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The implications of global and  
domestic credit cycles for  
emerging market economies:  
measures of  
finance-adjusted output gaps

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## Abstract

We present estimates of finance-adjusted output gaps which incorporate the information on the domestic and global credit cycles for a sample of emerging market economies (EMEs). Following recent BIS research, we use a state-space representation of an HP filter augmented with a measure of the credit gap to estimate finance-adjusted output gaps. We measure the domestic and global credit gaps as the deviation of private-sector real credit growth and net capital flows to EMEs from long-term trends, using the asymmetric Band-Pass filter. Overall, we find that financial cycle information is associated with cyclical movements in output. In the current circumstances, the estimates suggest that if financing and credit conditions were to tighten, it would be associated with a moderation in activity in some EMEs.

**Keywords:** Domestic credit cycle, global financial cycle, output gap

**JEL Classifications:** C32, E32, F32

## Non-Technical Abstract

The experience of advanced economies during the financial crisis has emphasised the importance of integrating financial variables in standard economic models. A large body of literature has examined the different channels through which financial frictions affect macroeconomic conditions, notably the financial accelerator by which temporary positive shocks to output lead to easier lending conditions and higher credit growth, which in turn supports activity. In recession, the opposite occurs: negative shocks hit firms' and households' net worth, banks become less willing to lend, and access to credit diminishes which weighs on output growth.

For emerging markets, Rey (2015) argues that there is a global financial cycle in capital flows, asset prices and in credit growth which co-moves with uncertainty and risk aversion in financial markets. The global financial cycle can create booms and busts in emerging markets, with surges in capital flows contributing to excess credit creation and profoundly shaping business cycles.

This paper contributes to analysis of the role of financial variables in shaping business cycles, using a framework to estimate "finance-adjusted output gaps". The work follows Borio et al. (2013) which presented a novel approach to estimating potential output and output gaps that allow financial factors to have a direct effect on the business cycle. That stems from concerns that "traditional" definitions of output gaps, which focus on the "non-inflationary" level of potential output, may be too restrictive for identifying the unsustainable growth path of an economy. Indeed, the pre-crisis experience in advanced economies showed that output can be on an unsustainable path even if inflation is low and stable, while financial imbalances accumulate.

Our paper contributes by providing estimates of "finance-adjusted" output gaps and "sustainable" growth for a large sample of emerging market economies, which could be useful for policy-makers to distinguish the level of output which is sustainable in the absence of financial imbalances. In general, our methodology is very similar to that proposed by Borio et al. (2013). One innovation, however, is to extend the approach to incorporate the global financial cycle, using a measure of aggregate capital flows to emerging markets.

The topic is highly relevant at the current juncture: buoyant credit growth in many EMEs has heightened concerns about rising imbalances and risks to the global outlook should the credit cycle turn. Significant impetus has also been provided by favourable global funding conditions which have encouraged strong capital flows towards EMEs. While loose global and domestic funding conditions may have helped to sustain EME growth in the short run, medium-term vulnerabilities have increased. As economic activity has slowed, fears have grown that a sharp correction of financial imbalances would have long-lasting effects on the outlook. Measures of finance-adjusted output gaps may be one way to identify the possible consequences of such credit booms. The measure of finance-adjusted trend growth could then be interpreted as the level of output which is sustainable in the absence of financial imbalances. Strong deviations of the finance-adjusted from conventional output gaps might be one warning sign of unsustainable growth.

Overall, we find that financial cycle information as captured by the behaviour of domestic and global credit aggregates is associated with cyclical movements in output in emerging markets. In several EMEs, including China, Thailand, Malaysia, and, to a lesser extent, Chile, Turkey and Mexico, we find that domestic credit growth was strongly associated with activity growth in recent

years. We also find that capital inflows were correlated with stronger economic activity in the aftermath of the global financial crisis.

Overall, that might suggest that economic prospects in EMEs are vulnerable to a turn in both the domestic and the global credit cycle. Our analysis would underscore the potential downside risk to the economic outlook in emerging market economies, in particular against the background of a potential reversal in capital flows away from EMEs following the start of normalisation in US interest rates.

## 1 Introduction

The experience of advanced economies during the financial crisis has emphasised the necessity of integrating financial variables in standard economic models. Ignoring the role of financial developments in shaping business cycles could prove costly, given the inherent inability of models to foresee problems originating in the financial system. Building on the seminal contribution of Bernanke and Gertler (1989), Kiyotaki and Moore (1997) and Bernanke et al. (1996), a large body of literature emerged explaining different channels through which financial frictions affect macroeconomic conditions. Notably, according to the “financial accelerator” mechanism temporary output shocks which increase the net worth of agents lead to easier lending conditions and higher credit growth, which in turn supports activity. In recession, the opposite occurs: negative shocks hit firms’ and households’ net worth and, with a lower value of assets which can be pledged as collateral, banks become less willing to lend, hampering the access to credit and weighting on output growth.

A number of papers document relationships between financial and business cycles. Claessens et al. (2012) explore the interactions between business and financial cycles during their different phases for a large number of advanced and emerging economies. They find that recessions associated with financial disruptions are typically deeper and recoveries weaker. They also find that business and financial cycles are more pronounced in emerging markets than advanced countries. Schuler et al. (2015) find that financial cycles in 13 European countries have been longer and more asymmetric than business cycles. Moreover, concordance of financial and business cycles is observed only two-thirds of the time. Runstler and Vlekke (2016) use multivariate unobserved components models to estimate trend and cyclical components in GDP, credit volumes and house prices for the United States and five large European economies. With the exception of Germany, they find cycles in credit and house prices are highly correlated with the medium-term component of GDP cycles.

Our work is related to recent empirical studies that propose a novel approach for understanding the impact of financial factors on the business cycle, estimating the direct effect on potential output and the output gap. The idea, pioneered by Borio et al. (2013), followed dissatisfaction with traditional definitions of output gaps. Arguably, the difference between actual output and the “non-inflationary” level of potential output may be too restrictive for identifying the unsustainable growth path of an economy. Inflation may not be the only symptom of an “unsustainable” expansion. The pre-crisis experience in advanced economies showed that output might be on an

unsustainable path even if inflation is low and stable, while financial imbalances accumulate. By extending the HP filter (Hodrick and Prescott (1997)) to incorporate information contained by financial variables, as captured by the behaviour of credit or house prices developments, the authors argue that financial factors help to explain a substantial portion of the cyclical movements in output gaps in several advanced economies.

Recent papers find a similar important influence of financial cycles for business cycles. Bernhofer et al. (2014), apply the same concept in a more general statistical set-up, namely by extending the unobserved component model proposed by Harvey (1989) and Harvey and Jaeger (1993) to several advanced economies (Austria, Ireland, Netherlands, US, Bulgaria, Estonia, Poland and Slovakia). The authors find a substantial impact of the financial cycle on business cycle fluctuations, particularly before and during the global financial crisis. Berger et al. (2015) also use a simple multivariate filtering approach to illustrate the role that financial variables play in driving potential or sustainable output for a group of European countries, finding that potential moves more steadily during financial boom and bust periods than implied by conventional HP filter estimates. Another extension of this concept is offered in Maliszewski and Zhang (2015) where estimates of finance-neutral output gaps for China are obtained in a multivariate filter framework which explicitly links the output gap with the credit gap and the housing price gap with the credit gap. By exploiting the data from a large sample of EMEs, Krupkina et al. (2015) also find that financial indicators (e.g credit to GDP ratio, broad measure of money to GDP ratio, stock market capitalization) matter for output gaps, in addition to the conventional indicators such as inflation rate or unemployment.

The importance of financial cycle information for understanding business cycle dynamics has encouraged studies of the impact on fiscal positions. Liu et al. (2015) argue that the global financial crisis demonstrated that movements in asset prices can have an important fiscal impact. Failing to account for the fiscal impact of asset price cycles can encourage a pro-cyclical policy stance. They outline an operational approach for incorporating the impact of asset price cycles in the calculation of structural fiscal balances. Borio et al. (2016) also extend the analysis of the role of financial cycles on fiscal positions, offering a new tool to estimate cyclically adjusted fiscal balances, based on estimates of sustainable output

This paper contributes to this on-going research agenda by providing estimates of finance-adjusted output gaps and sustainable growth for a large sample of emerging market economies, which could be useful for policy-makers to distinguish the level of output which is sustainable in the absence of financial imbalances. The topic is highly relevant at the current juncture: buoyant credit growth in many EMEs has heightened concerns about rising imbalances and risks to the global outlook should the credit cycle turn. In the period since the global financial crisis, domestic credit to the private sector has expanded by an average of about 9 percent per year in a sample of 15 large EMEs, with particularly steep increases in Brazil, Indonesia, Turkey and China. Credit has also risen relative to GDP in many countries. Significant impetus has also been provided by favourable global funding conditions which have encouraged strong capital flows towards EMEs. While loose global and domestic funding conditions may have helped to sustain EME growth in the short run, medium-term vulnerabilities have increased. As economic activity has slowed, fears

have grown that a sharp correction of financial imbalances would have long-lasting effects on the outlook. Measures of finance-adjusted output gaps may be one way to identify the possible consequences of such credit booms: strong deviations of finance-adjusted from conventional output gaps might be one warning sign of unsustainable growth dynamics arising from credit booms.

Our methodology is very similar to that one proposed by Borio et al. (2013), with two important distinctions. First, similar to Maliszewski and Zhang (2015) we choose to link the output gap with credit gap measures rather than to changes in real credit as in Borio et al. (2013). This formulation allows for a more intuitive interpretation of results: the output gap should be closed in the absence of financial imbalances (i.e. a credit gap of zero). Second, we extend the approach to incorporate the global financial cycle. Rey (2015) argues that there is a global financial cycle in capital flows, asset prices and in credit growth which co-moves with uncertainty and risk aversion of financial markets. The global financial cycle can create booms and busts in emerging markets, with capital flow surges contributing to excess credit creation and affecting the business cycle. We therefore extend the approach of Borio et al. (2013) and Borio et al. (2014) to incorporate a measure of the global financial cycle, following Blanchard et al. (2015) in constructing an aggregate of capital flows to emerging markets. In a similar set-up, Alberola et al. (2016) estimate the a measure of the output gap that filters out the impact of the commodity and net capital inflows booms for Latin American countries. This paper investigates within this framework the importance of the global financial cycle and capital flows for a wider set of EME business cycles.

