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# PERIODIC BUSINESS AND EXCHANGE RATE CYCLES: EVIDENCE FROM 7 EMERGING MARKETS

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## ABSTRACT

The paper investigates exchange rate cycles and their relationship to the business cycle in 7 major emerging market economies. We document the presence of periodic cycles in nominal US-dollar exchange rates and show that these are closely aligned with cycle frequencies in real output. Joint fluctuations in exchange rates and output exhibit frequencies between 4 and 8 years. We consider external and internal driving forces of those periodic cycles. There is moderate evidence of co-movements in exchange rates across countries that are strongly linked to global commodity prices, but only weakly so to US monetary policy or global uncertainty shocks. However, estimated periodicities in external factors do not match the periodicities found in exchange rates, thus leaving an important cycle property unexplained. We therefore test for the presence of a cyclical interaction mechanism between exchange rates and output that may transform external shocks into periodic oscillations. We find evidence for such an interaction mechanism, consistent with the recent literature on the financial channel of exchange rates, for Chile and South Africa, and partly for the Philippines.


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# Periodic business and exchange rate cycles: evidence from 7 emerging markets*

Karsten Kohler† Engelbert Stockhammer‡

**Abstract**

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**Keywords:** Business cycles, exchange rate cycles, emerging market economies, global financial cycle, commodity prices, monetary policy spillovers, financial channel of exchange rates

**JEL Codes:** E12, E32, F31, C32

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# 1 Introduction

Business and financial cycles in emerging market economies (EMEs) are known to be considerably more volatile compared to advanced economies (AEs) (Calderón & Fuentes 2014, Claessens et al. 2012). One aspect of this is high exchange rate volatility. Duarte et al. (2007) report that nominal exchange rates in middle-income countries are on average more than twice as volatile than in high-income countries. Over the last decades, many large EMEs have moved towards greater exchange rate flexibility in the form of semi-flexible exchange rate regimes, especially managed floats (Ghosh et al. 2015). At the same time, extreme events such as hyperinflation and currency crashes have become rarer (Ilzetzki et al. 2019). As a result, exchange rate volatility in many large EMEs has taken the form of continuous fluctuations as opposed to episodes of stability interrupted by discrete crashes. This raises the question how regular fluctuations in nominal exchange rates relate to the business cycle.

Several empirical studies found nominal exchange rates in EMEs to be procyclical: currencies appreciate during booms and depreciate during busts (Cordella & Gupta 2015, Duarte et al. 2007). By contrast, currencies of AEs tend to be counter- or acyclical.[1] Exchange rate procyclicality is especially pronounced in countries that are commodity exporters and subject to procyclical capital flows (Cordella & Gupta 2015). Indeed, an influential literature highlights the relevance of external factors such as the global financial cycle, US monetary policy spillovers, and world commodity prices for macroeconomic dynamics in EMEs (Carrière-Swallow & Céspedes 2013, Cesa-Bianchi et al. 2015, Drechsel & Tenreyro 2018, Fernández et al. 2017, 2018, Kalemli-Özcan 2019, Miranda-Agrippino & Rey 2019, Rey 2015). Variance decompositions of real output suggests that a significant share of business cycle fluctuations is accounted for by external shocks. However, these exercises do not ask what *kind* of (co-)variation in exchange rates and output is generated by external factors. Do external factors account for irregular fluctuations, including contractionary currency crashes, or do they generate regular ups and downs?

This paper investigates periodic cycles in exchange rates and real output, i.e. fluctuations with a certain regularity.[2] Periodicity is an important property of time series that can point

[1] A procyclical relationship is also found for real exchange rates in EMEs. The fact that the real exchange rate is strongly correlated with the nominal exchange rate suggest that the relationship between output and real exchange rates is largely driven by the nominal exchange rate. However, the real exchange rate is a composite variable that also capture changes in domestic or foreign price levels, which are likely to be governed by very different economic mechanisms. This paper thus focuses on nominal exchange rates.

[2] Strictly speaking, we focus on *quasi*-periodicities that stem from auto-regressive stochastic processes whose roots are complex (see, e.g., Subba Rao 2018, chap. 1). Such a process will have both periodic and irregular

towards the presence of endogenous cyclical mechanisms. This sets periodicity apart from the much more frequently studied auto- and cross-correlations that capture how endogenous variables respond to exogenous shocks. If exchange rates exhibit dominant cycle frequencies, this implies they are either driven by other periodic processes or they are part of a cyclical mechanism that endogenously generates periodicities. To investigate periodicities in exchange rates and their sources, we draw on time series methods in both the frequency- and time-domain, comprising parametrically estimated spectral density functions, dynamic factor models and vector-autoregressions. Analysing a sample of 7 major EMEs over the post-Bretton Woods period, we document joint periodic fluctuations in exchange rates and output at conventional business cycle frequencies between 4 and 8 years. US monetary policy, global uncertainty shocks, and world commodity prices are considered as potential external driving forces of these fluctuations. We show that these external factors, especially global commodity prices, are a source of co-movement in exchange rates across EMEs, but do not match the periodicities found in exchange rates and GDP. External factors thus cannot completely account for regular cycles in exchange rates. We therefore consider a novel explanation for periodic exchange rate-output cycles based on a cyclical interaction mechanism between exchange rates and GDP. If currency depreciations are contractionary and output contractions feed back positively into exchange rate dynamics via an external adjustment channel, periodic fluctuations between exchange rates and output at business cycle frequency may emerge. Such an internal mechanism may then transform (irregular) external shocks into periodic oscillations.

Estimation results from vector-autoregressions yield robust evidence for the presence of such a cyclical interaction mechanism in South Africa and Chile, and to a lesser extent for the Philippines – the countries in the sample with the longest spells of (semi-)flexible exchange rate regimes. For Mexico and South Korea there is some, but less robust, evidence for a cycle mechanism; possibly because these countries underwent major crises and changing exchange rate regimes during the first part of the sample period. For Brazil and Thailand, there is no evidence for a cycle mechanism; in Brazil, this is arguably because of numerous chaotic exchange rate episodes, whereas Thailand had a fixed exchange rate throughout most of the sample period.

The phenomenon of periodic cycles investigated in this paper relates to the recent literature on financial cycles in AEs (Aikman et al. 2015, Borio 2014, Drehmann et al. 2012, Rünstler & Vlekke 2017, Stockhammer et al. 2019, Strohsal et al. 2019). This research reports regular medium-term cycles in private credit and house prices with lengths of around 8 to 18

components. For simplicity, we will use the terms periodic and quasi-periodic interchangeably in this paper.

years. The presence of periodic fluctuations in macroeconomic variables has also re-ignited interest in endogenous cycle processes. Beaudry et al. (2020) build a New Keynesian model with demand complementarities that produces endogenous cycles to explain periodic 10-year cycles in US labour market indicators. Stockhammer et al. (2019) highlight the critical role of cyclical interaction mechanisms in financial cycle models (e.g. Asada 2001, Kiyotaki & Moore 1997). Periodic oscillations are generated in these approaches by an interaction mechanisms between financial and real variables, whereby the real variable accelerates the financial variable which in turn drags down the real variable.

While the recent literature thus highlights periodicities in financial and real variables of AEs, periodicities in nominal exchange rates of EMEs and their sources have not yet been investigated. This is a shortcoming as exchange rate procyclicality suggests a potentially important and distinctive role of exchange rates in EME business cycles. Indeed, research on the 'financial channel of exchange rates' argues that exchange rates impact real activity differently in EMEs (Avdjiev et al. 2019, Banerjee et al. 2020, Kearns & Patel 2016). According to this channel, an appreciation of the US dollar against the domestic currency worsens balance sheets of domestic borrowers that hold foreign currency debt. Domestic currency depreciation thereby worsens their access to credit. If this effect outweighs the trade channel of exchange rates according to which depreciations increase net exports, currency depreciations discourage spending. The financial channel is expected to be especially relevant in EMEs, where balances sheets of domestic borrowers often exhibit currency mismatches. However, it is an open question whether this mechanism can also give rise to periodic fluctuations in output and exchange rates.

The contribution of the present paper is to investigate the presence and sources of periodic exchange rate cycles in emerging markets. We present evidence suggesting that major EMEs with flexible exchange rates exhibit joint periodic fluctuations in nominal exchange rates and output that are only partially driven by external factors. We consider an internal interaction mechanism between exchange rates and output, consistent with the financial channel of exchange rates, that transforms external shocks into more regular fluctuations. Our results provide evidence for such a mechanism in a number of major EMEs. This implies that the financial channel of exchange rates not only transmits exogenous shocks but can become an endogenous sources of business cycle fluctuations. The much-discussed external factors, by contrast, do not tell the full story and need to be combined with internal cycle mechanisms to account for the periodicities found in the data.

The remainder of the paper is structured as follows. Section 2 presents evidence for the presence of periodic business and exchange rate cycles in EMEs. Section 3 considers potential external drivers of these fluctuations: US monetary policy, global risk aversion, and commodity terms of trade. Section 4 discusses an internal cycle mechanism between exchange rates and GDP that can drive periodic fluctuations along with external shocks, and presents evidence from vector-autoregressions for the presence of such a cycle mechanism. The last section concludes.

# 2 Periodic business and exchange rate cycles

We consider a group of 7 major EMEs over the (maximum) period 1972Q1 to 2019Q3: South Africa, Brazil, Chile, Mexico, South Korea, the Philippines, and Thailand.[3] In contrast to panel analyses that maximise the number of countries subject to data-availability constraints, we use a time-series approach that allows for cross-country heterogeneity, which is likely to be substantial for EMEs.[4] An important source of cross-country heterogeneity is the exchange rate regime. Regular fluctuations in exchange rates are expected to emerge only in countries with a sufficient degree of exchange rate flexibility. Likewise, a country that is frequently plagued by discrete exchange rate crashes is unlikely to exhibit stable periodic frequencies. Especially for our multivariate analysis in section 4, we purposefully choose a sample of countries that reflects a broad spectrum to assess whether the regime makes a difference.

Based on the exchange rate regime classification in Ilzetzki et al. (2019), four groups of countries can be identified in our sample.[5] First, South Africa, Chile, and with exceptions the Philippines are the countries with longest spells of semi-flexible or flexible exchange rate regimes.[6] Second, Mexico and South Korea are intermediate cases with episodes of both fixed and flexible exchange rate regimes that were interrupted by currency crashes in the 1980s (Mexico) and 1990s (Mexico and South Korea). Third, Thailand had a fixed exchange rate regime throughout most of the sample period, which was succeeded by a semi-flexible regime after the East Asian crisis in 1998. Fourth, Brazil had chaotic episodes throughout most of the sample period with hyperinflation and repeated currency crises that were stabilised only by the end of the century.

[3] Detailed information on the data set can be found in Appendix A.

[4] Research on financial cycles in AEs is often conduced on a country-by-country basis and has revealed notable differences across countries (Rünstler & Vlekke 2017, Stockhammer et al. 2019, Strohsal et al. 2019).

[5] See Figure A1 in Appendix B for details.

[6] South Africa since 1973 and Chile since 1983. The Philippines had (semi-)flexible exchange rates most of the time but interrupted by a few currency crashes and short-lived peg. South Africa had a parallel market between 1985 and 1995, but the official exchange rate appears to be flexible during this period.

To study cyclical properties of nominal exchange rates, we focus on the (logged) bilateral nominal exchange rate with the US dollar ($XR$), defined as domestic currency unit per foreign currency unit.[7] As discussed in Bruno & Shin (2014, 2015) and Avdjiev et al. (2019), the US dollar is the dominant currency for external borrowing by emerging markets through global banks.[8] Our preferred method to extract cyclical components is the regression filter proposed in Hamilton (2018) (see Appendix C for a description). Hamilton (2018) argues that unlike the frequently used Hodrick-Prescott filter, the regression filter does not generate spurious dynamics and prevents filtered values at the end of the sample from behaving differently from those in the middle. An alternative approach is to take (annualised) growth rates; however, growth rates are known to amplify higher frequencies and may remove lower frequencies in the data (Hamilton 1994, p. 171). This is especially problematic for nominal exchange rates series which are likely to exhibit substantial high-frequency fluctuations that are unrelated to the business cycle.

Appendix C reports detrended series for both filters. As expected, many series are heavily affected by extreme crises episodes in the first three decades of the sample to which the growth rate filter is especially sensitive (Figure A2). Many of these episodes were driven by idiosyncratic events, such as hyperinflation and currency reforms, that are not directly related to regular business cycles. To enable an examination of periodic cycles, we exclude these episodes from our analysis in this section.[9] When excluding those episodes, Hamilton's filter and the growth rate filter broadly yield similar results, but the latter accentuates higher frequencies (Figure A3). We therefore use Hamilton's filter as our preferred detrending method.[10]

Figure 1 reports cyclical components in $XR$ and (seasonally adjusted) logged real GDP, where the sample start was set so as to exclude major currency crises episodes and fixed exchange rate regimes.[11] Cyclical behaviour is apparent in all exchange rate series. Cycles are most pronounced in South Africa and Chile, which seem to have a frequency in the

[7] An increase in $XR$ thus represents a depreciation of the domestic currency vis-á-vis the US dollar.

[8] Nominal effective exchange rates, which are trade-weighted exchange rates with respect to a basket of currencies, would be an alternative, but these series have a substantially lower time span.

[9] Note that previous empirical studies that document procyclicality of exchange rates in EMEs (Cordella & Gupta 2015, Duarte et al. 2007) do not exclude crises episodes from the sample. This makes it difficult to assess whether procyclicality is driven by extreme episodes (e.g. contractionary currency crashes) or a feature that also holds during normal times.

[10] We use the growth rate filter in robustness tests.

