, specialization, and synchronisation', *Review of Economics and Statistics*, Vol. 86, pages 723-34.

IMF (2006), 'Financial systems and economic cycles', *World Economic Outlook*, September.

Kaminsky, G, Reinhart, C and Vegh, C (2003),' The unholy trinity of financial contagion', *Journal of Economic Perspectives*, Vol. 17(4), pages 51-74.

Kim, J K and Nelson, C R (1999), 'State-space models with regime switching: classical and Gibbs-sampling approaches with applications', MIT Press.

Kose, A, Otrok, C and Prasad, E (2008), 'Global business cycles: convergence or decoupling?', *NBER Working Paper No. 14292.*

Kose, A, Otrok, C and Whiteman, C (2003),'International business cycles: world, region and country specific factors', *American Economic Review*, Vol. 93(4), pages 1,216-39.

Mackowiak, B (2006), 'How much of the macroeconomic variation in Eastern Europe is attributable to external shocks?', *Comparative Economic Studies*, Vol. 48(3), pages 523-44.

Mumtaz, H and Surico, P (2008), 'Evolving international inflation dynamics: evidence from a time-varying dynamic common factor model', *Bank of England Working Paper No. 341*.

Rueffer, R, Sanchez, M and Shen, J (2007), 'Emerging Asia's growth and integration: how autonomous are business cycles?', *ECB Working Paper No. 715*.

Walti, S (2009), 'The myth of decoupling', Swiss National Bank, *mimeo.*