## 2 Methodology, Data and Estimation

In the spirit of Borio et al (2013)<sup>1</sup> we estimate measures of sustainable output and “finance-neutral” output gaps by augmenting the Hodrick-Prescott filter with credit gap variables. Hodrick and Prescott define the trend  $y_t^*$  of a times series  $y_t$  (in our case log of real GDP) in a way that minimises equation 1 for a given parameter of  $\lambda$  (the smoothing parameter), under the assumption that real GDP follows an I(2) process and, thereby, the trend growth is time-varying.

$$\min \sum_t^T (y_t - y_t^*)^2 + \lambda * \sum_{t=2}^{T-1} [(y_{t+1}^* - y_t^*) - (y_t^* - y_{t-1}^*)]^2 \quad (1)$$

If the business cycle component  $y_t - y_t^*$  and the second difference of  $y_t^*$  are normally and independently distributed, then the  $\lambda$  is given by the ratio of the two variances  $\lambda = \sigma_{y_t - y_t^*}^2 / \sigma_{\Delta^2 y_t^*}^2$ . The same model can be represented in state-space form:

$$y_t = y_t^* + \epsilon_{gap} \quad (2)$$

$$\Delta y_t^* = \Delta y_{t-1}^* + \epsilon_{trend} \quad (3)$$

Equation 2 (the measurement equation) decomposes the log of real GDP ( $y_t$ ) into a trend component  $y_t^*$  and a business cycle component  $\epsilon_t^{gap}$ . Equation 3 (the state equation) assumes the

<sup>1</sup>We thank Claudio Borio, Piti Disyatat and Mikael Juselius for sharing their Matlab Code with us. The model is implemented using the IRIS Toolbox



growth rate of trend GDP follows a random walk.  $\epsilon_t^{gap}$  and  $\epsilon_t^{trend}$  are normally and independently distributed errors with mean zero and variance  $\sigma_{gap}^2$  and  $\sigma_{trend}^2$ . The functional form of the system together with the noise-to-signal ratio ( $\lambda = \sigma_{gap}^2 / \sigma_{trend}^2$ ) jointly determine the relative variability of trend output. If  $\lambda$  tends to infinity the potential output approaches a linear trend, while if  $\lambda$  tends to zero, the trend approaches the actual GDP series. In accordance with the standard view that business cycles usually last at most 8 years, the signal to noise ratio of the HP filter is usually set to 1600 for quarterly data or 100 for annual data.

Next, we augment the measurement equation (2) to allow credit cycles to inform the estimates of output gap. The model thus indirectly identifies the level of output that may be sustained in the absence of financial imbalances.

$$y_t - y_t^* = \gamma_i * X_i + \epsilon_{gap} \quad (4)$$

where  $X_i$  stands for the *domestic – credit*<sub>t</sub><sup>gap</sup> and/or the *global – credit*<sub>t</sub><sup>gap</sup> as proxies for the domestic and global financial cycles.

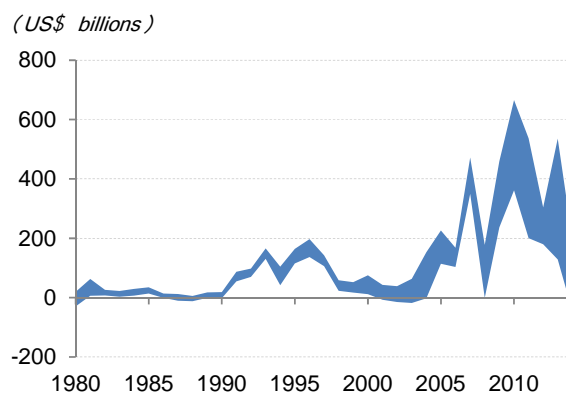
For domestic variables, the choice is motivated by BIS research, which argues that domestic credit aggregates (as a proxy for leverage) and property prices (as a measure of available collateral) play a key role in identifying financial cycles. However, with low quality and short samples of data for property prices for EMEs, we restrict the analysis to credit aggregates. In addition, reflecting the literature on the importance of the global financial cycle and capital flows for EMEs (e.g. Rey (2015)), we construct a measure of global capital flows to EMEs. We follow Blanchard et al. (2015) in aggregating (net) capital flows across EMEs (but omitting for each country their own inflows), which Blanchard et al. (2015) argue provides a plausibly exogenous measure of capital flows. Algebraically, it is expressed as:

$$GFC_t = \sum_{i \neq j} GKF_{it} \quad (5)$$

where  $GKF_{it}$  is global capital flows to each emerging market economy  $i$ . The measure is specific to each country but shows a clear common global cycle (Chart 1).

Similar to Maliszewski and Zhang (2015) we choose to link the output gap with credit gap measures rather than to changes in real credit as in Borio et al. (2013) and others. Such a formulation allows for a more intuitive interpretation of results: the output gap should be closed in the absence of financial imbalances (i.e. a credit gap of zero). This choice is also motivated by the particular characteristics of financial variables in EMEs. While credit growth in advanced economies seems to offer a good representation of the financial cycle for advanced economies, it does not for EMEs. Credit growth is much more volatile across EMEs and a large amount of higher frequency movements will make such estimation more difficult, since we are trying to inform a relative smooth variable, the output gap.

**Chart 1: Range of country-specific measures of global capital flows**



Sources: IMF and National statistics.

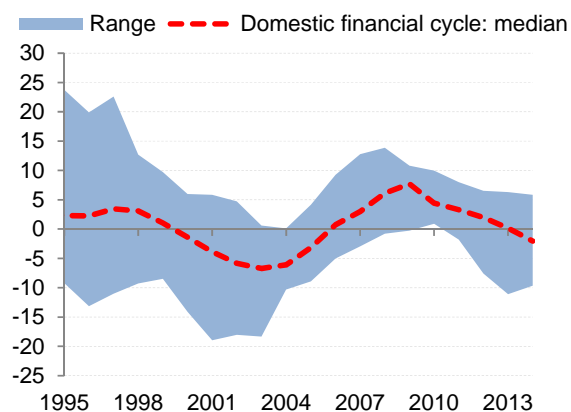
Notes: See main text for construction of aggregate net capital flows measures.

We determine the credit gap outside of the model. That helps to limit the number of parameters to be estimated in a short-sample for several EMEs. We model credit gaps, either domestic or global, as the deviations of variables from their long-term trends, which we extract by applying the asymmetric Band-Pass filter. However, in doing so, we need to make a judgement about the typical frequency of financial cycles. The common view in the literature is that financial cycles last longer than traditional business cycles but no consensus about the specific frequency has been reached. Drehmann et al. (2012) examine variables across a number of countries and find the average duration of the financial cycle to be about 16 years. We take as our benchmark credit gap measure a filter isolating cycles with duration of between 8 and 20 years, applying the filter to both the domestic credit and global capital flow series. Charts 2 and 3 show the range of filtered domestic and global cycles across the sample of EMEs.



**Chart 2: Filtered measures of domestic credit cycles**

(percentage deviation from trend)

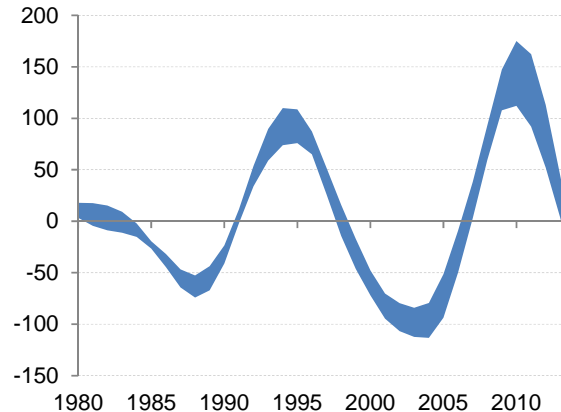


Sources: IMF, national statistics and own calculations and estimations.

Notes: Estimates of credit cycles in sample of 15 EMEs. Red line shows median for sample; range shows 10–90 percentiles across sample.

**Chart 3: Filtered measures of global financial cycles**

(US\$ billions)



Sources: IMF, national statistics, own calculations and estimations.

Notes: Estimates of global capital flow cycles in sample of 15 EMEs. Red line shows median; range shows 10–90 percentiles across sample.

Our country sample consist of 15 EMEs: China (CN), India (IN), Indonesia (ID), Korea (KR), Malaysia (MY), Thailand (TH), Russia (RU), South Africa (SA), Turkey (TK), Brazil (BR), Chile (CL), Mexico (MX), Poland (PL), Hungary (HU) and Czech Republic (CZ). The primary source of data is national sources and the IMF database for real GDP data, the BIS database for total credit to the private non-financial sector and the IMF Database for net private capital flows (i.e. financial account excluding reserve accumulation). Data availability constrains our estimation to start at different points (from the early 1980s or mid-1990s) and end in 2014. The general set-up of our model, comprising equations 3 and 4, is estimated in three separate specifications. In model 1, we include only the domestic credit gap (DCG) in equation (4); in model 2, we include only the global credit gap (GFC); in model 3, both the domestic credit and the global credit gap measures. These models are estimated separately for each emerging market, at an annual frequency, with a Bayesian approach using informative priors. The gamma parameters ( $\gamma_i$ ) are estimating assuming a gamma distribution and restricted to be positive. The priors are set based on the Borio et al. (2013) results for the US economy and are described in detail in Annex 1. In line with Borio et al. (2013), the signal-to-noise ratio is calibrated to correspond with a conventional HP filter. That is chosen to allow direct comparability with the HP filter measures. In Section IV we examine the robustness of the results to this assumption.