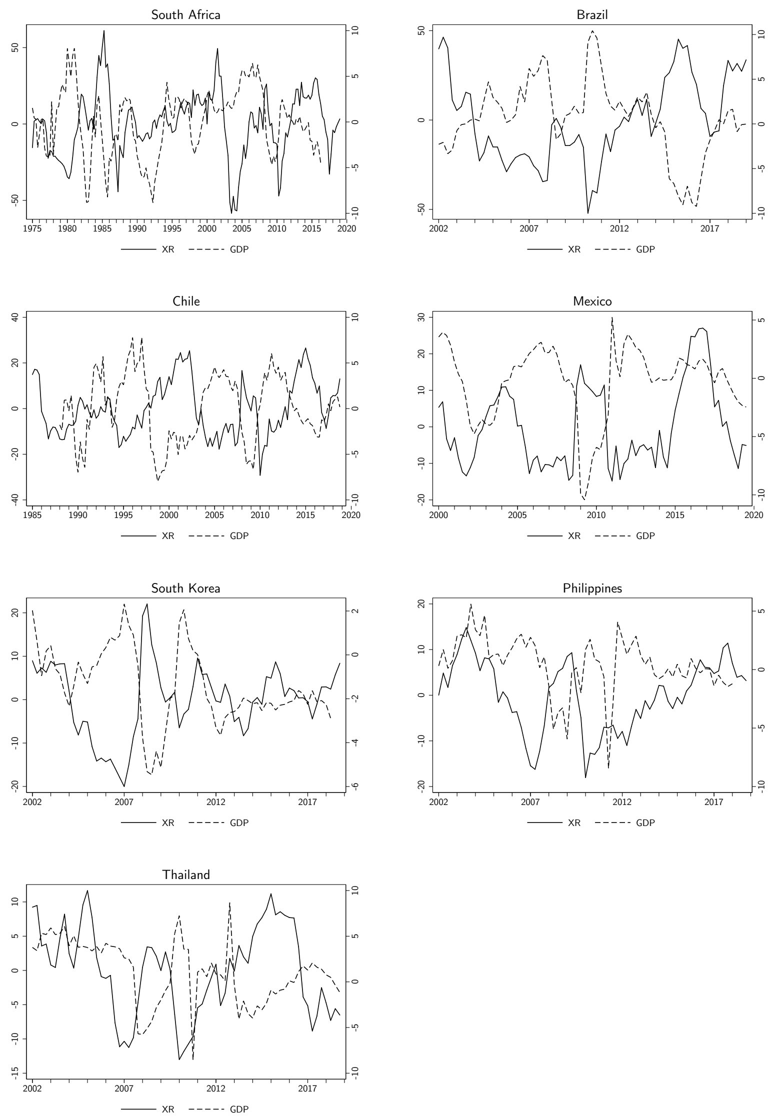
[11] To exclude fixed exchange rate regimes and crises episodes, we relied on the coarse classification in Ilzetzki et al. (2019) (scores 1 and 5; see notes to Figure A1). In some cases, a few additional data points in the vicinity of crises were excluded if the series still exhibited extreme values. The restricted sample starts are: South Africa: 1972Q4, Brazil: 1999Q4, Chile: 1983Q1, Mexico: 1997Q2, South Korea: 2000Q1, Philippines: 2000Q1, Thailand: 2000Q1.

range of 8 to 10 years. Exchange rate cycles are also visible in Mexico, the Philippines, and South Korea, albeit a bit more erratic and with a shorter frequency. By contrast, it is more difficult to identify regular cycles in Brazil and Thailand, which display largely idiosyncratic fluctuations.

With respect to the relationship between *XR* and *GDP*, there generally is a negative co-movement (except for the Philippines), which is especially strong in Brazil, Chile, and South Korea. This confirms previous findings of a strong procyclicality of exchange rates in EMEs (Cordella & Gupta 2015).[12] Notably, strong procyclicality can be observed despite the absence of major currency crashes, which suggests that procyclicality can, at least partly, be attributed to joint periodicities in exchange rates and business cycles rather than discrete shocks. Figure 1 is suggestive of such joint periodic behaviour, especially in Chile, but a more rigorous approach is required to identify any specific periodicities.

[12] Recall that *XR* is defined as units of domestic currency per foreign currency unit. A negative correlation thus implies that economic expansion go together with currency appreciation.

**Figure 1: Nominal US-dollar exchange rate (left scale) and real GDP (right scale), cyclical components**




*Notes: XR*: logged nominal US-dollar exchange rate (cyclical component); *GDP*: logged real GDP (cyclical component). Cyclical components are the residual from the regression $x_{t+8} = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \beta_3 x_{t-2} + \beta_4 x_{t-3} + \nu_{t+8}$.

To this end, we parametrically estimate spectral density functions (Hamilton 1994, chap. 6). A spectral density function represents a time series in the frequency-domain and describes how much of the total variance of the series is due to different frequencies.[13] Parametric

[13]More formally, any covariance-stationary time series $x_t$ can be expressed as a weighted sum of cosine and sine waves: $x_t = \mu + \int_0^\pi \alpha(\omega)\cos(\omega t)d\omega + \int_0^\pi \beta(\omega)\sin(\omega t)d\omega$, where $\omega \in [0, \pi]$ denotes the frequency corresponding to the period $T = 2\pi/\omega$. The population spectral density function of $x_t$ is given by $s_x(\omega) =$

spectral density estimation has been used in Strohsal et al. (2019) to study business and financial cycles in AEs, but has not been applied to exchange rates in EMEs.[14] Isolated peaks in a spectral density function indicate dominant periodic cycles and their length. Importantly, if a spectral density function does not exhibit distinct peaks, the series is mostly driven by irregular components. For example, the spectral density functions of AR(1) or MA(1) processes with white noise errors are either monotonically increasing or decreasing, but not hump-shaped. Spectral density functions thereby allow to asses whether fluctuations in a time series have a periodic character or not. Furthermore, the more the spectral density function is concentrated around a modal value, the more regular the cycle length indicated by that peak.

Parametric estimation of the spectral density function of a time series $x_t$ is based on ARMA(p, q) models, which can be written as:

$$\theta(L)x_t = \delta + \phi(L)\epsilon_t, \tag{1}$$

where $\theta(L)$ and $\phi(L)$ are lag polynomials of order $p$ and $q$, respectively, and $\epsilon_t$ is a white noise error term with variance $\sigma_\epsilon^2$. The spectral density function of $x_t$ can then be obtained as:

$$s_x(\omega) = \frac{\sigma_\epsilon^2}{2\pi}\frac{|\phi(e^{-i\omega})|^2}{|\theta(e^{-i\omega})|^2}, \tag{2}$$

where $\omega \in [0, \pi]$ denotes the frequency and $i$ is the imaginary number $i^2 = -1$. We estimate individual ARMA models for each time series, starting from a lag length of 10, which is then successively tested down to achieve a parsimonious specification with serially uncorrelated errors.[15]

In addition to univariate spectral density functions for *XR* and *GDP*, we also estimate a dynamic factor model (Stock & Watson 2011) to extract a common factor in the cyclical components of exchange rates and output. Dynamic factor models have been used in the literature on the global financial cycle; for instance, to identify common global factors in risky asset prices (Miranda-Agrippino & Rey 2019) and gross capital flows (Cerutti et al.

$\frac{1}{2\pi}\sum_{j=-\infty}^{\infty}\gamma_j e^{-i\omega j} = \frac{1}{2\pi}\left(\gamma_o + 2\sum_{j=1}^{\infty}\gamma_j\cos(\omega j)\right)$, where $\gamma_j$ is the $j$th autocovariance of $x_t$ and $i$ is the imaginary number $i^2 = -1$.

[14] The main advantage of parametric estimation is its efficiency as it requires fewer degrees of freedom. Non-parametrically estimated spectral density functions are sometimes also used, e.g., in Aikman et al. (2015), Beaudry et al. (2020), and Stockhammer et al. (2019).

[15] Estimated ARMA models are reported in Appendix E.

2019). We use them to examine periodic co-movements in exchange rates and output. The dynamic factor model can be written as:

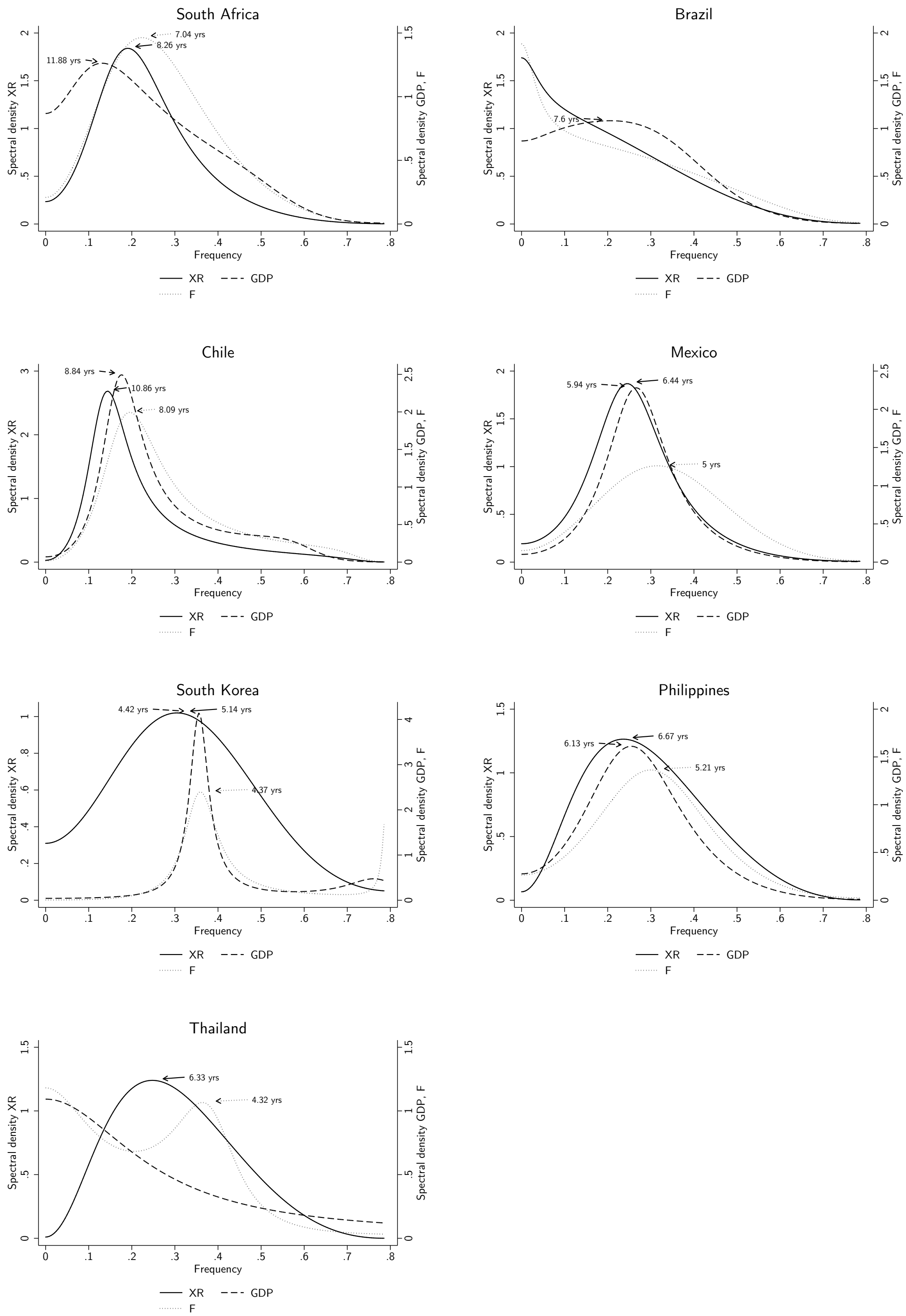
$$x_t = \Lambda F_t + u_t \tag{3}$$

$$F_t = \sum_{i=1}^{r} \Phi_i F_{t-i} + \eta_t, \tag{4}$$

where $x_t$ is a vector of endogenous variables, $\Lambda$ is a matrix of factor loadings, and $F_t$ is a vector of common factors, which are assumed to follow a vector-autoregressive process. Any residual autocorrelation is captured by $u_t$. The model is written in state-space form and estimated by maximum likelihood using the Kalman filter. For each country, we insert the cyclical components of *XR* and *GDP* into the vector $x_t$ and assume a single factor which follows an AR(2) process ($r = 2$).

Regression tables for the dynamic factor models are reported in Appendix D. For all EMEs, except Mexico and the Philippines, the dynamic factor is a statistically significant predictor for both *XR* and *GDP*, confirming the visual evidence for joint fluctuations in Figure 1. To assess the periodicity of the common factor, we estimate a univariate spectral density function based on an ARMA model of the dynamic factor.

**Figure 2: Spectral densities of nominal US dollar exchange rates, real GDP, and a common dynamic factor**




*Notes: XR*: logged nominal US-dollar exchange rate (cyclical component); *GDP*: logged real GDP (cyclical component), *F*: common factor in *XR* and *GDP* from an estimated dynamic factor model. Spectral densities were estimated parametrically from ARMA models (see Appendix E). Arrows indicate the cycle length (in years) associated with the peak in the spectral densities. For the dynamic factor in Thailand, the peak is at zero frequency, so the length implied by the second peak is reported instead.

Figure 2 displays univariate spectral densities for $XR$, $GDP$, and the estimated dynamic factor $F$.[16] All countries, except for Brazil, exhibit a dominant cycle frequency in $XR$. Estimated cycle lengths range from 4 1/2 years (South Korea) to almost 11 years (Chile). Estimated business cycle frequencies are in a similar range; from around 5 years in South Korea up to almost 12 years in South Africa. In several countries, the dominant frequency in $XR$ closely corresponds to the business cycle frequency, notably Chile, Mexico, South Korea, and the Philippines. Only Thailand does not exhibit a dominant periodicity in business cycles. Exchange rate cycles are particularly pronounced in South Africa, Chile, and Mexico, whose spectral density functions are strongly centred on a dominant peak. Periodicities appear to be less pronounced in the Asian countries, where spectral densities are more dispersed around the peak. The dominant frequencies of the estimated dynamic factor are generally similar to the frequencies in $XR$ and $GDP$ for most countries, but in some cases slightly higher. Estimated lengths range from 4 to 8 years.

Two main findings emerge. First, several major EMEs exhibit periodic exchange rate cycles. These cycles are closely aligned with business cycles, especially in South Africa, Chile, Mexico, South Korea and the Philippines. Although major currency crises episodes were excluded from the sample, there is a strong negative correlation between exchange rates and GDP in most countries, suggesting that a procyclical relationship also holds during normal times and is not driven by extreme episodes. Second, the length of joint exchange rate and output cycles ranges from 4 to 8 years and is thus at conventional business cycle frequency. Overall, this confirms not only a strong link between nominal US dollar exchange rates and EME business cycles, but also uncovers the presence joint periodic cycles.

# 3 External drivers of exchange rate cycles

The literature on global uncertainty shocks, the global financial cycle, and commodity price shocks suggests that macroeconomic fluctuations in EMEs are strongly affected by external factors (Carrière-Swallow & Céspedes 2013, Cesa-Bianchi et al. 2015, Drechsel & Tenreyro 2018, Fernández et al. 2018, Kalemli-Özcan 2019, Miranda-Agrippino & Rey 2019, Rey 2015, 2016). However, an open question which we address in this section is whether these external factors can explain the periodicities uncovered by the spectral density functions in section 2. As a first check, we assess whether there is strong co-movement of cycles across countries, which would indicate an important role for external drivers.

[16] Appendix F also reports spectral densities for $XR$ with the growth rate rather than Hamilton's filter. The results are similar.

Table 1 displays average cross-country correlations ($\rho$) of exchange rate and business cycles, respectively. In addition, it reports how much of the variance in these series can be explained by a common factor represented by the first component ($pc_1$) from a principal component analysis (PCA).[17]

We report results for the full sample starting in the post-Bretton Woods period and for the restricted sample that excludes crises episodes.[18] For comparison, we also report results for a sample of 7 small open advanced economies (AEs): United Kingdom, France, Norway, Sweden, Canada, Japan, Australia.

**Table 1: Cross-country co-movements in nominal US dollar exchange rates and real GDP (cyclical components)**

| | **XR** | | | | **GDP** | |
|---|---|---|---|---|---|---|
| | **1974Q4 – 2019Q3** | | **2002Q4 – 2019Q3** | | **2002Q4 – 2016Q4** | |
| | $\rho$ | $pc_1$ | $\rho$ | $pc_1$ | $\rho$ | $pc_1$ |
| **EMEs** | 0.216 | 0.380 | 0.411 | 0.529 | 0.402 | 0.540 |
| **ACs** | 0.394 | 0.539 | 0.642 | 0.723 | 0.634 | 0.717 |

*Notes*: $\rho$: correlation coefficient (average of bilateral correlation coefficients); $pc_1$: variance explained by first principal component; *XR*: logged nominal US-dollar exchange rate (cyclical component); *GDP*: logged real GDP (cyclical component); EMEs: South Africa, Brazil, Chile, Mexico, South Korea, the Philippines, Thailand. AEs: United Kingdom, France, Norway, Sweden, Canada, Japan, Australia. For France, the franc exchange rate was used before 1991Q1 and the euro exchange rate after.

We note a low average correlation coefficient in exchange rates across EMEs (0.22) and a modest but higher correlation across AEs (0.39). Similarly, the first common factor only explains around 38% of the variation in XR in EMEs and about 54% in AEs. When excluding crises episodes and thus focusing on a later time period starting around 2003, the correlation becomes higher, but the difference between EMEs and AEs remains, with a substantially stronger co-movement in exchange rates across AEs. Similar results are found for business cycles, with a cross-correlation of around 0.4 for EMEs compared to 0.6 in AEs. Overall, only a bit more than half of the variation in exchange rates and output in EMEs can be

[17] PCA of a $k \times 1$ vector of $k$ variables $x_t$ is based on a diagonalisation of the variance-covariance matrix of $x_t$, denoted as $\Sigma_x$, such that $\Sigma_x = \Phi P \Phi'$, where $P$ is a diagonal matrix that contains (in descending order) the eigenvalues $\lambda_i$ of $\Sigma_x$ and $\Phi$ is a matrix of mutually orthogonal eigenvectors. The factors $f_t$ are then given by $f_t = \Phi^{-1} x_t$ and the eigenvalues in $P$ represent the variance associated with those factors, whose sum adds up to the total variance in $x_t$. The share of the total variance in $x_t$ explained by the first factor is given by $pc_1 = \frac{\lambda_1}{\sum_{i=1}^{k} \lambda_i}$.

[18] For GDP, we only report the restricted sample as we do not have quarterly GDP series for all EMEs going back to the 1970s.

attributed to a common factor; even in the restricted sample that excludes crisis episodes and covers a period of strong trade and financial integration. This contrasts with AEs, where the joint factor explains more than 70% of cyclical variation in GDP. These results suggest that while there is a notable co-movement in exchange rates and output across EMEs in our sample, there is also a substantial amount of independence.

To investigate potential global drivers of these co-movements, we again estimate a dynamic factor model, but now extract a single common factor in exchange rates across our sample of 7 EMEs, so that $x_t$ in (3)-(4) becomes a $7 \times 1$ vector of (detrended) nominal US dollar exchange rates. We again assume the factor follows an AR(2) process and set $r = 2$. Having obtained common dynamic factors, we consider several external variables that are potential drivers of the joint fluctuations in exchange rates captured by the dynamic factor. Following the literature on the global financial cycle and US monetary policy spillovers, we consider the real US monetary policy rate, defined as the Federal Funds rate minus the (annualised) US CPI inflation rate (*FFUNDS*)[19] and the (logged) VXO, a precursor to the VIX, which measures implied volatility in the S&P 100 and serves as a measure for global risk aversion.[20] In addition, movements in international commodity prices may also exert strong effects on exchange rates. To estimate this channel, we consider a global (logged) primary commodity price index (denominated in US dollars) (*CMP*), which is a weighted average based on global import shares and contains 68 commodities covering energy, agricultural products, fertilizers and metals. Following Fernández et al. (2018), we deflate it by the US consumer price index.[21]

We then assess external drivers of joint fluctuations in *XR* by estimating auto-regressive distributed lag (ARDL) models of the dynamic factor as a function of global variables $z_{tj}$. The ARDL of the dynamic factor $F_t$ can be written as

$$\Omega(L)F_t = \beta + \sum_{j=1}^{k} \Gamma(L) z_{tj} + \epsilon_t, \tag{5}$$

[19] The US policy rate is a common measure for spillover effects from US monetary policy (Bruno & Shin 2015, Cerutti et al. 2019, Kalemli-Özcan 2019). The series goes back to the beginning of the post-Bretton Woods period.

[20] The VXO is similar to the VIX but uses a smaller set of stock prices. It starts in 1986, whereas the VIX starts in 1990. The VXO and VXO are highly correlated (0.99). The VXO/VIX have become standard proxies of the global financial cycle (Avdjiev et al. 2019, Bruno & Shin 2014, 2015, Carrière-Swallow & Céspedes 2013, Cerutti et al. 2019, Forbes & Warnock 2012, Kalemli-Özcan 2019, Miranda-Agrippino & Rey 2019, Obstfeld et al. 2019, Rey 2015).

[21] *CMP* starts in 1992. Fernández et al. (2018) show that individual commodity prices are strongly correlated, which reinforces the use of an index.

where $\Omega(L)$ is a lag polynomial of autoregressive terms of order $m$ and $\Gamma(L)$ is a lag polynomial of order $n_j$ representing the distributed lag of the $j = 1, ..., k$ regressors. A combination of $m$ and $n_j$ was chosen that minimises the Akaike information criterion.[22] In the first three specifications reported in Table 2, the dynamic factor is regressed on one global variable each, while the fourth specification contains all three global variables. We also report p-values of Wald tests of the joint significance of all coefficients on the lagged explanatory variables.

The US policy rate is never jointly statistically significant. The VXO is jointly statistically significant only in the specification where it enters as the sole explanatory variable. However, it loses its statistical significance in specification (4) with all global variables. By contrast, the commodity price index is jointly significant both in the bivariate and multivariate specification. Note also that the adjusted $R^2$ of 90% in specification (4) with all variables is barely higher than the adjusted $R^2$ of specification (3) with the commodity price index only. This suggests that the global commodity price index explains the largest share of the variance of the dynamic factor among the external variables under consideration. Finally, specification (5) is a distributed lag model with commodity prices only, where the lagged dependent variable from specification (3) has been dropped. Notably, the adjusted $R^2$ is still about 82%, which is impressively high for a bivariate model. Appendix G reports additional results for the unrestricted sample, which are qualitatively similar.

[22]We consider a maximum of four lags.

**Table 2: ARDL of common dynamic factor in nominal US dollar exchanges on global variables**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| L.F | 0.854*** | 0.908*** | 0.449*** | 0.479*** | |
| | (0.000) | (0.000) | (0.000) | (0.000) | |
| FFUND | 0.003 | | | -0.001 | |
| | (0.186) | | | (0.129) | |
| L.FFUND | -0.000 | | | | |
| | (0.985) | | | | |
| L2.FFUND | -0.007** | | | | |
| | (0.037) | | | | |
| L3.FFUND | 0.004** | | | | |
| | (0.025) | | | | |
| VXO | | 0.006 | | -0.000 | |
| | | (0.355) | | (0.943) | |
| L.VXO | | 0.020*** | | 0.004 | |
| | | (0.010) | | (0.458) | |
| L2.VXO | | -0.011 | | 0.002 | |
| | | (0.149) | | (0.693) | |
| L3.VXO | | -0.011* | | -0.009** | |
| | | (0.070) | | (0.030) | |
| CMP | | | -0.033*** | -0.034*** | -0.041*** |
| | | | (0.001) | (0.001) | (0.001) |
| L.CMP | | | -0.067*** | -0.061*** | -0.073*** |
| | | | (0.000) | (0.000) | (0.000) |
| L2.CMP | | | 0.052*** | 0.047*** | 0.018 |
| | | | (0.000) | (0.000) | (0.120) |
| Constant | -0.053 | -0.013 | 0.042 | -0.030 | 0.216 |
| | (0.773) | (0.930) | (0.678) | (0.804) | (0.105) |
| p Wald FFUND | 0.112 | | | 0.129 | |
| p Wald VXO | | 0.001 | | 0.226 | |
| p Wald CMP | | | 0.000 | 0.000 | 0.000 |
| Period | 2003Q4 | 2003Q4 | 2003Q4 | 2003Q4 | 2003Q4 |
| | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q3 |
| Adj. R-squared | 0.726 | 0.761 | 0.897 | 0.900 | 0.815 |

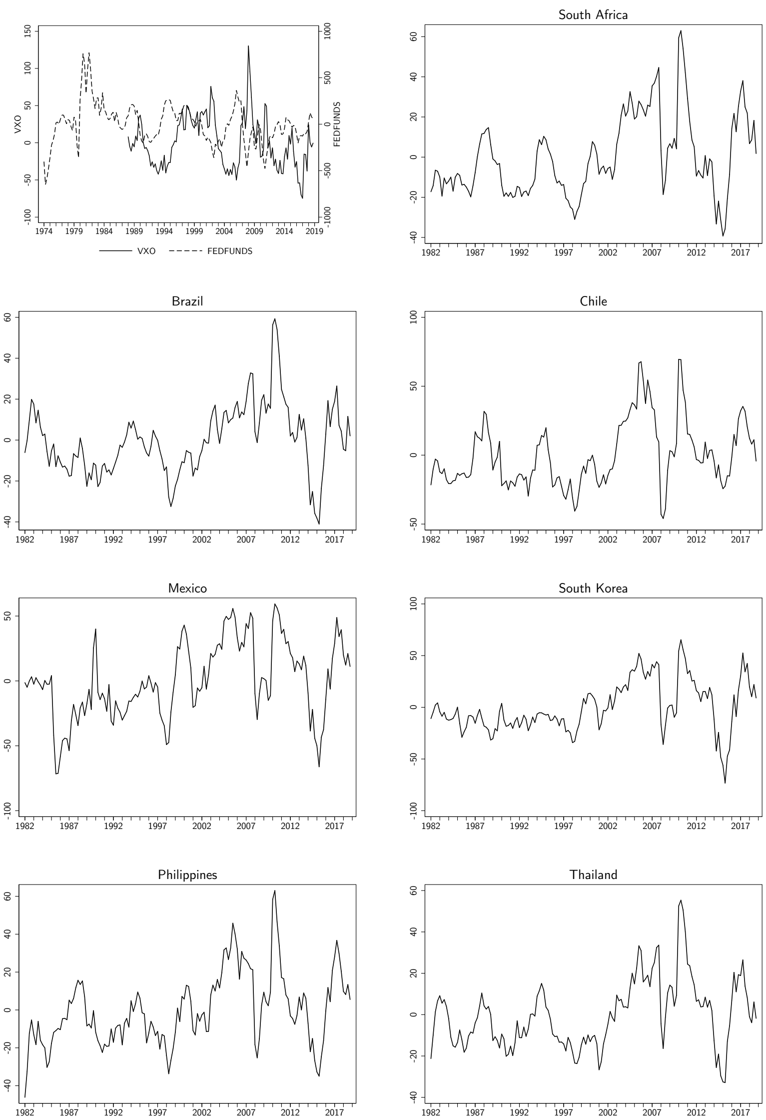
*Notes*: Dependent variable: dynamic factor extracted from a dynamic factor model of the logged nominal US-dollar exchange rate (cyclical component) for South Africa, Brazil, Chile, Mexico, South Korea, the Philippines, Thailand (see Table A8). The dynamic factor was specified as an AR(2) process. *FFUND*: real federal funds rate (cyclical component), *VXO*: logged implied volatility index (cyclical component), *CMP*: logged global commodity price index (cyclical component). p-values in parentheses.

Global commodity price dynamics and, to a lesser extent, global financial shocks are thus potentially strong drivers of joint exchange rate fluctuations across EMEs. But do they also account for the country-specific periodicities documented in section 2? If periodic cycles in *XR* stem from global factors, one would expect similar periodicities in those variables. To better account for the country-specific influence of commodity prices, we replace the global commodity price index $CMP$ by a country-specific (logged) commodity terms of trade index provided by Gruss & Kebjah (2019) that weights global commodity prices by the share of commodity $j$ in the total commodity exports ($CMP^W$) of the respective country.[23] This allows to asses whether global commodity prices that are most relevant for the countries in our sample display dominant periodicities. A further advantage of $CMP^W$ is that the series go back to 1980.

Figure 3 displays cyclical components of the $VXO$, $FFUND$, and $CMP^W$. The US policy rate (upper left panel, dashed line) largely exhibits erratic behaviour, with two large spikes in the early 1980s (the Volcker shock), then a period of cyclical behaviour, and then two major dips during the Global Financial Crisis (GFC). As documented in the literature on global financial cycles, the *VXO* (solid line) is strongly correlated with US monetary policy. Cyclical behaviour in the *VXO* is apparent from the sample start in the second half of the 1980s, but similar to *FFUNDS*, the dynamics have been more erratic since the mid-2000s. The country-specific commodity terms of trade exhibit cyclical behaviour too, but with a change in frequency: in the 1980s and 1990s, many countries experienced short cycles of around 5 years, which then turned into a 10-year boom during the 2000s that was interrupted by the GFC. After that, commodity prices bounced back quickly and appear to have resumed their 5-year periodicity. From the time series, it is thus not clear whether the series exhibit dominant cycle frequencies.

[23]The measure constructed by Gruss & Kebjah (2019) covers international prices of 45 commodities $j$ that are deflated by a unit value index for manufactured exports. A similar measure is used in Drechsel & Tenreyro (2018) who study the impact of commodity terms of trade shocks on Argentina's business cycles in a general equilibrium framework.