### 3 Empirical results

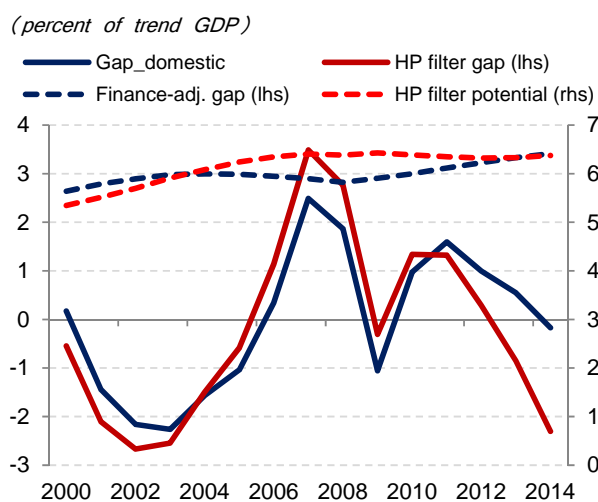
Overall, we find that financial cycle information, as captured by the behaviour of domestic and global credit aggregates, is associated with a significant part of the cyclical movements in output.

Table A1 shows estimated coefficients on the domestic and/or global cycle variables in our models. Models 1 and 2 include the domestic credit cycle or the global financial cycle variables separately; the third model includes the two variables together. The gamma coefficients differ quite considerably across countries. The differences are partly a reflection of the different amplitudes of the credit and business cycles in the countries in our sample. For example, Brazil, Turkey, Mexico and Indonesia have a relatively higher variance of credit to GDP ratios over the sample. However, differences also reflect the relative strength of the association of the business and financial cycles detected by the model.

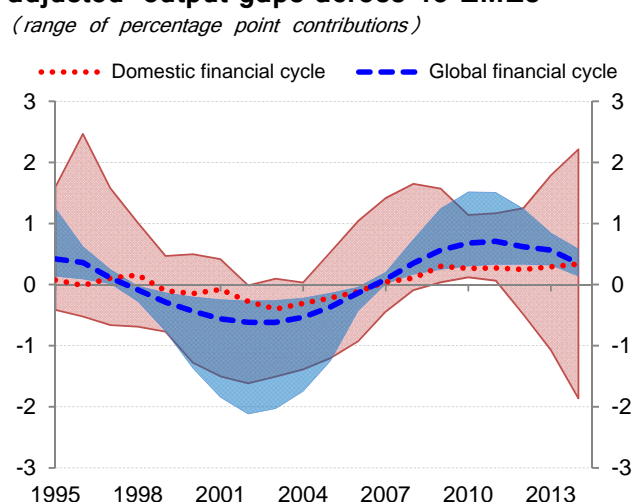
In aggregate across the sample of EMEs, the domestic and global credit variables have shown a reasonably strong association with business cycle dynamics. The estimated average (GDP-PPP weighted) finance-adjusted potential output measure (based on the model including both global and domestic financial variables) diverges from the conventional HP measure. The standard HP filter measure suggests that potential output rose during the mid-2000s and was sustained over the next few years, falling very slightly from 2010. By contrast, the finance-adjusted measure is lower through most of this period. As domestic credit rose across emerging market economies and capital flows surged, the finance-adjusted measure suggests that sustainable output remained lower. The gap between the two measures is about 0.3-0.5pp on annual GDP growth over this period. As a consequence, the estimated average (GDP-weighted) EME finance-adjusted output gap was higher than the HP filtered measure, particularly in recent years. By 2014, while the HP filter measure suggests that EMEs were operating significantly below potential, the finance-adjusted measure suggests an output gap close to zero (Chart 4). Overall, the estimates suggest that the supportive financing and credit environment provided an important support for activity in some EMEs.

The model does not allow for a structural interpretation but contribution analysis based on the model can help to show the different roles of domestic and global financial cycles and their association with business cycles (see figure A2). For the EME aggregate, large capital inflows coincided with a stronger economic activity particularly in the aftermath of the global financial crisis. However since 2013 this contribution has begun to decline, as capital flows towards EMEs have moderated. The timing chimes with developments during that period: in 2013 EMEs suffered during the so-called taper tantrum when speculation about monetary normalisation in the US sparked a tightening of external financing conditions for many EMEs. Domestic credit cycles across EMEs are more varied and the range of contributions is therefore wider (Chart 2). However, in aggregate the upswing in domestic credit cycles in this sample of EMEs has been associated with a strengthening of activity growth in recent years.

**Chart 4: Aggregate EME ‘finance-adjusted’ output gap**



**Chart 5: Range of contributions of global and domestic credit variables to ‘finance-adjusted’ output gaps across 15 EMEs**

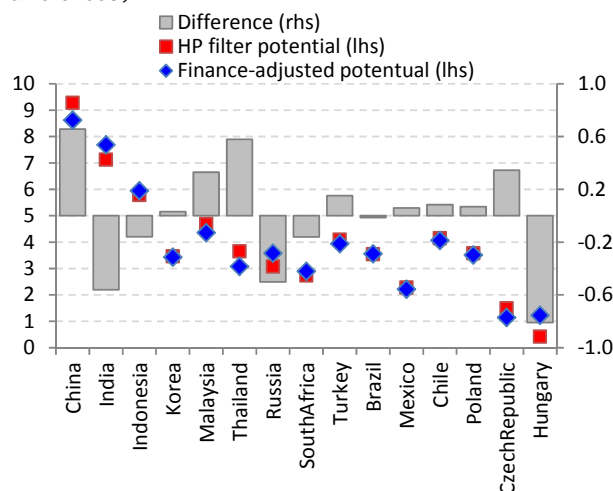


Notes: Contributions to estimates of output gap from domestic credit (band-pass filtered real private sector credit) and global financial variable (aggregate net capital flows to EMEs). Range shows 16–84 percentiles across the 15 EMEs.

Nonetheless, the estimates also point to significant variation across countries in the association of the financial cycle variables (see Chart 5 and Figure A2) with business cycles in recent years. In part, that reflects different domestic credit developments across countries in recent years (see also Chart 2). Over the period studied here, the co-movement of EME domestic credit cycles has not been particularly high: since 2000, the average bivariate correlation between EME domestic credit cycles has been 0.27. The same is true also within regions. For example, the average bivariate correlation within the Emerging Asia countries in the sample has been 0.24; for the Latin American and European economies is 0.05 and 0.31 respectively. However, one commonality is that in recent years, several EMEs have seen sharp increases in domestic credit. China, Thailand and Malaysia, and, to a lesser extent, Turkey, Chile and Mexico has seen sharp upswings in domestic credit cycles. In these countries, over the past five years, estimates of potential output according to the HP filter measure have been higher than the finance-adjusted measure (Chart 6). In other countries, however, the credit gap measure had already turned negative by 2014. These countries include commodity exporters such as Russia, South Africa and Brazil, which have been hit by deteriorating terms of trade dynamics reflecting the end of the commodity super cycle. In addition, in central and eastern European countries, domestic credit dynamics are also in a downswing. The model associates such developments in the credit cycle as providing a drag on activity.

**Chart 6: Potential output average 2010–2014: finance-adjusted and HP filter measures**

(lhs - annual percentage changes; rhs – percentage point differences)

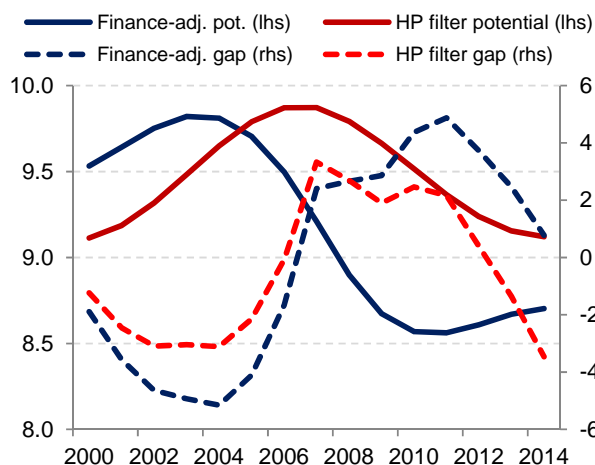


Sources: IMF and National statistics.

Notes: See main text for construction of aggregate net capital flows measures.

**Chart 7: China – ‘finance-adjusted’ output gap**

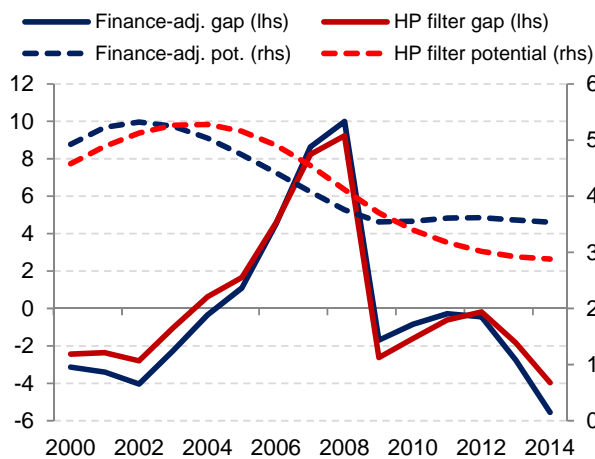
(percent of trend GDP)



Source: Authors' calculations.

**Chart 8: Russia – ‘finance-adjusted’ output gap**

(range of percentage point contributions)



Source: Authors' calculations.

In China, the most systemically important emerging economy, the results also point to a striking difference between the sustainable output growth and the conventional HP trend growth estimate. While the HP trend growth estimate suggests only a modest slowdown in growth in the

past four years, the finance-adjusted measure is lower (Chart 7). The model implies that the economy has been operating above potential since 2010, boosted in part by strong expansion of credit in response to the global downturn. Without the strong credit growth, the interactions between credit and business cycles discerned by the model implies that growth would typically have been less buoyant: i.e. the pace of expansion, absent strong credit growth, would have been lower. By 2014 the finance-adjusted output gap was more than 4pp higher than the output gap measured by a simple HP filter, suggesting to a heavy reliance of Chinese growth on credit in the post-crisis period. The statistical evidence is in line with a common concern that the build-up in credit in China, notably in the corporate sector is unlikely to be sustainable over the long term (IMF (2015)). The model is not structural, so strong interpretations should be avoided. It might nonetheless add some weight to suggestions that growth prospects in China have become increasingly vulnerable to a turn in the credit cycle.