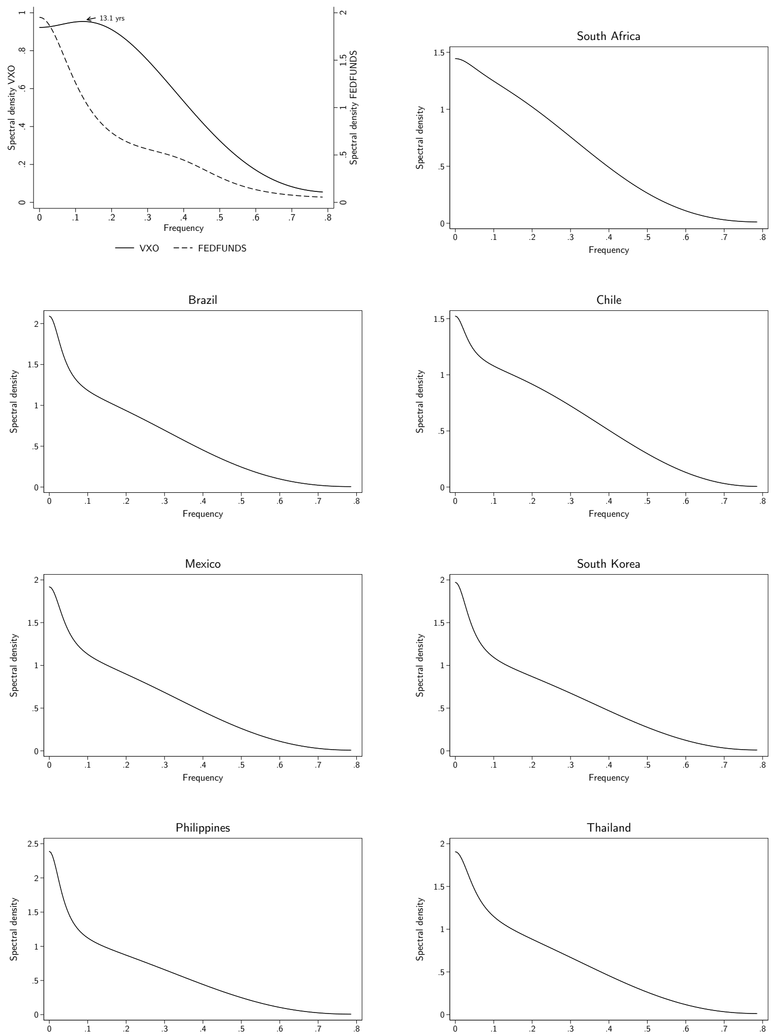
**Figure 3: Real federal funds rate and VXO (upper left panel) and country-specific commodity terms of trade (remaining panels), cyclical components**




*Notes: VXO*: logged volatility index (cyclical component); *FEDFUNDS*: real federal funds rate (cyclical component). Cyclical components are the residual from the regression $x_{t+8} = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \beta_3 x_{t-2} + \beta_4 x_{t-3} + \nu_{t+8}$.

Figure 4 reports the corresponding spectral density functions. The only variable that exhibits a dominant cycle frequency is the *VXO* with an estimated cycle length of 13 years. This is above the estimated frequencies for exchange rates in EMEs, which range from 4 to 11 years. Note also that the *VXO*'s spectral density is widely dispersed around the peak, suggesting that the 13-year periodicity in *VXO* is not very pronounced. For *FFUND* and $CMP^W$, no dominant periodicity can be found, which most likely reflects the fact that these series exhibit erratic dynamics or time-varying periodicities. Overall, spectral analysis of global factors does not suggest dominant periodicities that would match the periodicities found in *XR* and *GDP* fluctuations. Global factors alone thus do not seem to explain the joint periodicities in *XR* and *GDP* documented in section 2.

**Figure 4: Spectral densities of real federal funds rate and VXO (upper-left panel), and country-specific commodity terms of trade (remaining panels)**




*Notes: Notes: VXO*: logged volatility index, *FEDFUNDS*: real federal funds rate. Parametrically estimated spectral densities from ARMA models (see Appendix E

# 4 Internal drivers of exchange rate cycles

As external drivers do not seem to fully account for the periodicities found in exchange rates, we consider internal mechanisms that may generate periodic fluctuations. Recent macroeconomic research has rediscovered the notion of periodic cycles that are driven by endogenous cycle mechanisms (Beaudry et al. 2020). The idea of cyclical mechanisms has also been entertained in research on financial cycles as a possible explanation for periodic cycles in house prices and private debt, which are difficult to explain by exogenous shocks only (Borio 2014). A specific aspect that has received some attention is the interaction between business and financial cycles in advanced countries (Stockhammer et al. 2019, Strohsal et al. 2019). Stockhammer et al. (2019) investigate whether endogenous interaction mechanisms between financial variables and output can give rise to joint oscillations in those variables. In this section, we build on their approach and extend it to the interaction of exchange rates and business cycles in EMEs.

Consider a generic 2D first-order system of difference equations:

$$\begin{bmatrix} y_t \\ s_t \end{bmatrix} = \begin{bmatrix} a_0 \\ b_0 \end{bmatrix} + \begin{bmatrix} a_1 & a_2 \\ b_1 & b_2 \end{bmatrix} \begin{bmatrix} y_{t-1} \\ s_{t-1} \end{bmatrix}. \tag{6}$$

The system in (6) can be regarded as a linearised reduced-form representation of a class of cycle models in two state variables, e.g. Kiyotaki & Moore (1997) or the reduced form in Beaudry et al. (2020, pp.18-21). The presence of a pair of complex conjugate eigenvalues in (6) generates periodic fluctuations. A necessary condition for complex eigenvalues in (6) is[24]

$$a_2 b_1 < 0. \tag{7}$$

Intuitively, oscillations in (6) stem from an interaction mechanism between $y_t$ and $s_t$, in which an increase in one variable induces an acceleration of the second variable, which in turn drags down the first.

How can this framework be applied to the interaction of output and exchange rates in EMEs?

[24]To see this, recall that the eigenvalues of the coefficient matrix in (6) are the roots of the characteristic equation $\lambda^2 - \lambda Tr + Det = 0$, where $Tr$ and $Det$ are the trace and determinant of the coefficient matrix, respectively. The roots of the characteristic equation are given by $\lambda_{1,2} = \frac{Tr \pm \sqrt{Tr^2 - 4Det}}{2}$. Complex roots emerge when the discriminant of this expression becomes negative. This requires $(a_1+b_2)^2 - 4(a_1 b_2 - a_2 b_1) < 0$, which simplifies to $(a_1 - b_2)^2 + 4(a_2 b_1) < 0$. From this, it is immediate that $a_2 b_1 < 0$ is a necessary condition for complex eigenvalues (Stockhammer et al. 2019).

Suppose $y_t$ represents output and $s_t$ the exchange rate. First, the effect of a depreciation on output depends on the financial channel and the trade channel (Avdjiev et al. 2019, Banerjee et al. 2020, Bruno & Shin 2014, Kearns & Patel 2016). Through the conventional trade channel, depreciations are expansionary as they increase net exports. By contrast, the financial channel is contractionary, as depreciation against the US dollar tightens borrowing constraints and discourages private spending. If the financial channel dominates, we get $a_2 < 0$, if the trade channel dominates, $a_2 > 0$. Second, $b_1$ captures feedback effects of output on exchange rates. In traditional flow-approaches such as the Mundell-Fleming model, output expansion leads to currency depreciation through rising demand for foreign currency from imports, so that $b_1 > 0$.[25] In the modern view, stock-equilibria and valuation effects on foreign assets are more prominent (see Gourinchas & Rey (2007) for an influential study and Gourinchas (2008) for a review). In this approach, a sustained rise in demand for foreign goods is associated with an increase in external debt and a nominal depreciation due to excess supply of domestic assets on international financial markets. Insofar output expansions come with an increase in net imports and external debt, this implies a loss in the external value of the domestic currency ($b_1 > 0$). The combination of the financial channel of exchange rate with such an external adjustment channel can thus give rise to a cyclical interaction mechanism $a_2 b_1 < 0$ between output and exchange rates that may produce periodic fluctuations.

Stockhammer et al. (2019)'s framework given by (6) considers only two variables, both of which are endogenous. However, their approach can easily be augmented by a vector of exogenous variables $\mathbf{z_t}$. Written in compact form, we have:

$$\mathbf{y_t} = \alpha + A\mathbf{y_{t-1}} + B\mathbf{z_{t-h}}, \tag{8}$$

where $A$ corresponds to the coefficient matrix in (6) and $B$ contains the coefficients on the exogenous variables. In the system given by (8), the second term represents the (lagged) effect of (unmodelled) exogenous variables ($\mathbf{z_{t-h}}$) on the vector of endogenous variables ($\mathbf{y_t}$). For example, in small open economy models foreign variables such as the world interest rate are typically treated as exogenous. These variables can be a source of shocks and drive some of the dynamics in the endogenous variables. However, unless $\mathbf{z_{t-h}}$ exhibits periodic frequencies itself, oscillations in the endogenous variables are the outcome of the interaction mechanism in $A$, given by (7). It is then the interaction mechanism that transforms irregular shocks into regular fluctuations.

[25] See Blanchard et al. (2010) and Krugman (2014) for more recent applications of the traditional flow approach.

This simple framework thus combines (irregular) external shocks with a domestic propagation mechanism that may generate periodic business cycle fluctuations. External and internal drivers of exchange rate cycles are thus not mutually exclusive but may jointly account for periodic fluctuations.

### 4.1 Estimating exchange rate cycle mechanisms

How can the coefficient matrix $A$ containing the cycle mechanism of interest be estimated? Stockhammer et al. (2019) discuss the case without exogenous variables ($B = 0$). If the system was a correct specification of the DGP, estimation of a linear VAR(1) would provide consistent estimates of $a_2$ and $b_1$. However, estimation of a VAR(1) is problematic as the empirical DGP is likely to be higher-dimensional or higher-order. If the relevant higher-order lags are not included in the VAR, the error terms will be serially correlated. A more appropriate specification is thus a VAR(p), where the lag length $p$ is chosen so as to remove serial correlation in the error terms. From the VAR(p), the coefficients $a_2$ and $b_1$ can be retrieved, which allows to evaluate the critical condition for the existence of a cycle mechanism ($a_2 b_1 < 0$).[26]

Extension of this procedure to the case with exogenous variables is straightforward. Instead of a VAR(p), we get a (reduced-form) VARX(p, h):[27]

$$\mathbf{y_t} = \alpha + \sum_{i=1}^{p} A_i \mathbf{y_{t-i}} + \sum_{j=0}^{h} B_j \mathbf{z_{t-h}} + \epsilon_{\mathbf{t}}. \tag{9}$$

As in the case of the VAR(p), the coefficients of interest can be obtained from the off-diagonal of the coefficient matrix $A_1$.[28]

To estimate the VARX in (9) with real GDP and nominal US dollar exchange rates, we use annual data. Stockhammer et al. (2019) argue that annual data are more suitable for estimating the interaction mechanism on the first-order lags of the system, as VARs with quarterly data typically require a larger number of lags, which exacerbate multicollinearity problems, may introduce irrelevant high-frequency fluctuations, and overall make it difficult

[26]Stockhammer et al. (2019) further show that if the DGP is a VAR(1) with serial correlated errors, only the coefficients $a_2$ and $b_1$ are identified in the VAR(p).

[27]See Lütkepohl (2005, chap.10) for a general treatment of VARXs.

[28]From the polar representation of the complex eigenvalues $\lambda = |\lambda|(\cos\theta \pm i.\sin\theta)$ of the VAR's companion matrix, one can further obtain the implied cycle length $CL = \frac{2\pi}{\theta} = \frac{2\pi}{\arccos(Re/|\lambda|)}$. Note that these complex eigenvalues cannot be directly mapped to the interaction mechanism in $A_1$ as they may also stem from the coefficients on the higher order terms $A_{i+1}$, $i = 1, ...p-1$.

to attribute cyclical dynamics to the coefficients on the first-order lags. The results in section 2 have shown that joint exchange rate and GDP cycles are at frequencies of 4 to 8 years, suggesting that annual data are suitable to pick up those frequencies. To determine the appropriate lag length $p$ for the endogenous variables, we start with a minimum lag length of 2. We then check for serial correlation in the residuals and successively increase the number of lags up to 6 until all serial correlation is removed. Mindful of the relatively small sample size and the fact that data are at annual frequency, we set the lag structure of the exogenous variables to $j = h = 1$, aiming for parsimony.[29]

While the methods used so far in this paper required stationarity and were thus applied to detrended data, the VARX is estimated in (log-)levels.[30] In order to maximise degrees of freedom, we use the full time span and set the sample start to 1972. As a result, currency crises and hyperinflation episodes reported in Figure A1, which were excluded from the analyses in sections 2 and 3, will be included in the estimations. We deal with this problem in two ways: first, by augmenting the bivariate VARs with the global variables we considered in section 3. Based on the small open economy assumption, we treat these as exogenous, thus obtaining the VARX in (9). Insofar as crises were triggered by shocks to the global variables, the VARX will control for those episodes.

Second, we also report a bivariate VAR specification with step indicator saturation (SIS) to capture crises events (Castle et al. 2015). SIS is based on the split half approach: first, create step indicators for the entire sample period, which are dummy variables that are equal to 1 from a specific break year onwards and otherwise zero. Then estimate the model on the full sample, first with only the first half of step indicators, and then with the second half. Retain those step indicators from both estimations whose p-value is equal or below $1/T$ and re-estimate the model with only those step indicators. Lastly, exclude step indicators whose p-value exceeds $1/T$. As we are interested in controlling for exogenous shifts in the $XR$ series, we select those step indicators that are statistically significant in the $XR$-equation. Step indicators have the advantage that they capture outliers *and* mean shifts and thus mitigate both heteroskedasticity and structural breaks.[31]

[29] We check the robustness of our baseline specification to the case where $j = h = 0$.

[30] This is common when it is unclear whether the relevant variables contain a unit root and/or are cointegrated. As Kilian & Lütkepohl (2017, chap. 3) point out, there is an asymmetry between incorrectly imposing a unit root (and then overdifferencing the data) and failing to impose a unit root when there is one. While the former renders the VAR-estimator inconsistent under standard assumptions, the latter approach preserves consistency and may only come with a loss in efficiency. The VAR(X) in levels can be consistently estimated with asymptotically normal standard errors even if some variables are I(1) because the presence of lags would allow the I(1) variables to be re-written as coefficients on differenced and thus I(0) variables (Sims et al. 1990).

[31] Note that as the VARX is in log-levels, most of the extreme episodes visible in the detrended series in

It is possible that these remedies will not fully address the problem of crises episodes. We therefore expect point estimates of those countries that underwent major crisis episodes (e.g. Brazil) during the sample period to be less reliable compared to those that had fewer or no crises (e.g. South Africa, Chile). Similarly, countries that had fixed or semi-fixed exchange rate regimes throughout most of the sample period, such as Thailand before the East Asian crisis, are less likely to exhibit a cycle mechanism over the full sample period.

## 4.2 Estimation results

For the baseline specification (Table 3), $CMP^W$ is the preferred external variable as it turned out to be a strong driver of co-movements in $XR$ across EMEs in section 3. The condition for a cycle mechanism ($a_2 b_1 < 0$) is satisfied in South Africa and Chile (with both coefficients statistically significant),[32] Korea and the Philippines (with only one of the two coefficients statistically significant) and Mexico (with statistically insignificant coefficients). The signs correspond to the financial channel of exchange rates where currency depreciations are contractionary ($a_2 < 0$) and to an external adjustment channel where output expansions lead to downward pressure on currencies ($b_1 > 0$). By contrast, the signs on the coefficients for Brazil and Thailand do not meet the condition for a cycle mechanism and are statistically insignificant. It can further be seen that an improvement in $CMP^W$ is generally associated with an expansion of output (which is, however, only statistically significant in Brazil) and an appreciation of the domestic currency for most countries, in line with EME business cycle models that account for commodity price shocks (Drechsel & Tenreyro 2018, Fernández et al. 2018).

Table 3 also reports cycle lengths (CL) implied by the complex eigenvalues ($\lambda$) of the estimated coefficient matrix of the VARX. For South Africa and Chile, the VARX yields cycle frequencies of around 6 1/2 and 8 1/2 years, respectively, that are very similar to the estimated frequency in the joint dynamic factor with quarterly data (Figure 2). For the other countries, estimated frequencies are substantially longer, which is likely to be due to the presence of currency crises episodes that are not captured by $CMP^W$.

Figure A2 will take the form of mean shifts.

[32] In the VARX for Chile, the null hypothesis of no serial correlation was rejected at the 10% level on the first lag of the error. This did not vanish with the inclusion of up to 6 lags. When adding $FFUND$ to the model (see Table A12) serial correlation vanishes and the results are very similar.

Table 3: **Estimation results for VARX(p) with $GDP$, $XR$, and $CMP^W$**

| | **ZAF** | **BRA** | **CHL** | **MEX** | **KOR** | **PHL** | **THA** |
|---|---|---|---|---|---|---|---|
| **GDP** | | | | | | | |
| L.GDP | 1.195*** | 1.010*** | 1.018*** | 0.921*** | 0.837*** | 1.198*** | 1.270*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| L.XR | -0.073*** | 0.002 | -0.065** | -0.028 | -0.002 | -0.142*** | -0.074 |
| | (0.002) | (0.739) | (0.023) | (0.353) | (0.975) | (0.006) | (0.485) |
| L.$CMP^W$ | 0.005 | 0.041* | 0.010 | 0.011 | -0.016 | 0.017 | -0.028 |
| | (0.685) | (0.069) | (0.674) | (0.472) | (0.159) | (0.226) | (0.139) |
| **XR** | | | | | | | |
| L.GDP | 1.940** | 1.989 | 0.931* | 1.684 | 1.097* | 0.494 | -0.427 |
| | (0.017) | (0.400) | (0.091) | (0.138) | (0.087) | (0.309) | (0.287) |
| L.XR | 1.075*** | 1.635*** | 1.941*** | 1.538*** | 1.217*** | 1.221*** | 0.898*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| L.$CMP^W$ | -0.211** | -0.921*** | 0.022 | -0.179* | 0.006 | -0.125*** | -0.060 |
| | (0.010) | (0.005) | (0.797) | (0.050) | (0.860) | (0.007) | (0.129) |
| Lags | 2 | 2 | 3 | 2 | 2 | 2 | 2 |
| $\lambda_1$ | $0.32 \pm 0.44$ | $0.78 \pm 0.19$ | $0.58 \pm 0.51$ | $0.71 \pm 0.30$ | $0.51 \pm 0.24$ | $0.32 \pm 0.25$ | $0.61 \pm 0.16$ |
| $\lambda_2$ | | | $-0.01 \pm 0.36$ | | | | |
| CL 1 | 6.689 | 25.763 | 8.744 | 15.535 | 14.220 | 9.620 | 24.686 |
| CL 2 | | | 3.939 | | | | 2 |
| $a_2 b_1 < 0$ | YES | NO | YES | YES | YES | YES | NO |

*Notes*: Sample period: 1972-2017. p-values in parentheses. $GDP$: logged real GDP; $XR$: logged nominal US-dollar exchange rate; $CMP^W$: logged commodity terms of trade. A constant term was included in each equation (not reported). Only the coefficients on the first lags are reported. The VARX for Chile exhibits serial correlation on the first lag. $\lambda$: complex eigenvalues of estimated coefficient matrix; CL: cycle lengths (in years) implied by the complex eigenvalues computed as $\frac{\pi}{2\arccos(\frac{re}{mod})}$, where $re$ is the real part of the eigenvalue and $mod$ is the modulus.

Next, we asses whether the cycle mechanism is robust to the inclusion of other global factors. Tables 4 and 5 report results from VARX estimations, where instead of $CMP^W$ we used $FFUND$ and $VXO$, respectively. In Table 4, the estimated coefficients on $FFUND$ confirm the notion of monetary policy spillovers: an increase in $FFUND$ is associated with a depreciation of domestic currencies against the US dollar, in line with the risk-taking channel of monetary policy discussed in Bruno & Shin (2015). The effects on $GDP$ are contractionary, indicative of a worsening of domestic borrowing cost (Kalemli-Özcan 2019). The main results with respect to the cycle mechanism are robust to the inclusion of *FFUND*. South Africa, Chile, the Philippines[33] and Mexico still exhibit a cyclical interaction mechanism. For Korea, the coefficient on *XR* in the *GDP*-equation switches signs, indicating a lack of robustness.

**Table 4: Estimation results for VARX(p) with $GDP$, $XR$, and $FFUND$**

| | **ZAF** | **BRA** | **CHL** | **MEX** | **KOR** | **PHL** | **THA** |
|---|---|---|---|---|---|---|---|
| **GDP** | | | | | | | |
| L.GDP | 1.208*** | 1.091*** | 0.885*** | 0.839*** | 0.894*** | 1.185*** | 1.439*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| L.XR | -0.074*** | -0.004 | -0.059** | -0.050 | 0.019 | -0.147*** | 0.033 |
| | (0.001) | (0.507) | (0.026) | (0.162) | (0.792) | (0.002) | (0.728) |
| FFUND | | | | | | -0.003* | |
| | | | | | | (0.083) | |
| L.FFUND | -0.001 | -0.002 | -0.010*** | -0.005** | 0.001 | | -0.001 |
| | (0.657) | (0.295) | (0.006) | (0.019) | (0.529) | | (0.706) |
| **XR** | | | | | | | |
| L.GDP | 1.362* | -0.320 | 1.486*** | 2.129* | 0.687 | 0.519 | -0.227 |
| | (0.084) | (0.893) | (0.006) | (0.061) | (0.263) | (0.272) | (0.522) |
| L.XR | 1.138*** | 1.777*** | 1.925*** | 1.679*** | 1.055*** | 1.281*** | 0.988*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| FFUND | | | | | | 0.017*** | |
| | | | | | | (0.001) | |
| L.FFUND | 0.015** | 0.028 | 0.035** | 0.043*** | 0.012* | | 0.005 |
| | (0.048) | (0.375) | (0.010) | (0.001) | (0.061) | | (0.190) |
| Lags | 2 | 2 | 3 | 3 | 2 | 2 | 2 |
| $a_2 b_1 < 0$ | YES | NO | YES | YES | NO | YES | YES |

*Notes*: Sample period: 1972-2017. p-values in parentheses. $GDP$: logged real GDP; $XR$: logged nominal US-dollar exchange rate; $FFUND$: real federal funds rate. Only the coefficients on the first lags are reported. For the Philippines, the contemporaneous value of *FFUND* was used to obtain serial uncorrelated errors.

When using *VXO* instead of *FFUND* (Table 5), the sample start shifts to 1987. Due to the low degrees of freedom ($< 25$), the results have to be taken with caution. As documented in research on the effects of global uncertainty shocks (Carrière-Swallow & Céspedes 2013), VXO shocks have contractionary real effects on EMEs and are associated with currency depreciation for most countries. With respect to the cycle mechanism, the results for South

[33] For the Philippines, the contemporaneous value of *FFUND* was used as the lagged value introduced serial correlation in the errors.

Africa, Chile, and the Philippines hold up. For the remaining countries, the condition is either not satisfied or not robust.

**Table 5: Estimation results for VARX(p) with $GDP$, $XR$, and $VXO$**

| | **ZAF** | **BRA** | **CHL** | **MEX** | **KOR** | **PHL** | **THA** |
|---|---|---|---|---|---|---|---|
| **GDP** | | | | | | | |
| L.GDP | 1.377*** | 1.058*** | 0.610*** | 0.806*** | 0.549** | 1.166*** | 1.174*** |
| | (0.000) | (0.000) | (0.007) | (0.000) | (0.031) | (0.000) | (0.000) |
| L.XR | -0.044** | 0.023*** | -0.145** | 0.074** | -0.007 | -0.034 | -0.057 |
| | (0.031) | (0.007) | (0.037) | (0.048) | (0.930) | (0.478) | (0.614) |
| L.VXO | -0.014* | -0.012 | -0.020 | -0.029** | -0.031* | -0.007 | -0.008 |
| | (0.071) | (0.433) | (0.108) | (0.039) | (0.091) | (0.561) | (0.709) |
| **XR** | | | | | | | |
| L.GDP | 1.406 | 3.033 | 1.701*** | 1.268 | 2.327*** | 1.642** | 0.055 |
| | (0.195) | (0.350) | (0.004) | (0.150) | (0.006) | (0.024) | (0.922) |
| L.XR | 1.197*** | 1.410*** | 1.630*** | 1.021*** | 1.199*** | 1.116*** | 1.140*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| L.VXO | -0.047 | 0.009 | 0.035 | 0.012 | 0.087 | 0.095** | 0.043 |
| | (0.478) | (0.976) | (0.296) | (0.858) | (0.154) | (0.029) | (0.349) |
| Lags | 2 | 6 | 2 | 2 | 2 | 2 | 2 |
| $a_2 b_1 < 0$ | YES | NO | YES | NO | YES | YES | YES |

*Notes*: Sample period: 1987-2017. p-values in parentheses. $GDP$: logged real GDP; $XR$: logged nominal US-dollar exchange rate; $VXO$: logged volatility index. A constant term was included in each equation (not reported). Only the coefficients on the first lags are reported.

Currency crises and hyperinflation episodes that are unrelated to the cycle mechanism and not captured by any of the external factors may affect the results in the previous specifications. Table 6 therefore reports additional results from bivariate VARs in which endogenously selected step indicators that absorb unexplained mean shifts in the exchange rate were included (Castle et al. 2015). The step indicators capture many of the crises and changes in exchange rate regimes documented in Ilzetzki et al. (2019) and reported in Figure A1. Step indicators also pick up other events related to external factors, e.g. strong depreciations in the Philippines and Thailand during the Great Recession of 2009. The cycle condition is again satisfied in South Africa, Chile, and the Philippines, and is statistically significant for all three countries. It is noteworthy that these are also the three countries for which visual evidence from the filtered exchange rate series in Figures 1 and A2 is most suggestive of a relatively stable cycle.[34] By contrast, Brazil, South Korea, and Thailand, which either underwent numerous crises episodes or substantial exchange regime shifts throughout the sample period, display no evidence for a stable cycle mechanism even when controlling for these shifts through step indicators.

Table 6 also reports implied cycle lengths from the VAR with step indicators. Insofar as the specification with step indicators controls for crises events, estimated cycle lengths should be comparable to the univariate spectral density estimates in Figure 2. Indeed, for all countries except Mexico, the VAR yields a cycle frequency that is very close (up to around 1 year) to the estimated frequency in the joint dynamic factor displayed in Figure 2. Cycle lengths range from 3 years (South Korea) to almost 8 years (Chile).[35] Mexico and Thailand also display lower frequencies of 10 and 12 1/2 years, respectively, which were not present in Figure 2, presumably because of the unrestricted sample period used for the VAR estimations.

Overall, estimated cycle lengths confirm the presence of joint fluctuations in exchange rate and output at conventional business cycle frequencies of 3 to 8 years. The robustness of this finding across different data types (quarterly and detrended vs annual and log-level) and estimation methods (univariate ARMA vs multivariate VAR) is remarkable.

Further robustness tests are reported in Online Appendix H. The main results hold up. In a VAR specification without exogenous variables, South Africa, Chile, Mexico, and the Philippines meet the condition for a cycle mechanism between exchange rates and GDP. Results from a VARX with $CMP^W$ entering contemporaneously rather than lagged are qualitatively identical with respect to the cycle mechanism. Finally, in a VARX with both $CMP^W$ and $FFUND$, the cycle condition holds for all countries except Brazil and Thailand, with both coefficients statistically significant in South Africa and Chile, and partially significant coefficients in Mexico and the Philippines.

[34] For Chile, this only begins at around 1983 after chaotic episodes at the sample start. Most of these erratic episodes are absorbed by the step indicators. It is also notable that the Philippines is the only one of the three East Asian countries for which no step indicator is retained that would capture the 1998 crisis. This confirms visual evidence in Figures A1 and A2 that 1998 did not involve a structural break for the Philippines.

[35] In addition, there are also higher frequencies of 2 to 3 years.

**Table 6: Estimation results for VAR(p) with $GDP$ and $XR$, step indicator saturation**

| | ZAF | BRA | CHL | MEX | KOR | PHL | THA |
|---|---|---|---|---|---|---|---|
| **GDP** | | | | | | | |
| L.GDP | 1.216*** | 1.117*** | 0.491*** | 0.879*** | 0.709*** | 1.084*** | 1.113*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| L.XR | -0.075*** | 0.006 | -0.175*** | 0.112*** | 0.128*** | -0.104** | -0.018 |
| | (0.003) | (0.605) | (0.000) | (0.000) | (0.003) | (0.012) | (0.784) |
| **XR** | | | | | | | |
| L.GDP | 2.101*** | -1.004* | 0.653*** | 0.984** | 0.989** | 0.870** | -0.051 |
| | (0.004) | (0.095) | (0.007) | (0.018) | (0.014) | (0.035) | (0.857) |
| L.XR | 0.932*** | 1.044*** | 1.625*** | 0.630*** | 0.987*** | 1.125*** | 1.123*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Lags | 4 | 2 | 3 | 2 | 3 | 2 | 3 |
| $\lambda_1$ | $0.36 \pm 0.61$ | | $0.54 \pm 0.57$ | $0.30 \pm 0.21$ | $0.42 \pm 0.48$ | $0.27 \pm 0.40$ | $0.74 \pm 0.40$ |
| $\lambda_2$ | $-0.02 \pm 0.56$ | | $-0.24 \pm 0.35$ | | $-0.21 \pm 0.53$ | | $0.01 \pm 0.36$ |
| $\lambda_3$ | $-0.16 \pm 0.23$ | | | | | | |
| $\lambda_4$ | | | | | | | |
| CL 1 | 6.075 | | 7.748 | 10.320 | 7.331 | 6.515 | 12.562 |
| CL 2 | 3.926 | | 2.898 | | 3.218 | | 4.075 |
| CL 3 | 2.873 | | | | | | |
| SI | 1983, 2002 | 1979, 1982, 1987-92, 1994, | 1972-73, 1976, 1981, 1983-86, 1992 | 1976-77, 1981-82, 1984-86, 1994 | 1974, 1979, 1997-99, 2001 | 1982, 2009 | 1996, 1998, 1999, 2009 |
| $a_2 b_1 < 0$ | YES | NO | YES | NO | NO | YES | NO |

*Notes*: Sample period: 1972-2017. p-values in parentheses. $GDP$: logged real GDP; $XR$: logged nominal US-dollar exchange rate; SI: step indicator. A constant term was included in each equation (not reported). Only the coefficients on the first lags are reported. $\lambda$: complex eigenvalues of estimated coefficient matrix; CL: cycle lengths (in years) implied by the complex eigenvalues computed as $\frac{\pi}{2\arccos(\frac{re}{mod})}$, where $re$ is the real part of the eigenvalue and $mod$ is the modulus.