A contrasting experience is seen in another large emerging market economy, Russia. Having fallen in the aftermath of the crisis in the last 1990s, domestic credit grew rapidly in the 2000s, with annual credit growth in double-digit figures from 2001 until 2008. The standard HP filter measure suggests that potential output rose strongly during that period. By contrast, the finance-adjusted measure is lower through most of this period (Chart 8). Since the global financial crisis, credit dynamics in Russia have moderated and the credit gap measure moved deep into negative territory. While the conventional HP filter measure shows a continued gradual decline in potential output, the finance-adjusted potential measure implies that the absence of strong support from credit has affected activity. The sustainable level of potential output according to the finance-adjusted model is higher.

## 4 Robustness

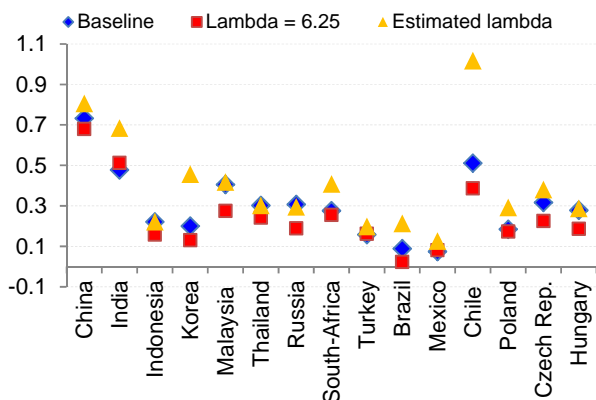
In this section, we subject our model to a series of robustness tests.

First, we investigate alternative specifications for the ratio between the variances of the output gap and potential output. In line with Borio et al. (2013), in the baseline specification, the signal-to-noise ratio ( $\sigma_{gap}^2 / \sigma_{trend}^2$ ), which determines the relative variability of the potential output and output gap estimates, was calibrated to correspond with a conventional Hodrick-Prescott filter with a lambda of 100. That was helpful because it allowed direct comparisons with the HP filter measures. However, to check the robustness of the results, we also investigated alternative signal-to-noise ratios. First, we test an alternative lambda. For quarterly data, most researchers have followed Hodrick and Prescott (1980) and Hodrick and Prescott (1997) in using the value of 1600 for the smoothing parameter but there is less agreement for other frequencies (see Morten and Uhlig (2002)). We follow Morten and Uhlig (2002) in using a lambda of 6.25. In a second step, we estimate the signal-to-noise ratio freely. We used a functional form for the shock variances ( $\sigma_{gap}^2$ ) and ( $\sigma_{trend}^2$ ) of an inverted gamma distribution and set the priors to correspond to a lambda of 100. Overall, we find the coefficient estimates are relatively robust to these changes. Charts 9 and 10 present estimates of the coefficients in our combined model, which incorporates both credit variables in equation 4. With a couple of exceptions, the coefficients on both the domestic credit

and global financial cycle variables in these alternative specification are broadly similar to those in our baseline model.

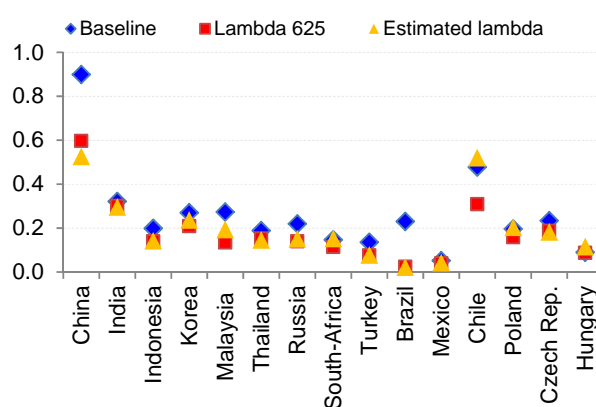
**Chart 9: Robustness checks: coefficients on domestic credit cycle variable**

*(estimates of coefficients on domestic credit cycle)*



**Chart 10: Robustness checks: coefficients on global financial cycle variable**

*(estimates of coefficients on global financial cycle)*



Source: Authors' calculations.

Notes: Blue diamonds show coefficients in the baseline model (see also Table 1, model 3). Red squares show estimates using a lambda of 6.25 rather than 100 as in the baseline specification. Yellow triangles show estimates from freely estimated signal-to-noise ratio.

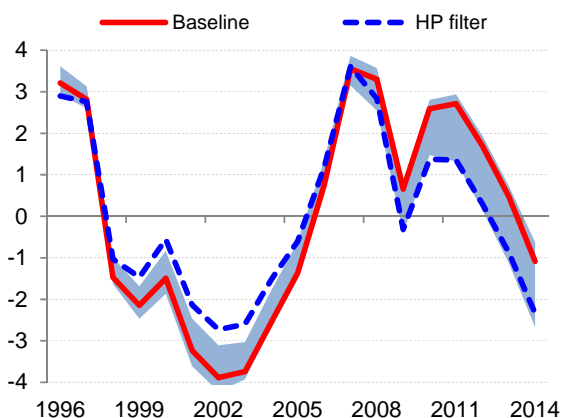
Second, we investigate our choice of measure for the global financial cycle. In our baseline model we used aggregate net capital flows to EMEs (measured in US dollars). However, alternative measures of the global capital flows may also be appropriate. We investigated the sensitivity of the results to using three alternatives: (1) narrow measures of (net) capital flows such as portfolio flows; (2) measures of capital flow accounting only for non-resident *inflows* to EMEs (and excluding outflows from EME residents); (3) measuring capital flows relative to EME GDP. Finally, we also checked our data against those of the Institute of International Finance, which compiles aggregate capital flow data for a larger set of emerging markets. While there is some co-movement across the series, there are also clear differences: in particular, compared to the US dollar measure, capital inflows since the global financial crisis look somewhat smaller when measured relative to GDP (Figures A3 and A4). We filter these series using the same band-pass procedure, with a frequency of 8 to 20 years (Figures A5 and A6) and included the alternative measures of the global financial cycle in our model and estimate the finance-adjusted output gap. To isolate the impact of different measures of the global financial cycle, we estimate the model including only the global financial cycle variable. Chart 11 shows estimates of the aggregate EME "finance-adjusted" output gap using those alternative measures. Chart 12 shows the range of estimated contributions of the global financial cycle to the output gap using the alternative measures. Overall, the estimates suggest the results are reasonably robust to the choice of global capital flow variable. For most countries in our sample, the range of estimates of the finance adjusted output gap in 2014 is also reasonably small (see Figure A7).



Third, we analyse whether the results are robust to alternative measures of the domestic credit cycle. As discussed in section 2, there is considerable debate in the literature about the duration of financial cycles (Drehmann et al. (2012)). Chart 13 shows an EME aggregate (GDP-weighted) estimate of the domestic credit cycle filtered at different frequencies (10-20, 10-25, 10-15, 10-20, 8-15, 8-25 and 8-30 years). Based on these alternative filters, there is considerable uncertainty surrounding the identification of the financial cycle. We use these alternative measures of the domestic credit cycle in our model and estimate the finance-adjusted output gap. To analyse the impact of the different frequency filters, we estimate the model including only the domestic credit cycle variable. Over the whole sample, for the EME aggregate, the range of finance-adjusted output gaps is relatively small. However, it increases towards the end of the sample to about 1.5pp (Chart 14), reflecting a wider range of the estimated contribution of the domestic credit variable (Figure A8). There is also a wider range of estimated finance-adjusted output gaps for some countries in the later year of estimation. (Figure A9).

**Figure 11: Aggregate EME “finance-adjusted” output gaps – estimates using alternative measures of the global financial cycle**

(percent of trend GDP)

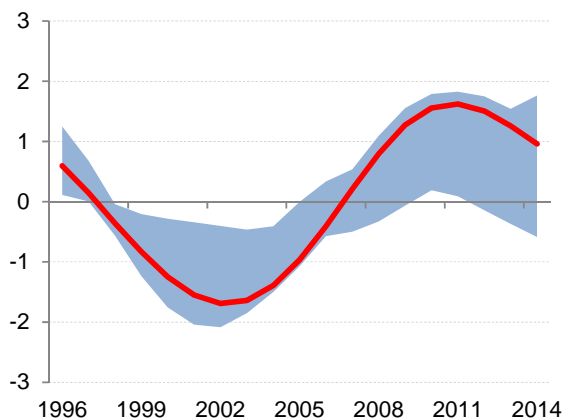


Source: Authors' calculations.

Notes: Finance-adjusted output gaps calculated using alternative measures of global financial cycle (see charts A2 to A5).

**Figure 12: Contributions of global financial cycle to “finance-adjusted” output gaps for aggregate EMEs**

(range of percentage point contributions)



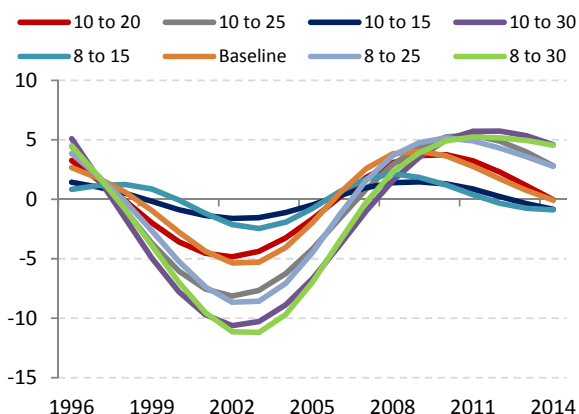
Source: Authors' calculations.

Notes: Estimates of contributions of global financial cycle to finance-adjusted output gaps calculated using alternative measures of global financial cycle (See charts A2 to A5).

These charts show the average for the EMEs in our sample, weighted by GDP (at purchasing power parity).

**Chart 13: EME aggregate domestic credit cycle - using band pass filter with alternative frequencies**

*(estimates of domestic credit cycle)*

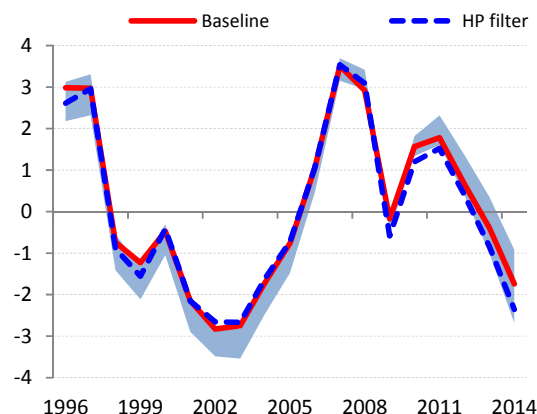


Source: Authors' calculations.