In summary, we find robust evidence for the presence of a cyclical interaction mechanism between exchange rates and output in South Africa, Chile, and the Philippines (the latter only partly significant). Results for Mexico and South Korea are mixed and not fully robust. For Brazil and Thailand, the cycle condition is never satisfied or significant. We also found evidence for spillover effects of US monetary policy, global risk appetite, and global commodity prices that were in line with theoretical channels in the existing literature.

Heterogeneity across countries with respect to the presence of a cycle mechanism between exchange rates and GDP appears to be related to the exchange rate regime. Countries with relatively stable regimes of flexible or semi-flexible exchange rate during the post-Bretton Woods period (South Africa, Chile, Philippines) exhibit evidence for a cycle mechanism. By contrast, countries that underwent multiple crises episodes and/or shifts in the exchange rate regime at a relatively late stage of the sample period (Mexico, South Korea) do not exhibit robust evidence of a stable interaction mechanism. Especially Brazil was heavily affected by numerous chaotic episodes, which may explain the complete absence of a stable endogenous interaction mechanisms. Lastly, Thailand had a pegged exchange rate throughout most of the sample period, which may have prevented the emergence of a cycle mechanism.

Overall, these results suggest that flexible exchange rates in combination with the financial channel of exchange rates can give rise to a cycle mechanism that may transform external shocks into periodic fluctuations. External and internal drivers of joint exchange rate and output cycles should thus not be regarded as mutually exclusive. On the contrary, external variables can expose the economy to shocks, which may then be propagated into periodic oscillations by the interaction between exchange rates and output.

# 5 Conclusion

The present paper has investigated periodicity as a key property of nominal exchange rate and business cycles in 7 emerging market economies during the post-Bretton Woods period. It showed that there are periodicities in exchange rates of a few major emerging markets that are pronounced and closely aligned with business cycle frequencies. Estimated spectral density functions uncovered joint periodic fluctuations in exchange rates and output at conventional business cycle frequencies between 4 and 8 years in most countries. Exchange rate fluctuations are correlated across EMEs, but only moderately so. Co-movements across countries are mostly related to global commodity prices and only weakly to US monetary policy and global risk appetite. However, the periodicities displayed by these external factors does not match those found in exchange rates and output; thus leaving a key cyclical property unexplained.

To provide an explanation for those periodicities, we considered a cyclical interaction mechanism between exchange rates and output that may transform external shocks into periodic oscillations, in line with business cycle theories that highlight the endogenous generation of periodic cycles (e.g. Asada 2001, Beaudry et al. 2020, Kiyotaki & Moore 1997, Stockhammer et al. 2019). If depreciations are contractionary due to balance sheet effects (the financial channel of exchange rates) and output expansions feed back negatively into exchange rate dynamics via an external adjustment channel, periodic oscillations may emerge. We tested for the presence of such an interaction mechanism through vector-autoregressions, controlling for external factors.

There is strong evidence for such cycle mechanisms in South Africa and Chile, and to a lesser extent for the Philippines, which are the countries in the sample with the longest spells of uninterrupted (semi-)flexible exchange rate regimes. Mexico and South Korea also display evidence for an interaction mechanism in some specifications, but lack robustness; we conjecture that this is due to changes in exchange rate regimes and other extraneous factors. There is no evidence for Brazil, where fluctuations are mostly idiosyncratic and for Thailand which had a fixed exchange rate regime throughout most of the sample period.

Overall, our results suggest, first, that fluctuations in nominal exchange rates and output in several major EMEs are periodic. This is a novel finding. The previously documented procyclicality of exchange rates in EMEs is thus, as far as the countries in this study are concerned, not driven by extreme events such as currency crises, but has to be regarded as a cyclical phenomenon. The presence of such dominant cycle frequencies cannot be explained by exogenous shocks only and points to the relevance of endogenous cyclical mechanisms. Second, we contend that periodicities cannot fully be explained by external drivers but may stem from cyclical interaction mechanisms that translate external shocks into periodic oscillations. This highlights the importance of internal cycle mechanisms and may explain why exchange rate cycles are not highly synchronised across EMEs and also differ in their lengths. While external drivers of fluctuations have received much attention in recent research, we argue that they have to be analysed in conjunction with internal propagation mechanisms, such as the financial channel of exchange rates.

Our results provide some interesting perspectives for research on business cycles and exchange rates in emerging markets, as well as periodic (financial) cycles. First, with respect to the literature on the global financial cycle and external shocks (Carrière-Swallow & Céspedes 2013, Cesa-Bianchi et al. 2015, Kalemli-Özcan 2019, Miranda-Agrippino & Rey 2019, Rey 2015, 2016), we confirm an important role of global commodity prices for joint exchange rate and output fluctuations in emerging markets, which complements previous studies that have reported correlations of commodity prices with output and real exchange rates (Drechsel & Tenreyro 2018, Fernández et al. 2018) but have not studied the effects on nominal exchange rates nor controlled for other financial factors. Second, we argue that when the financial channel of exchange rates (Avdjiev et al. 2019, Banerjee et al. 2020, Bruno & Shin 2014, 2015, Kearns & Patel 2016) is coupled with an external adjustment mechanism whereby output expansions lead to gradual depreciation, a cycle mechanism is present which can give rise to periodic oscillations in output and exchange rates. This implies that the financial channel can become an endogenous source of fluctuations. This is also noteworthy from the perspective of recent research on the interaction of business and financial cycles in advanced countries (Stockhammer et al. 2019, Strohsal et al. 2019). While this research has mostly focused on private debt and house prices, our results suggest that the nominal US dollar exchange rate is an important interacting variable in some major emerging markets.

Lastly, our results also have implications for economic policy. Recent theoretical work on sterilised foreign exchange intervention (Adler et al. 2019, Alla et al. 2019, Benes et al. 2015) suggests that exchange rate management can play an important role for macroeconomic stabilisation. The results presented in this paper support this view and suggest that the exchange rate may indeed become a driver of business cycle fluctuations. This provides a rationale for managed floating, where central banks smooth exchange rate fluctuations through targeted interventions (Frankel 2019, Ghosh et al. 2016). It is likely that this approach will gain further prominence in an era of increased volatility.

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# Appendix

# A Dataset

**Table A1: Data definitions and sources**

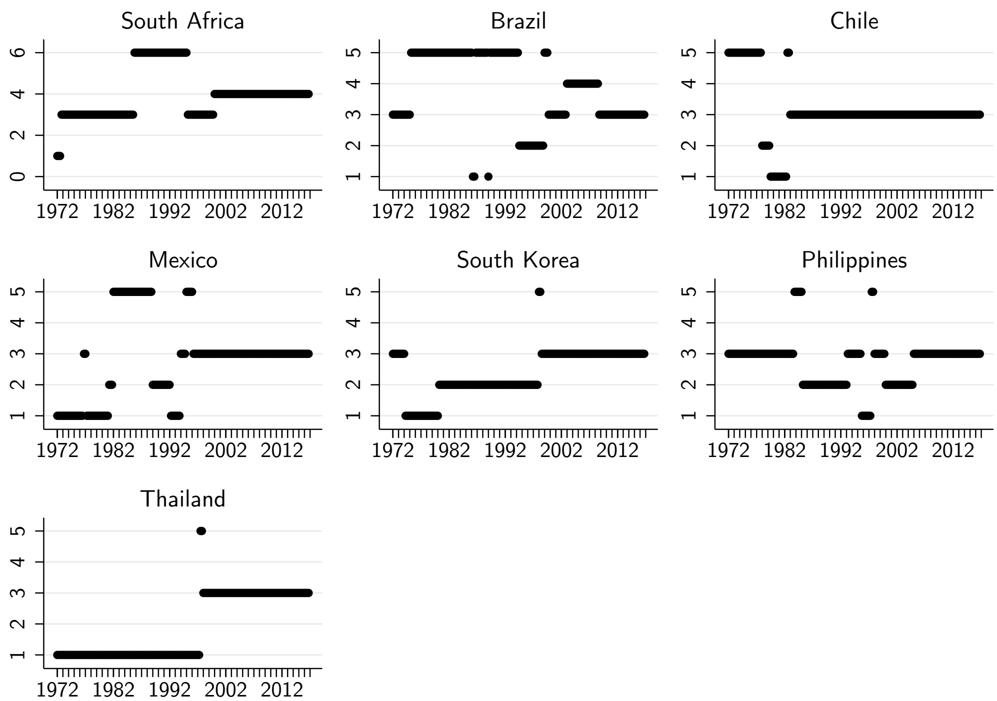
| Variable | Definition | Source(s) | Sample range & notes |
|---|---|---|---|
| $CMP$ | Global commodity price index, deflated by US CPI, natural log, average over period | IMF | 1991Q1-2019Q3; weighted average over 68 commodities based on global import shares |
| $CMP^W$ | Country-specific global commodity terms of trade index, deflated by manufacturing unit value (MUV), natural log, average over period | Gruss and Kebjah (2019) | 1980Q1-2019Q3 (quarterly series); 1972-2017 (annual series); weighted average over 45 commodities based on the share of each commodity in the total commodity exports of the country |
| $FFUND$ | Real effective federal funds rate, constructed as nominal rate minus CPI inflation rate | FRED | 1972Q1-2019Q3 |
| $GDP$ | Real gross domestic product, natural log | IMF (IFS), OECD, World Bank (WDI) | Quarterly series are seasonally adjusted. Where adjusted series were not available, seasonal adjustment was performed manually using the X-13 ARIMA SEATS routine of the United States Census Bureau. The routine was accessed through the R-package *seasonal*. |
| $VXO$ | CBOE S&P 100 Volatility Index (implied volatility of stock options), natural log, average over period | FRED | 1986Q1-2019Q3. |
| $XR$ | Nominal US dollar exchange rate, natural log, average of period | IMF (IFS) | |

**Table A2: Country-specific sample range**

| | Quarterly | | | Annual | |
|---|---|---|---|---|---|
| **Country** | ***XR*** | ***GDP*** | **Restricted sample period** | ***XR*** | ***GDP*** |
| South Africa | 1972Q1-2019Q3 | 1972Q1-2016Q4 | 1972Q4-2019Q3 | 1972-2017 | 1972-2017 |
| Brazil | 1972Q1-2019Q3 | 1996Q1-2019Q3 | 1999Q4-2019Q3 | 1972-2017 | 1972-2017 |
| Chile | 1972Q1-2019Q3 | 1986Q1-2019Q3 | 1983Q1-2019Q3 | 1972-2017 | 1972-2017 |
| Mexico | 1972Q1-2019Q3 | 1980Q1-2019Q3 | 1997Q2-2019Q3 | 1972-2017 | 1972-2017 |
| South Korea | 1972Q1-2019Q3 | 1972Q1-2019Q1 | 2001Q1-2019Q3 | 1972-2017 | 1972-2017 |
| Philippines | 1972Q1-2019Q3 | 1981Q1-2018Q4 | 2001Q1-2019Q3 | 1972-2017 | 1972-2017 |
| Thailand | 1972Q1-2019Q3 | 1993Q1-2019Q3 | 2001Q1-2019Q3 | 1972-2017 | 1972-2017 |

# B Exchange rate regimes

**Figure A1: Exchange rate regimes, 1972Q1 – 2016Q4**




*Data source*: Coarse exchange rate regime classification in Ilzetzki et al. (2019).
*Notes* 1: fixed exchange rate (no separate legal tender; currency board; pre-announced or de facto peg; or pre-announced horizontal band $\leq \pm 2\%$); 2: semi-fixed (pre-announced or de facto crawling band $\leq \pm 2\%$); 3: semi-flexible (pre-announced crawling band $\geq \pm 2\%$; de facto crawling band $\leq \pm 5\%$; moving band $\leq \pm 2\%$; managed floating; 4: flexible; 5: freely falling (inflation $> 40\%$ p.a. and/or currency crash $> 25\%$ p.m. (and 10%-pts greater than that of the previous month)); 6: parallel market with unavailable exchange rate data. Monthly data were converted into quarterly medians.

# C Detrended exchange rate series

Hamilton (2018)'s filter is based on the regression:

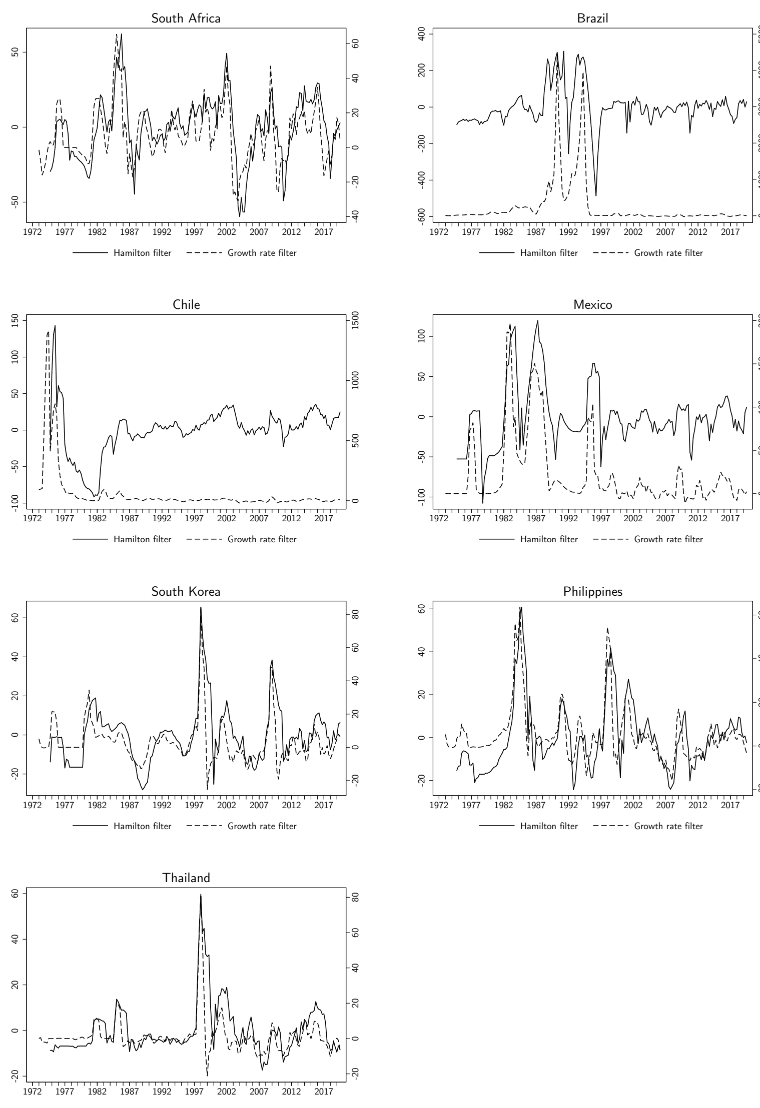
$$x_{t+h} = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \beta_3 x_{t-2} + \beta_4 x_{t-3} + \nu_{t+h} \tag{10}$$

from which one obtains the residuals as

$$\hat{\nu}_{t+h} = x_{t+h} - \hat{\beta}_0 - \hat{\beta}_1 x_t - \hat{\beta}_2 x_{t-1} - \hat{\beta}_3 x_{t-2} - \hat{\beta}_4 x_{t-3}. \tag{11}$$