Notes: Domestic credit cycle is estimated for each EME separately, using asymmetric band-pass filter at different frequencies. Legend denotes years (e.g. 10–20 year filter). The chart shows the average for the EMEs in our sample, weighted by GDP (at purchasing power parity).

**Chart 14: EME aggregate finance-adjusted output gap - using band pass filter with alternative frequencies**

*(percent of trend output)*



Source: Authors' calculations.

Notes: Domestic credit cycle is estimated for each EME separately, using asymmetric band-pass filter at different frequencies. Legend denotes years (e.g. 10–20 year filter). The chart shows the average for the EMEs in our sample, weighted by GDP (at purchasing power parity).

## 5 Real-time performance

One function of output gap measures is to inform policymakers about the state of the economy. To be useful, however, they should be reliable real-time gauges of the cyclical position of an economy. But the literature has observed that the accuracy of real-time estimates of the output gap is often poor (Orphanides and Norden (2002)), with large ex-post revisions to gap estimates. In part, those problems stem from the unreliability of end-of-sample estimates of trend output. To investigate the real-time performance of our estimates of finance-adjusted output gaps, we conduct the following exercise. We estimate our model over successively increasing samples, i.e. up to 2007, 2008, ... 2014. In each case, we re-estimate the domestic and global financial cycles using data only over these periods. We then estimate the state-space model to derive estimates of the finance-adjusted output gaps, using the assumptions described in section 2. For each calendar year from 2007 onwards, therefore, we can observe how estimates of the finance-adjusted output gap have evolved as data for subsequent years has become available. We conduct an equivalent exercise for the (benchmark) HP filters. This exercise allows us to judge the combined effects of revisions generated by: changes in the end-of-sample estimates of the cycle underlying domestic credit and capital flow data; changes to the coefficients in the state space model as the sample is extended; and the end-of-sample estimates from the state-space model itself. We do not test, however, for the effects of any revisions to GDP, credit or capital flow data, which would require a large database of real-time data.

Table 1 describes the percentage point revisions for each calendar year between the first available estimate (e.g. the estimate of the output gap in 2007, using data up to 2007) and latest estimate (e.g. the estimate of the output gap in 2007 using data up to 2014). In some cases, for both the finance-adjusted and HP filter measures of the output gap, the revisions are large, particularly around turning points in the business cycle, such as in 2007 (see Appendix Figure A10). However, in general the absolute size of the revisions to the finance-adjusted output gap compare favourably to those seen from the standard HP filter (Table 1).

**Table 1: Comparison of revisions to estimates of output gap: finance-adjusted measures and HP-filter**  
(percentage point revisions between first estimate and latest estimate)

	2007		2008		2009		2010		2011		2012	
	FA	HP	FA	HP	FA	HP	FA	HP	FA	HP	FA	HP
China	<b>-0.3</b>	-1.9	-2.5	<b>0.5</b>	3.5	<b>2.4</b>	<b>4.0</b>	4.3	<b>0.0</b>	5.7	<b>0.9</b>	6.2
India	-2.2	<b>0.6</b>	-4.6	<b>1.1</b>	-4.2	<b>1.5</b>	-2.7	<b>2.5</b>	<b>-1.2</b>	2.6	<b>-0.5</b>	1.6
Indonesia	-3.9	<b>-2.7</b>	-4.2	<b>-0.3</b>	-1.7	<b>1.3</b>	<b>-1.0</b>	2.5	<b>-1.2</b>	3.2	<b>0.3</b>	3.3
Korea	3.8	<b>2.7</b>	<b>1.9</b>	3.1	<b>1.4</b>	2.3	<b>1.6</b>	2.5	<b>0.5</b>	2.7	<b>-0.1</b>	2.3
Malaysia	0.9	<b>-0.5</b>	<b>-0.5</b>	1.1	-0.5	<b>0.2</b>	<b>0.0</b>	0.5	-2.3	<b>0.9</b>	-1.7	<b>1.4</b>
Thailand	2.0	<b>0.7</b>	<b>-1.2</b>	2.1	<b>0.3</b>	1.6	<b>1.6</b>	2.6	<b>-0.6</b>	2.4	<b>-0.1</b>	3.5
Russia	4.9	<b>4.4</b>	<b>5.1</b>	8.4	<b>1.7</b>	7.0	<b>-0.2</b>	5.8	<b>-1.3</b>	4.7	<b>-0.4</b>	3.5
SouthAfrica	<b>1.7</b>	1.8	<b>1.5</b>	3.5	<b>1.1</b>	3.2	<b>0.6</b>	2.7	<b>0.2</b>	2.3	<b>0.4</b>	1.6
Turkey	3.9	<b>2.2</b>	<b>0.1</b>	3.4	<b>-0.8</b>	1.0	-1.1	<b>0.7</b>	<b>-1.5</b>	2.1	<b>-1.8</b>	2.4
Brazil	<b>-1.4</b>	-2.0	0.5	<b>0.2</b>	0.7	<b>0.7</b>	<b>2.2</b>	2.4	<b>1.7</b>	3.7	<b>1.8</b>	4.0
Mexico	2.7	<b>2.0</b>	<b>1.6</b>	2.7	<b>0.1</b>	0.8	-0.7	<b>0.2</b>	-1.6	<b>0.4</b>	-1.3	<b>1.0</b>
Chile	2.2	<b>1.2</b>	<b>0.1</b>	2.2	-2.2	<b>1.0</b>	-2.4	<b>0.6</b>	-3.2	<b>0.9</b>	<b>-1.3</b>	1.4
Poland	1.5	<b>-0.5</b>	2.3	<b>1.1</b>	<b>0.8</b>	2.0	<b>1.7</b>	2.6	<b>-0.4</b>	3.4	<b>-0.7</b>	3.3
Czech Rep.	2.6	<b>2.3</b>	<b>3.3</b>	5.8	<b>2.0</b>	6.2	<b>3.1</b>	6.6	<b>1.0</b>	6.8	<b>-0.1</b>	5.9
Hungary	<b>6.9</b>	7.4	<b>6.6</b>	8.5	<b>4.4</b>	6.5	<b>1.6</b>	4.5	<b>0.0</b>	3.1	-1.4	<b>0.9</b>
Countries for which the revisions of finance-adjusted output gaps are smaller than for the HP filter ones	4		10		9		11		12		12	

Notes: FA = finance-adjusted output gap; HP = hp filter output gap. Percentage point estimate between first estimate of the output gap for particular calendar year (e.g. the estimate of the output gap in 2007, using data up to 2007) and latest estimate (e.g. the estimate of the output gap in 2007 using data up to 2014). Bold figures which estimate had the smallest absolute percentage point revision.

## 6 Conclusion

We present estimates of finance-adjusted output gaps which incorporate the information on the domestic and global credit cycles for a sample of emerging market economies. Following recent BIS research, we use a state-space representation of an HP filter augmented with a measure of the credit gap to estimate finance-adjusted output gaps. We measure the domestic and global credit gaps as the deviation of private-sector real credit growth and net capital flows to EMEs from long-term trends, using the asymmetric Band-Pass filter.

Overall, we find that financial cycle information is associated with cyclical movements in output in large emerging market economies. The model results are robust to alternative measures of the global capital flows and the choice of filter applied to extract the credit cycles. Analysis of the

real-time performance of the estimates is conducted from 2007 onwards. Revisions to estimates of the output gap are large in some instances, particularly around cyclical turning points, although the revisions of the finance-adjusted output gap is typically smaller than those from a standard HP filter.

While the model does not allow for a structural interpretation, our results might lend weight to concerns for the current conjuncture by highlighting the potential vulnerabilities for emerging markets economies which have seen sharp increases in domestic credit and strong capital inflows. Our estimates suggest that if financing and credit conditions were to tighten, it could remove a quantitatively important component of support for activity in some EMEs.

The paper proposes a simple statistical model that incorporates financial factors in the estimation of the business cycle in EMEs and leaves open avenues for further research such as (i) to explore the properties of different specifications for the trend-cycle decomposition that would allow for possible shifts/breaks in the trend of a time series, outliers or correlations between the trend and cycle component, (ii) to specify the process for the financial cycle inside of the state-space representation or (iii) to improve the story telling features of the model by augmenting it with structural equations such as Philips curves or Okun law.

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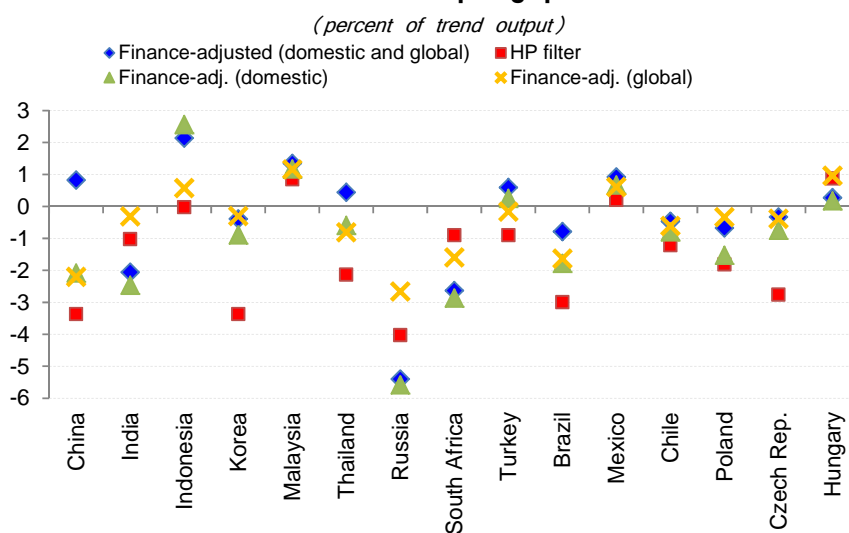
## Appendix

**Table A1: Coefficient estimates**

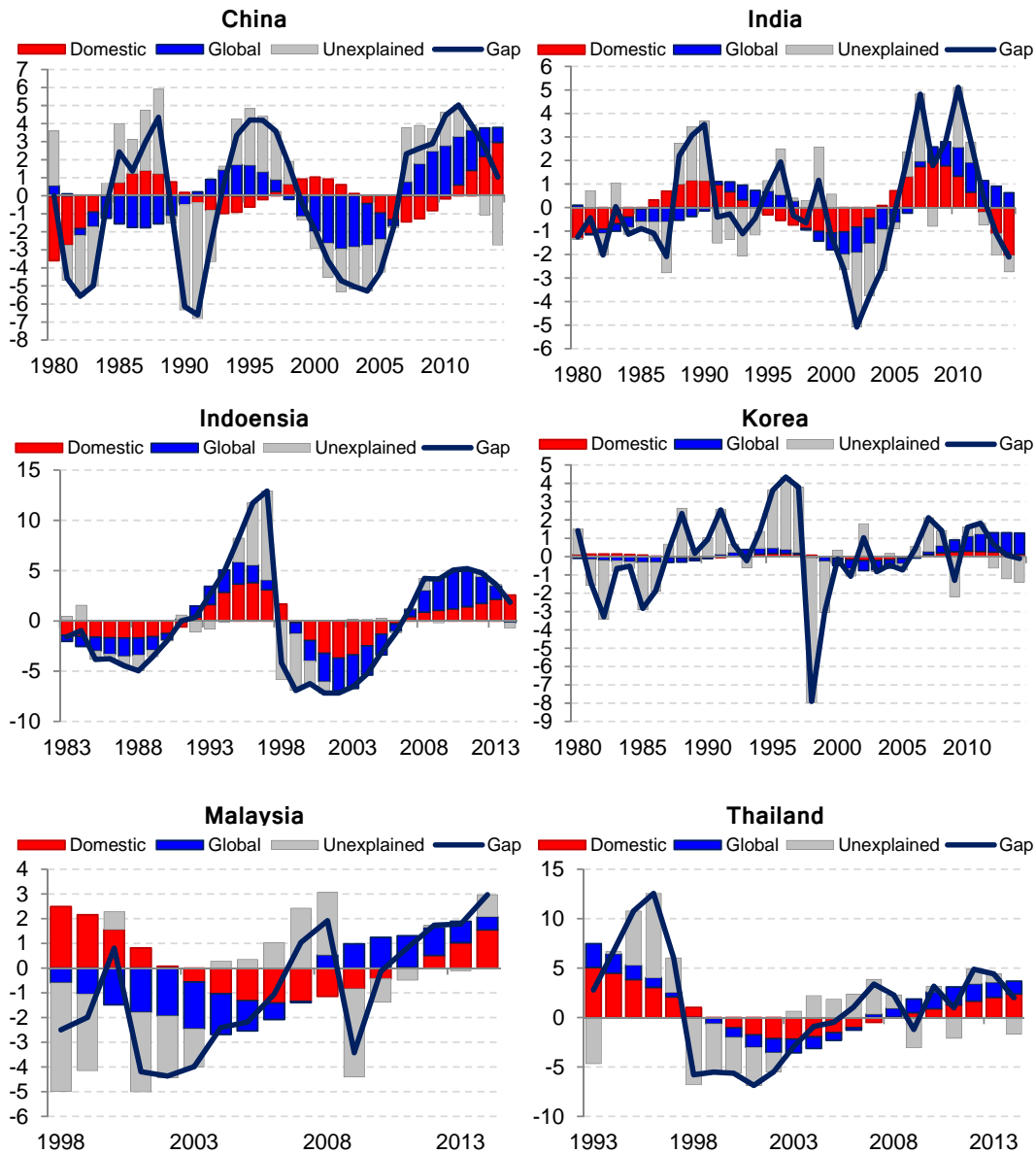
Country	Model 1	Model 2	Model 3	
	Domestic credit cycle	Global financial cycle	Domestic credit cycle	Global financial cycle
China	0.40	0.62	0.73	0.90
India	0.54	0.37	0.48	0.32
Indonesia	0.26	0.24	0.22	0.20
Korea	0.25	0.34	0.20	0.27
Malaysia	0.46	0.30	0.40	0.27
Thailand	0.34	0.22	0.30	0.19
Russia	0.33	0.25	0.31	0.22
South-Africa	0.30	0.16	0.28	0.15
Turkey	0.18	0.16	0.16	0.14
Brazil	0.09	0.25	0.09	0.23
Mexico	0.09	0.07	0.07	0.05
Chile	0.65	0.63	0.51	0.48
Poland	0.21	0.24	0.18	0.20
Czech Republic	0.41	0.34	0.32	0.23
Hungary	0.30	0.09	0.28	0.09

Notes: Model 1 includes only the domestic credit cycle variable; Model 2 includes only the global financial cycle variable; Model 3 includes both variables in equation 3 of the model. Coefficients show estimated maximum posterior modes.

**Figure A1: Finance-adjusted and HP filter estimates of output gap in 2014**

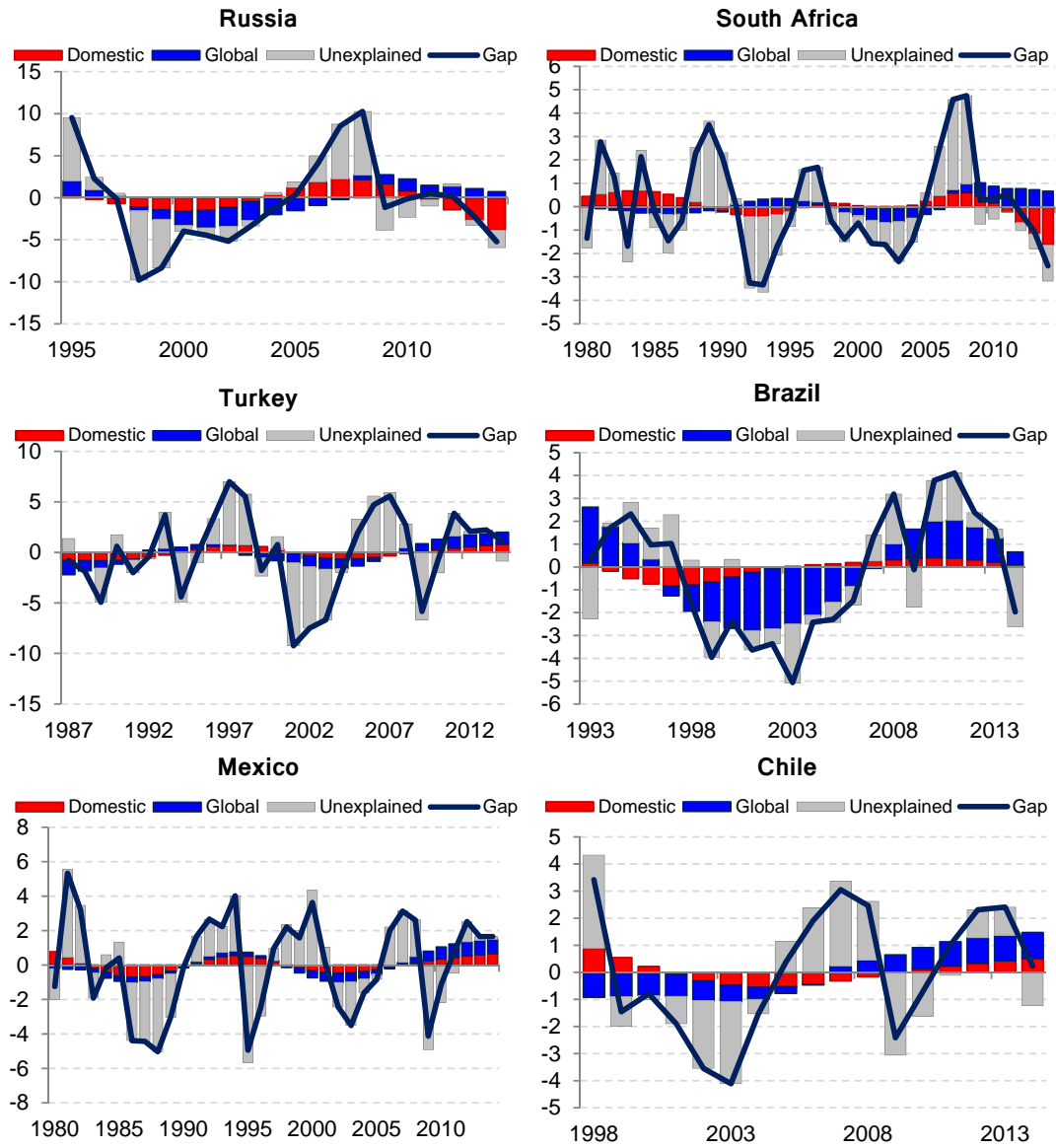


**Figure A2: Decomposition of finance-adjusted output gap - model 3**  
*(percentage of trend growth and percentage point contribution)*