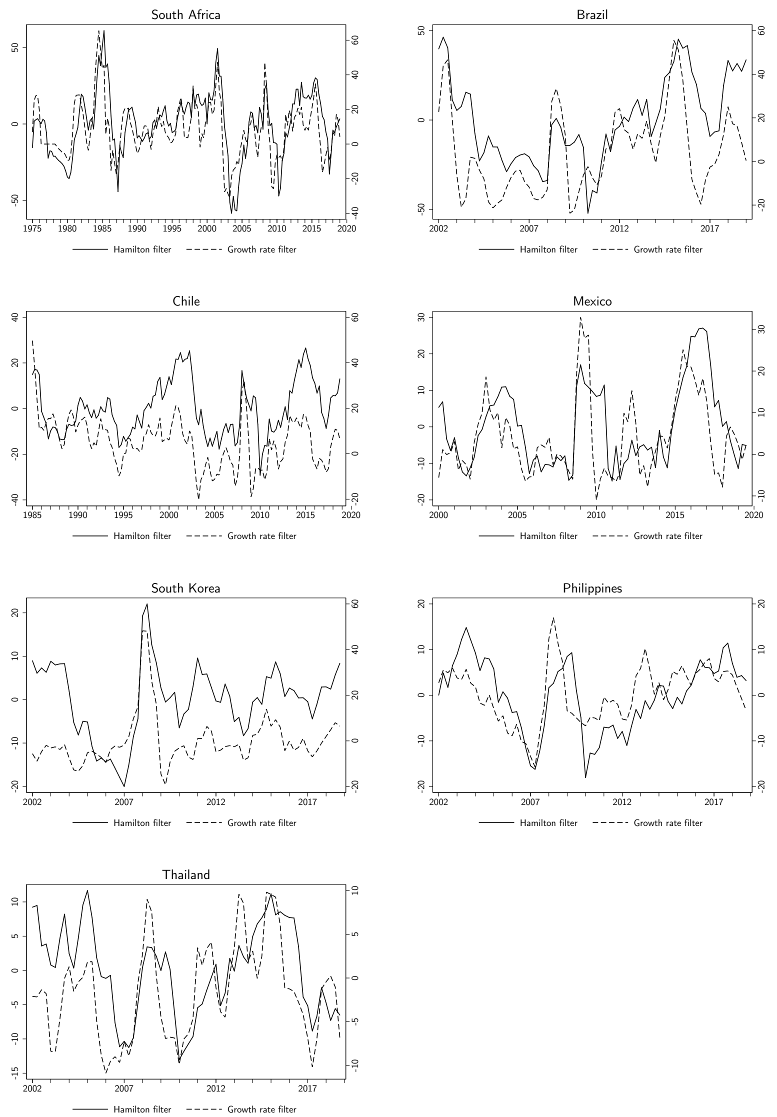
As suggested in Hamilton (2018) for quarterly data, $h = 8$ was used.

**Figure A2: Nominal US dollar exchange rates, cyclical components, full sample (1972Q1 – 2019Q3)**




*Notes* Hamilton-filter (left-axis) is the residual from the regression $x_{t+8} = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \beta_3 x_{t-2} + \beta_4 x_{t-3} + \nu_{t+8}$. Growth rate filter (right-axis) is obtained as $\frac{x_t - x_{t-4}}{x_{t-4}}$. Both series are measured in percent deviation from trend.

**Figure A3: Nominal US dollar exchange rates, cyclical components, restricted sample**




*Notes* Hamilton-filter (left-axis) is the residual from the regression $x_{t+8} = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \beta_3 x_{t-2} + \beta_4 x_{t-3} + \nu_{t+8}$. Growth rate filter (right-axis) is obtained as $\frac{x_t - x_{t-4}}{x_{t-4}}$. Both series are measured in percent deviation from trend.

# D Country-wise dynamic factor models of exchange rate and GDP

**Table A3: Dynamic factor model of exchange rate and GDP**

| | ZAF | BRA | CHL | MEX | KOR | PHL | THA |
|---|---|---|---|---|---|---|---|
| *GDP* | | | | | | | |
| *F* | -0.178*** | -1.284*** | 0.602*** | 0.495* | 0.421*** | 0.381*** | 0.327** |
| | (0.001) | (0.000) | (0.000) | (0.096) | (0.000) | (0.000) | (0.028) |
| *XR* | | | | | | | |
| *F* | 3.615*** | 10.944*** | -1.243*** | -0.416 | -1.413*** | -0.006 | -3.201*** |
| | (0.000) | (0.000) | (0.000) | (0.197) | (0.001) | (0.981) | (0.000) |
| Period | 1975Q3 | 2002Q3 | 1988Q4 | 2000Q1 | 2002Q4 | 2002Q4 | 2002Q4 |
| | 2016Q4 | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q1 | 2018Q4 | 2019Q3 |

*Notes: GDP*: logged real GDP (cyclical component); *XR*: logged nominal US-dollar exchange rate (cyclical component); p-values in parentheses. Factors were assumed to follow an AR(2) process, except for Brazil and Thailand where and AR(1) process was used to achieve convergence of the maximum likelihood estimator.

# E Estimated ARMA models

**Table A4: ARMA of nominal US dollar exchanges (XR) (cyclical components)**

| | ZAF | BRA | CHL | MEX | KOR | PHL |
|---|---|---|---|---|---|---|
| AR(1) | 0.845 | 0.951 | 1.129 | 0.766 | 1.168 | 1.097 |
| | (15.860) | (28.336) | (16.070) | (9.206) | (11.974) | (7.649) |
| AR(2) | | | -0.231 | | -0.278 | -0.224 |
| | | | (-3.182) | | (-2.414) | (-1.422) |
| AR(3) | 0.344 | | | 0.216 | | |
| | (4.165) | | | (2.286) | | |
| AR(4) | -0.204 | | | | | |
| | (-2.377) | | | | | |
| AR(6) | -0.104 | | | -0.208 | | |
| | (-1.508) | | | (-2.863) | | |
| AR(7) | | | 0.219 | | | |
| | | | (2.849) | | | |
| AR(8) | | | -0.238 | | | |
| | | | (-1.419) | | | |
| AR(9) | | | 0.254 | | | |
| | | | (1.353) | | | |
| AR(10) | | | -0.240 | | | |
| | | | (-2.095) | | | |
| MA(1) | 0.190 | | | | | |
| | (3.989) | | | | | |
| MA(8) | -0.757 | -0.607 | -0.864 | -0.467 | -0.802 | -0.913 |
| | (-11.611) | (-4.981) | (-7.298) | (-5.165) | (-3.977) | (-2.626) |
| Constant | 0.118 | 3.207 | -0.071 | -0.086 | -1.165 | -0.352 |
| | (0.053) | (0.402) | (-0.086) | (-0.055) | (-1.007) | (-0.463) |
| Period | 1975Q3 | 2002Q3 | 1985Q4 | 2000Q1 | 2002Q4 | 2002Q4 |
| | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q3 |
| p PMT | 0.897 | 0.125 | 0.691 | 0.451 | 0.392 | 0.993 |

*Notes*:$XR$: logged nominal US-dollar exchange rate (cyclical component); t-values in parentheses. p PMT: p-value of portmanteau test for white noise.

## Table A5: ARMA of real GDP (cyclical components)

| | ZAF | BRA | CHL | MEX | KOR | PHL | THA |
|---|---|---|---|---|---|---|---|
| AR(1) | 1.026 | 0.966 | 0.970 | 0.945 | 1.195 | 0.946 | 0.469 |
| | (22.514) | (15.014) | (18.387) | (14.130) | (9.299) | (12.626) | (5.113) |
| AR(2) | | | | | -0.773 | | 0.239 |
| | | | | | (-3.869) | | (2.029) |
| AR(3) | | | 0.220 | | 0.671 | 0.218 | |
| | | | (2.219) | | (3.823) | (1.764) | |
| AR(4) | -0.089 | | -0.354 | | -0.997 | -0.320 | |
| | (-1.760) | | (-4.603) | | (-6.421) | (-3.034) | |
| AR(5) | | | | | 0.738 | | |
| | | | | | (3.598) | | |
| AR(6) | | | | -0.155 | -0.623 | | |
| | | | | (-2.748) | (-2.666) | | |
| AR(7) | -0.141 | -0.231 | | | 0.712 | | |
| | (-2.168) | (-2.068) | | | (3.892) | | |
| AR(8) | | 0.182 | | | -0.979 | | |
| | | (1.682) | | | (-5.965) | | |
| AR(9) | 0.334 | | 0.181 | | 0.776 | | |
| | (3.658) | | (2.606) | | (3.836) | | |
| AR(10) | -0.208 | | | | -0.477 | | |
| | (-2.941) | | | | (-3.101) | | |
| AR(11) | | | -0.176 | | | | |
| | | | (-2.243) | | | | |
| MA(8) | -0.495 | -0.520 | -0.681 | -0.525 | | -0.454 | |
| | (-5.670) | (-4.182) | (-7.112) | (-6.119) | | (-2.760) | |
| Constant | -0.027 | -0.117 | 0.018 | -0.080 | -0.013 | -0.125 | -0.018 |
| | (-0.038) | (-0.091) | (0.058) | (-0.157) | (-0.111) | (-0.339) | (-0.014) |
| Period | 1975Q3 | 2002Q3 | 1988Q4 | 2000Q1 | 2002Q4 | 2002Q4 | 2002Q4 |
| | 2016Q4 | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q1 | 2018Q4 | 2019Q3 |
| p PMT | 0.804 | 0.784 | 0.660 | 0.377 | 0.750 | 0.526 | 0.799 |

*Notes*: *GDP*: logged real GDP (cyclical component); t-values in parentheses. p PMT: p-value of portmanteau test for white noise.

## Table A6: ARMA of common dynamic factor in XR and GDP

| | ZAF | BRA | CHL | MEX | KOR | PHL | THA |
|---|---|---|---|---|---|---|---|
| AR(1) | 1.186 | 1.025 | 1.317 | 1.329 | 1.234 | 1.191 | 0.885 |
| | (12.518) | (10.610) | (17.712) | (11.081) | (8.483) | (10.148) | (12.347) |
| AR(2) | -0.446 | | -0.345 | -0.488 | -1.044 | -0.464 | |
| | (-2.765) | | (-3.088) | (-3.966) | (-5.120) | (-2.413) | |
| AR(3) | 0.420 | -0.229 | | | 0.912 | 0.329 | |
| | (3.312) | (-1.458) | | | (4.308) | (1.915) | |
| AR(4) | -0.268 | | -0.400 | | -1.291 | -0.242 | |
| | (-3.832) | | (-3.698) | | (-7.453) | (-2.331) | |
| AR(5) | | 0.158 | 0.375 | | 1.107 | | |
| | | (1.501) | (3.349) | | (4.736) | | |
| AR(6) | | | | | -0.975 | | |
| | | | | | (-3.372) | | |
| AR(7) | | | | | 0.892 | | |
| | | | | | (3.615) | | |
| AR(8) | | | | | -0.926 | | -0.485 |
| | | | | | (-4.171) | | (-3.638) |
| AR(9) | | | | | 0.734 | | 0.420 |
| | | | | | (2.971) | | (3.344) |
| AR(10) | | | -0.080 | | -0.543 | | |
| | | | (-1.932) | | (-2.893) | | |
| MA(1) | 0.184 | | | | | | |
| | (3.100) | | | | | | |
| MA(8) | -0.765 | -0.635 | -0.852 | -0.549 | -0.638 | -0.392 | |
| | (-10.676) | (-4.871) | (-5.755) | (-7.337) | (-2.150) | (-2.752) | |
| Constant | 0.182 | -0.513 | 0.239 | -0.211 | -0.106 | 0.312 | 0.020 |
| | (0.301) | (-0.491) | (0.673) | (-0.206) | (-1.000) | (0.320) | (0.038) |
| Period | 1975Q3 | 2002Q3 | 1988Q4 | 2000Q1 | 2002Q4 | 2002Q4 | 2002Q4 |
| | 2016Q4 | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q1 | 2018Q4 | 2019Q3 |
| p PMT | 0.959 | 0.329 | 0.691 | 0.543 | 0.862 | 0.554 | 0.535 |

*Notes*: *GDP*: logged real GDP (cyclical component); *XR*: logged nominal US-dollar exchange rate (cyclical component); t-values in parentheses. p PMT: p-value of portmanteau test for white noise.