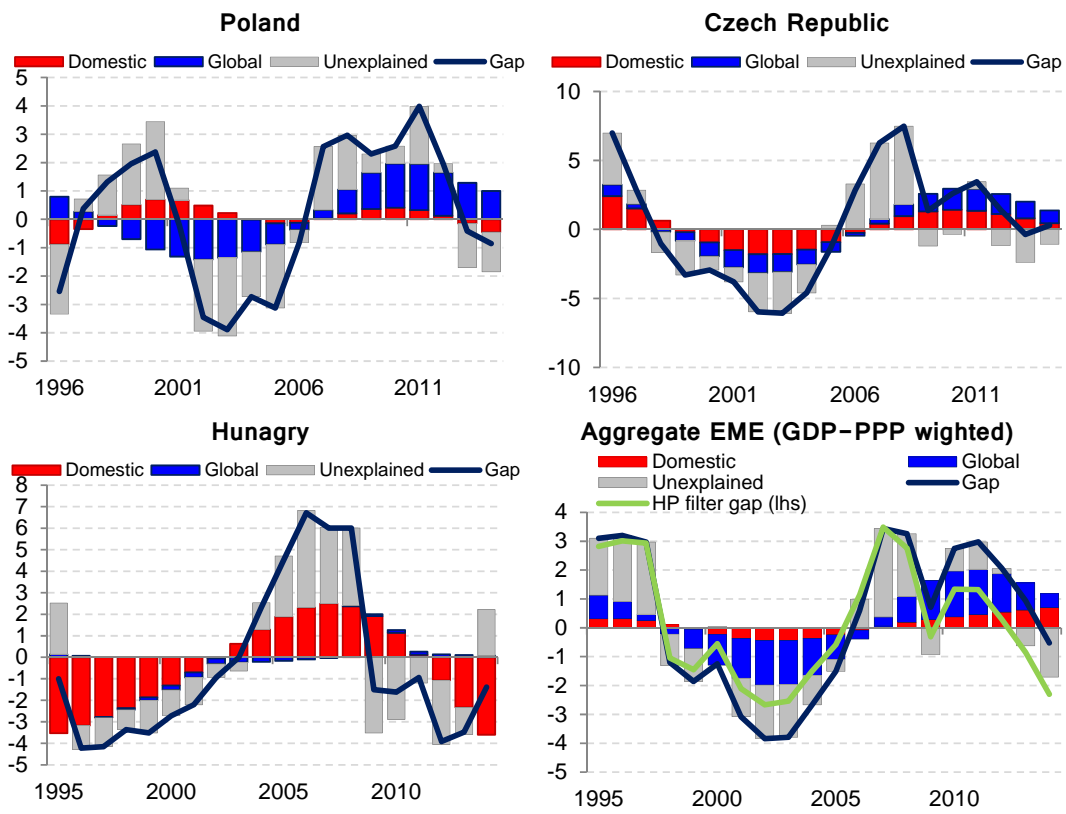
**Figure A2 Continued**

*(percentage of trend growth and percentage point contribution)*

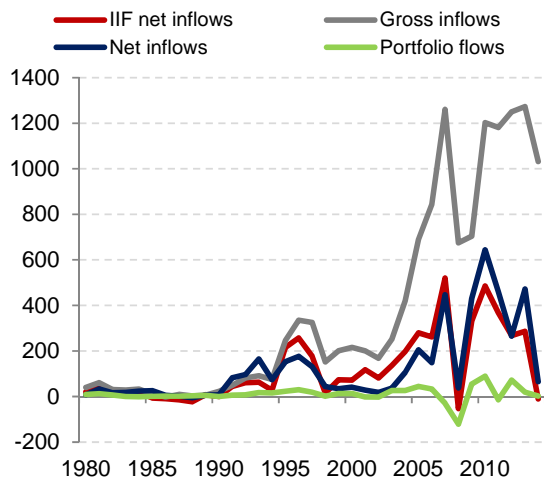


**Figure A2: Continued**

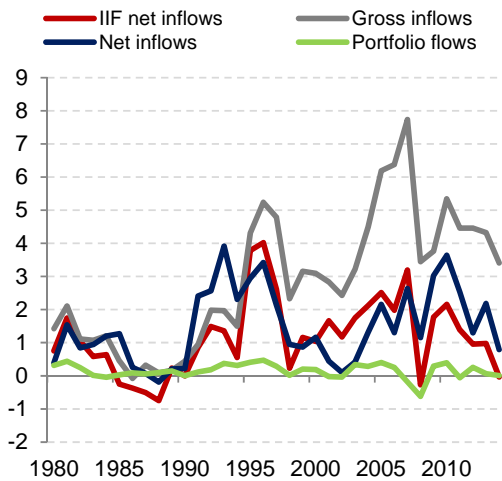
*(percentage of trend growth and percentage point contribution)*



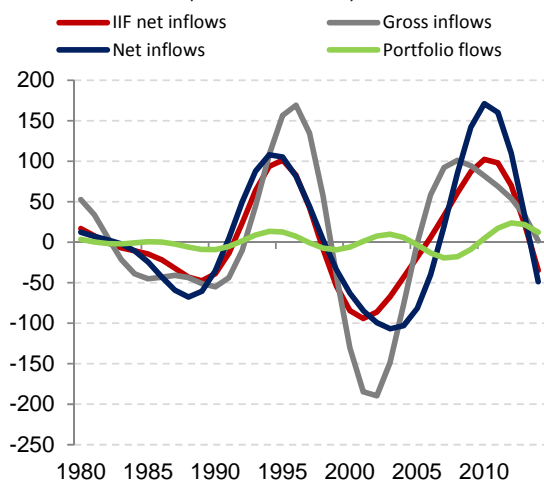
**Figure A3: Aggregate capital flows to EMEs**  
(US dollar billions)



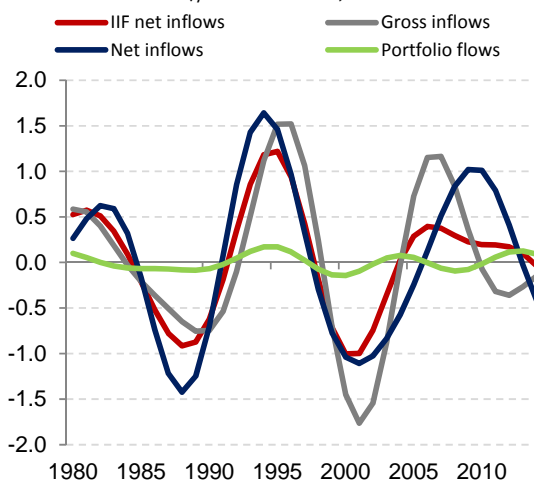
**Figure A4: Aggregate capital flows to EMEs**  
(relative to EME GDP)



**Figure A5: Filtered measures of global financial cycle**  
(US dollar billions)

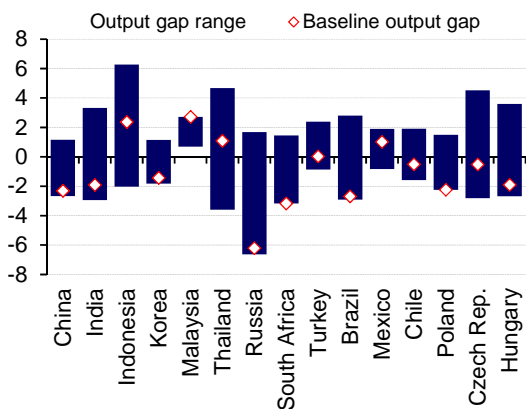


**Figure A6: Filtered measures of global financial cycle**  
(percent of GDP)



**Figure A7: Range of estimates of finance-adjusted output gap in 2014 using alternative measures of global financial cycle**

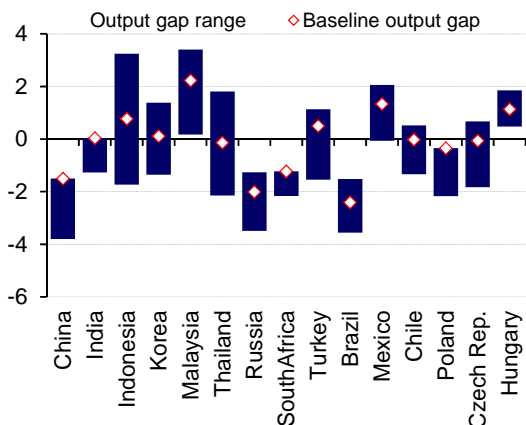
(percent of trend output)



Notes: finance-adjusted output gaps calculated using alternative measures of global financial cycle (see charts A2 to A5). The bars show the estimated range of finance-adjusted output gaps in 2014; the diamonds show the baseline estimate of the output gap.

**Figure A9: Range of estimates of finance-adjusted output gap in 2014 using filters of alternative frequencies for domestic credit cycle**

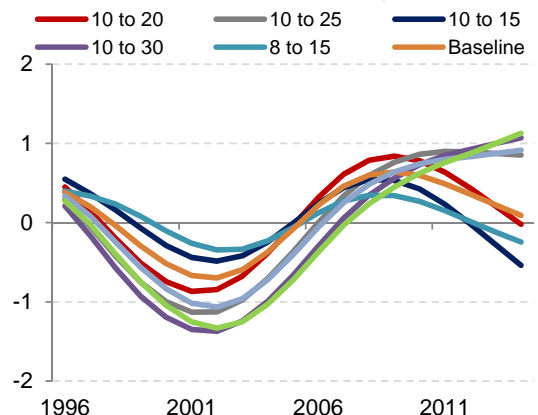
(percent of trend output)



Notes: finance-adjusted output gaps calculated using alternative measures of domestic credit cycle based on band-pass filter at different frequencies (10–20 years, 10–25 years, 10–15 years, 10–20 years, 8–15 years, 8–20 years, 8–25 years and 8–30 years). The bars show the estimated range of finance-adjusted output gaps in 2014; the diamonds show the baseline estimate of the output gap.

**Figure A8: EME aggregate contribution of domestic credit cycle-finance-adjusted output gap using filters of alternative frequencies**

(estimates of percentage point contributions of domestic financial cycle-finance-adjusted output gap)

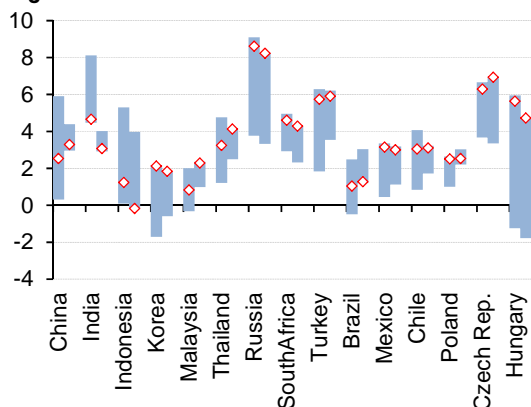


Notes: domestic credit cycle is estimated for each EME separately, using asymmetric band-pass filter at different frequencies. Legend denotes years (e.g. 10–20 year filter). The chart shows the average for the EMEs in our sample, weighted by GDP (at purchasing power parity).