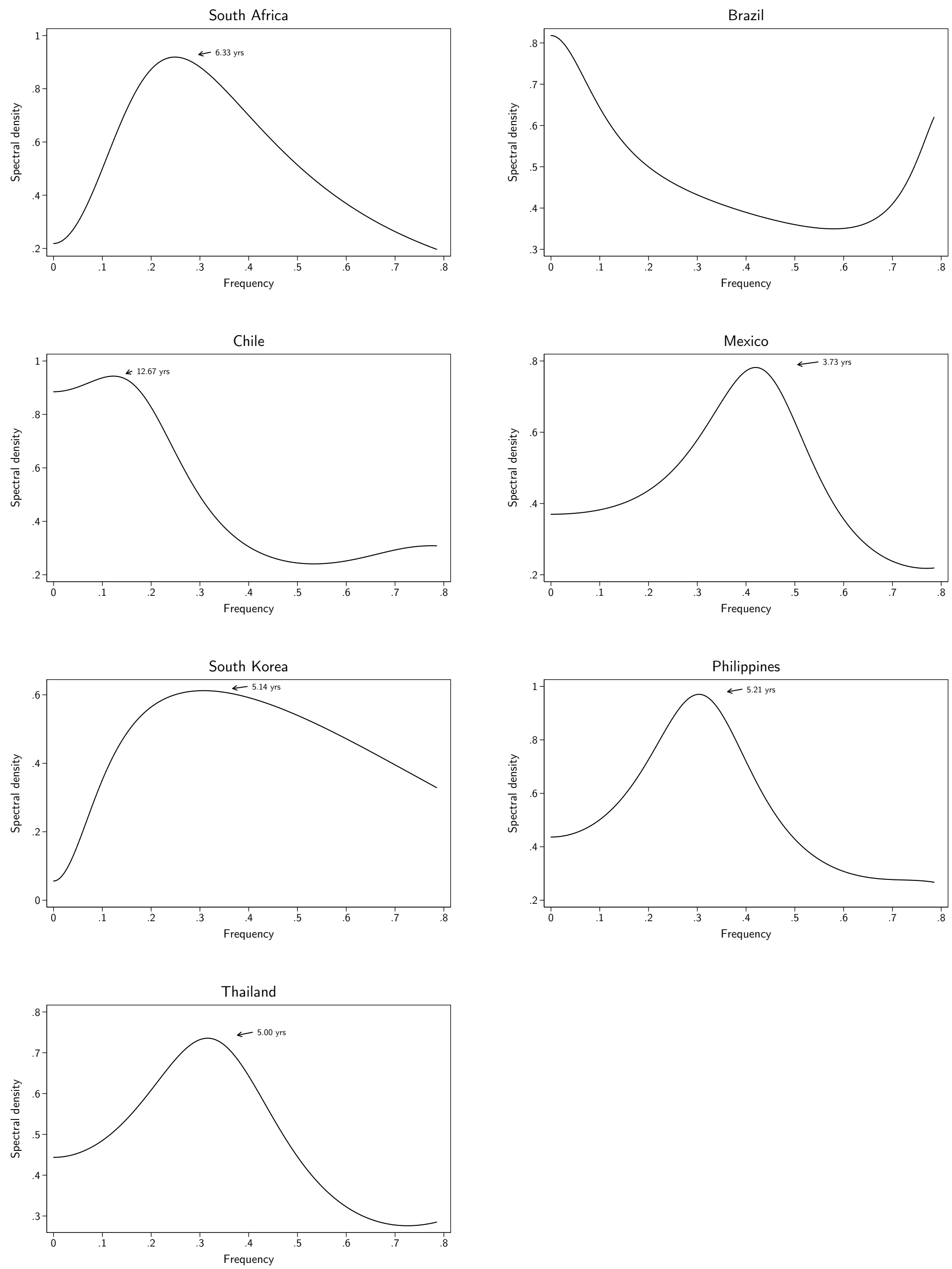
## Table A7: ARMA of external factors

| | $FFUND$ | $VXO$ | $CMP^W_{ZAF}$ | $CMP^W_{BRA}$ | $CMP^W_{CHL}$ | $CMP^W_{MEX}$ | $CMP^W_{KOR}$ | $CMP^W_{PHL}$ | $CMP^W_{THA}$ |
|---|---|---|---|---|---|---|---|---|---|
| AR(1) | 1.215 | 0.825 | 1.102 | 0.963 | 1.110 | 1.114 | 1.093 | 1.119 | 1.217 |
| | (15.376) | (16.901) | (16.973) | (41.338) | (10.709) | (14.057) | (15.280) | (12.363) | (11.197) |
| AR(2) | -0.512 | | -0.160 | | -0.255 | -0.338 | -0.236 | -0.323 | -0.489 |
| | (-4.232) | | (-2.552) | | (-2.204) | (-3.093) | (-2.751) | (-2.657) | (-3.558) |
| AR(3) | 0.283 | | | | | 0.181 | | 0.167 | 0.222 |
| | (2.581) | | | | | (2.838) | | (2.291) | (3.431) |
| AR(4) | -0.265 | | | | 0.107 | | 0.098 | | |
| | (-1.956) | | | | (2.139) | | (2.097) | | |
| AR(5) | 0.405 | | | | | | | | |
| | (3.644) | | | | | | | | |
| AR(6) | -0.326 | | | | | | | | |
| | (-4.998) | | | | | | | | |
| AR(9) | 0.080 | | | | | | | | |
| | (2.094) | | | | | | | | |
| MA(8) | | -0.272 | -0.536 | -0.659 | -0.709 | -0.627 | -0.618 | -0.632 | -0.556 |
| | | (-2.329) | (-11.365) | (-13.778) | (-12.049) | (-9.064) | (-10.575) | (-11.437) | (-12.058) |
| Constant | -7.835 | 0.328 | -0.753 | -0.510 | -1.039 | -0.303 | -0.684 | -2.037 | -1.115 |
| | (-0.126) | (0.037) | (-0.124) | (-0.096) | (-0.160) | (-0.031) | (-0.078) | (-0.329) | (-0.208) |
| Period | 1974Q4 | 1988Q4 | 1982Q4 | 1982Q4 | 1982Q4 | 1982Q4 | 1982Q4 | 1982Q4 | 1982Q4 |
| | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q3 |
| p PMT | 0.276 | 0.628 | 0.557 | 0.119 | 0.449 | 0.454 | 0.419 | 0.725 | 0.793 |

*Notes*: $FFUND$: real federal funds rate (cyclical component); $VXO$: logged volatility index (cyclical component) ; $CMP^W$: logged commodity terms of trade (cyclical component); t-values in parentheses. p PMT: p-value of portmanteau test for white noise.

# F Spectral densities of XR, growth rate filter

## Figure A4: Spectral densities of nominal US dollar exchange rates, growth rate filter




*Notes: XR*: logged nominal US-dollar exchange rate, growth rate filtered. Spectral densities were estimated parametrically from ARMA models. The sample start was set to the sample start of the Hamilton-filtered series. For Chile, the first four observations (1985Q4-1986Q3) were dropped due to extreme values during this period.

# G Dynamic factor model of EME exchange rates

**Table A8: Dynamic factor in EMEs nominal US dollar exchanges, restricted (1) and full sample (2)**

| | (1) | (2) |
|---|---|---|
| F | | |
| L.F | 1.306*** | 1.429*** |
| | (0.000) | (0.000) |
| L2.F | -0.421** | |
| | (0.013) | |
| $XR_{ZAF}$ | | |
| F | 4.352*** | -3.265*** |
| | (0.001) | (0.000) |
| $XR_{BRA}$ | | |
| F | 7.535*** | -0.749 |
| | (0.000) | (0.757) |
| $XR_{CHL}$ | | |
| F | 4.479*** | -1.627** |
| | (0.000) | (0.033) |
| $XR_{MEX}$ | | |
| F | 2.661*** | -0.713 |
| | (0.000) | (0.416) |
| $XR_{KOR}$ | | |
| F | 1.697*** | -3.015*** |
| | (0.000) | (0.000) |
| $XR_{PHL}$ | | |
| F | 1.210*** | -3.084*** |
| | (0.001) | (0.000) |
| $XR_{THA}$ | | |
| F | 1.509*** | -3.286*** |
| | (0.000) | (0.000) |
| Period | 2002Q4 | 1974Q4 |
| | 2019Q3 | 2019Q3 |

**Table A9: ARDL of common dynamic factor in EMEs nominal US dollar exchanges on global variables, full sample**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| L.F | 1.104*** | 1.085*** | 0.985*** | 0.965*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| L2.F | -0.262*** | -0.265*** | -0.292*** | -0.286*** |
| | (0.000) | (0.003) | (0.003) | (0.004) |
| FFUND | -0.000 | | | -0.001 |
| | (0.619) | | | (0.293) |
| VXO | | 0.006 | | 0.007 |
| | | (0.434) | | (0.378) |
| L.VXO | | -0.014* | | -0.015* |
| | | (0.052) | | (0.068) |
| CMP | | | 0.033*** | 0.028** |
| | | | (0.003) | (0.014) |
| Constant | -0.022 | -0.079 | -0.260 | -0.302 |
| | (0.837) | (0.594) | (0.166) | (0.122) |
| p Wald FFUND | 0.619 | | | 0.293 |
| p Wald VXO | | 0.070 | | 0.143 |
| p Wald CMP | | | 0.003 | 0.014 |
| Period | 1975Q4 | 1989Q4 | 1995Q4 | 1995Q4 |
| | 2019Q3 | 2019Q3 | 2019Q3 | 2019Q3 |
| Adj. R2 | 0.783 | 0.785 | 0.789 | 0.792 |

*Notes*: Dependent variable: dynamic factor extracted from a dynamic factor model of the logged nominal US-dollar exchange rate (cyclical component) for South Africa, Brazil, Chile, Mexico, South Korea, the Philippines, Thailand (see Table A8). The dynamic factor was specified as an AR(2) process. *FFUND*: real federal funds rate (cyclical component), *VXO*: logged implied volatility index (cyclical component), *CMP*: logged global commodity price index (cyclical component). p-values in parentheses.

# H VAR(X) estimations: robustness

**Table A10: Estimation results for VAR(p) with GDP and XR**

| | ZAF | BRA | CHL | MEX | KOR | PHL | THA |
|---|---|---|---|---|---|---|---|
| GDP | | | | | | | |
| L.GDP | 1.213*** | 1.142*** | 1.035*** | 0.903*** | 0.937*** | 1.235*** | 1.392*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| L.XR | -0.077*** | -0.005 | -0.064** | -0.039 | 0.036 | -0.162*** | -0.002 |
| | (0.000) | (0.383) | (0.025) | (0.144) | (0.582) | (0.001) | (0.981) |
| XR | | | | | | | |
| L.GDP | 1.212 | -1.001 | 0.967* | 1.973* | 1.059* | 0.217 | -0.199 |
| | (0.138) | (0.660) | (0.069) | (0.092) | (0.079) | (0.671) | (0.562) |
| L.XR | 1.244*** | 1.791*** | 1.942*** | 1.704*** | 1.203*** | 1.376*** | 1.103*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Lags | 2.000 | 2.000 | 3.000 | 2.000 | 2.000 | 2.000 | 4.000 |
| Period | 1972.000 | 1972.000 | 1972.000 | 1972.000 | 1972.000 | 1972.000 | 1972.000 |
| | 2017.000 | 2017.000 | 2017.000 | 2017.000 | 2017.000 | 2017.000 | 2017.000 |
| $a_2 b_1 < 0$ | YES | NO | YES | YES | NO | YES | NO |

*Notes*: Sample period: 1972-2017. p-values in parentheses. *XR*: logged nominal US-dollar exchange rate; *GDP*: logged real GDP. A constant term was included in each equation (not reported). Only the coefficients on the first lags are reported.

**Table A11: Estimation results for VARX(p) with GDP, XR, and CMP (contemporaneous)**

| | ZAF | BRA | CHL | MEX | KOR | PHL | THA |
|---|---|---|---|---|---|---|---|
| GDP | | | | | | | |
| L.GDP | 1.154*** | 0.952*** | 1.041*** | 1.003*** | 0.878*** | 1.168*** | 1.326*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| L.XR | -0.058** | 0.011 | -0.053* | -0.003 | 0.015 | -0.134*** | -0.048 |
| | (0.015) | (0.211) | (0.062) | (0.935) | (0.836) | (0.007) | (0.655) |
| $CMP^W$ | 0.018* | 0.072*** | 0.041* | 0.030** | -0.007 | 0.023* | -0.019 |
| | (0.097) | (0.000) | (0.065) | (0.036) | (0.525) | (0.068) | (0.287) |
| XR | | | | | | | |
| L.GDP | 2.012*** | 2.804 | 0.966* | 1.076 | 0.780 | 0.639 | -0.548 |
| | (0.008) | (0.198) | (0.070) | (0.320) | (0.235) | (0.173) | (0.140) |
| L.XR | 0.977*** | 1.736*** | 1.940*** | 1.381*** | 1.105*** | 1.199*** | 0.786*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $CMP^W$ | -0.247*** | -0.831*** | -0.009 | -0.272*** | -0.035 | -0.144*** | -0.090** |
| | (0.000) | (0.004) | (0.910) | (0.001) | (0.309) | (0.000) | (0.012) |
| Lags | 2.000 | 4.000 | 3.000 | 2.000 | 2.000 | 2.000 | 2.000 |
| Period | 1972.000 | 1972.000 | 1972.000 | 1972.000 | 1972.000 | 1972.000 | 1972.000 |
| | 2017.000 | 2017.000 | 2017.000 | 2017.000 | 2017.000 | 2017.000 | 2017.000 |
| $a_2b_1 < 0$ | YES | NO | YES | YES | NO | YES | NO |

*Notes*: Sample period: 1972-2017. *XR*: logged nominal US-dollar exchange rate; *GDP*: logged real GDP. p-values in parentheses. A constant term was included in each equation (not reported). Only the coefficients on the first lags are reported. The VAR for Chile exhibits serial correlation on the first lag.

**Table A12: Estimation results for VARX(p) with GDP, XR, CMP and FFUND**

| | ZAF | BRA | CHL | MEX | KOR | PHL | THA |
|---|---|---|---|---|---|---|---|
| GDP | | | | | | | |
| L.GDP | 1.200*** | 1.010*** | 0.888*** | 0.838*** | 0.831*** | 1.160*** | 1.270*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| L.XR | -0.072*** | 0.002 | -0.059** | -0.051 | -0.005 | -0.124*** | -0.059 |
| | (0.002) | (0.754) | (0.027) | (0.176) | (0.945) | (0.008) | (0.573) |
| $L.CMP^W$ | 0.003 | 0.040 | -0.003 | -0.001 | -0.015 | 0.003 | -0.039* |
| | (0.863) | (0.141) | (0.899) | (0.950) | (0.206) | (0.851) | (0.061) |
| L.FFUND | -0.000 | -0.000 | -0.010*** | -0.005** | 0.000 | -0.006*** | -0.003 |
| | (0.804) | (0.947) | (0.006) | (0.025) | (0.883) | (0.001) | (0.236) |
| XR | | | | | | | |
| L.GDP | 1.866** | 1.889 | 1.408*** | 2.022* | 0.821 | 0.812 | -0.426 |
| | (0.023) | (0.422) | (0.009) | (0.071) | (0.189) | (0.163) | (0.285) |
| L.XR | 1.066*** | 1.621*** | 1.919*** | 1.601*** | 1.105*** | 1.180*** | 0.879*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $L.CMP^W$ | -0.173* | -1.083*** | 0.067 | -0.111 | 0.033 | -0.083 | -0.046 |
| | (0.092) | (0.006) | (0.403) | (0.228) | (0.356) | (0.113) | (0.296) |
| L.FFUND | 0.006 | -0.026 | 0.037*** | 0.037*** | 0.014** | 0.016** | 0.003 |
| | (0.549) | (0.465) | (0.007) | (0.006) | (0.036) | (0.026) | (0.471) |
| Lags | 2.000 | 2.000 | 3.000 | 3.000 | 2.000 | 6.000 | 2.000 |
| Period | 1972.000 | 1972.000 | 1972.000 | 1972.000 | 1972.000 | 1972.000 | 1972.000 |
| | 2017.000 | 2017.000 | 2017.000 | 2017.000 | 2017.000 | 2017.000 | 2017.000 |
| $a_2 b_1 < 0$ | YES | NO | YES | YES | YES | YES | NO |

*Notes*: Sample period: 1972-2017. p-values in parentheses. $GDP$: logged real GDP; $XR$: logged nominal US-dollar exchange rate; $CMP^W$: logged commodity terms of trade. $FFUND$: real federal funds rate. A constant term was included in each equation (not reported). Only the coefficients on the first lags are reported.

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