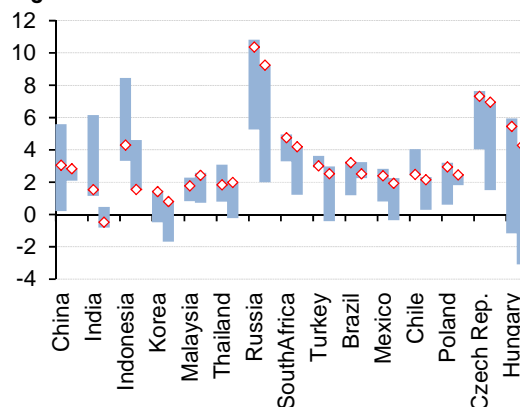


**Figure A10: Ranges of real-time estimates of finance-adjusted and HP filter output gaps for years 2007 to 2012\***

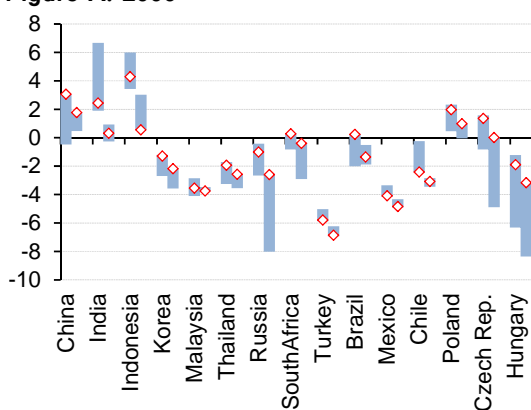
**Figure A: 2007**



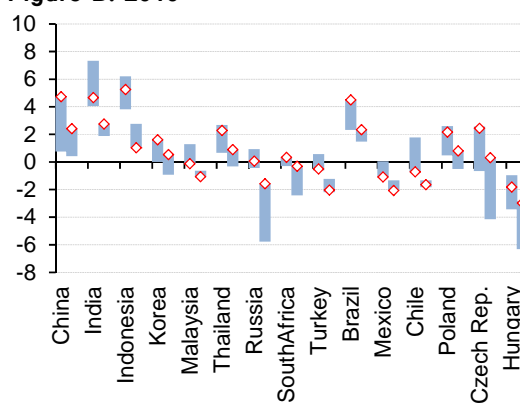
**Figure B: 2008**



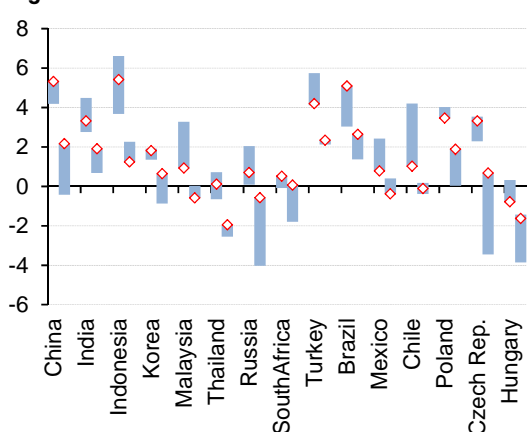
**Figure A: 2009**



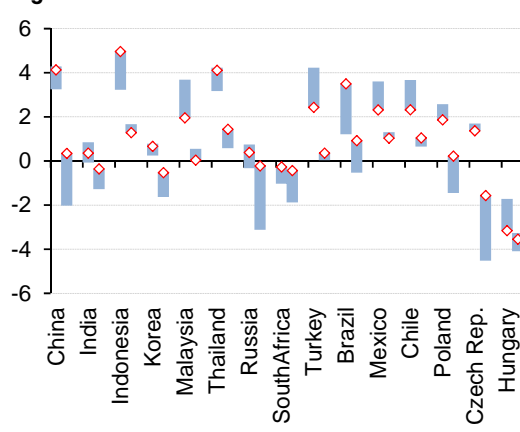
**Figure B: 2010**



**Figure A: 2011**



**Figure B: 2012**



\*Notes: for each country there are two columns: the left-hand shaded area shows the range of real-time estimates of finance-adjusted output gaps, and the diamond shows the final estimate (using data up to 2014). The right-hand shaded area shows the range of HP filter output gaps and the diamond shows the final estimate with the HP filter (using data up to 2014).

## Annex 1: Bayesian estimation and priors

We follow Borio et al. (2013) by estimating the parameters and variances of the model using a Bayesian approach with informative priors. For the gamma parameters in each model we are using as a prior distribution the gamma distribution. The parameter space is constrained to lie between 0 and infinity reflecting our judgement that there should be a positive causality running from the global and domestic financial cycles to the domestic economic cycle in emerging economies. As a starting point, we considered defining the gamma distribution priors with a mean of 0.6 and a standard deviation of 0.2. Those values correspond closely to the estimates for the US economy found by Borio et al. (2013). However, priors based on the US economy may not be appropriate for emerging market economies for which the amplitude of the credit cycles has differed significantly to that of the US. Thus, for each country, we adjusted the prior assumptions for the mean and standard deviations of the gamma distributions by scaling both parameters by the ratio of the standard deviations of the credit gap in each EME to that of the US. For example, for Russia, where the credit gap has a higher standard deviation to that of the US, the mean prior was set at 0.3, with a standard deviation of 0.1. By contrast for Korea, for which the credit gap has a lower standard deviation than the US over our sample, the mean prior was set at 0.8, with a standard deviation of 0.3. The functional form of the priors about shock variances is an inverted gamma distribution. We set loose priors on the standard deviations of the error term by allowing them to take infinite variance. We employed the Markov chain Monte Carlo algorithm to generate an estimate for the entire distribution of the parameters. We draw 100 000 simulations, out of which 20 percent of the draws are burned-in. The following charts present the prior and posterior distributions of the two gamma parameters for the baseline specifications.

Figure B1: Prior and posterior distribution of the coefficient on the domestic credit gap (gamma1) in the baseline model (Model 3)

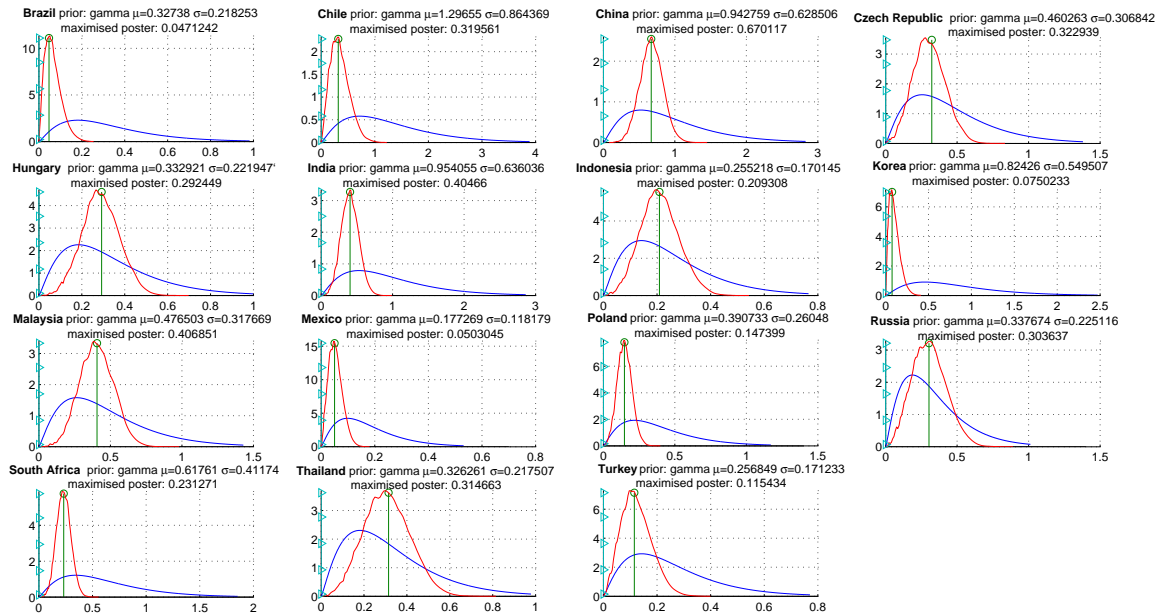
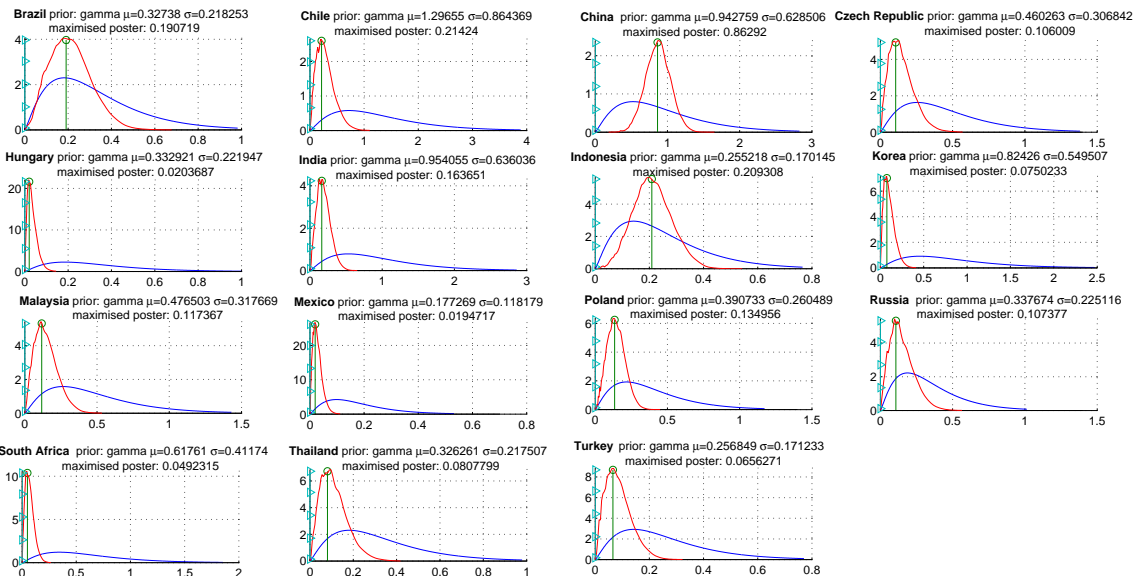


Figure B2: Prior and posterior distribution of the coefficient on the global credit gap (gamma2) in the baseline model (Model 3)



Legend: The blue line shows the prior gamma distribution of the gamma coefficients in Model 3, while the red line shows their posterior distributions obtained by Monte Carlo simulations.

## Acknowledgements

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