Monetary Policy Independence and the Strength of the Global Financial Cycle*

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Abstract

We propose a new strength measure of the global financial cycle by estimating a regime-switching factor model on cross-border equity flows. We then assess how this measure affects monetary policy independence, defined as central banks' responses to exogenous changes in inflation. We show that central banks tighten their policy rates in response to an unanticipated increase in inflation during times when global financial cycle strength is low, but their responses are muted when financial cycle strength is high. Finally, we show that capital controls, macroprudential policies, and a flexible exchange rate regime can increase monetary policy independence.

Keywords: Global Financial Cycle Strength, Monetary Policy Independence, Capital Controls, Macroprudential Policies

JEL Codes: F32, E4, E5, G15, F42, G18

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1 Introduction

The 2007-2009 global financial crisis has sparked a fast-growing literature documenting the presence of a global financial cycle and its implications for macroeconomic and financial stability in small open economies and emerging markets.[1] While the main focus of this literature is on the *dynamics* of the global financial cycle, considerably less attention has been paid to countries' time-varying sensitivities to the global financial cycle, or to the aggregated impact of these sensitivities: the *strength* of the global financial cycle.[2] In this paper, we close this gap in the literature by documenting the strength of the global financial cycle, assessing the impact of the cycle's strength on monetary policy independence, and highlighting three policy options that can help monetary policy to become less dependent on the global financial cycle.

An economic example that highlights the importance of distinguishing between the dynamics and the strength of the global financial cycle is the recovery of global stock markets after the 2007-2009 global financial crisis. In early 2009, when the global financial cycle passed its trough and entered a new expansion phase, the associated stock market recovery was shared by many countries. With the onset of the European debt crisis in late 2009, however, the number of countries contributing to the stock market boom started to fall. Eventually, when both the global financial cycle and the European debt crisis peaked in 2011, only a few countries were left to support the boom. Hence, by characterizing a situation where the global financial cycle is in a boom phase, but the strength of the global financial cycle is low, this episode illustrates why paying attention to the strength dimension of the global financial cycle is important.

Several recent developments underscore this importance. To begin, the widespread implementation of banking sector reforms around the world has raised questions about potential changes in the pattern of international capital flows (e.g., Forbes (2020)).[3] If

[1]See Rey (2013) as a starting point of this literature. We also follow Rey (2013) in defining the global financial cycle as a comovement in capital flows and/or asset prices across countries.

[2]To fix ideas, picture a choir that sings a song containing alternating sets of high- and low-pitched notes (the global financial cycle and its dynamics). Each member of the choir sings—sometimes softer, sometimes louder—and listens to the song at the same time (each country's time-varying sensitivity to the global financial cycle). The louder the choir sings on aggregate, the higher the volume of the music (the strength of the global financial cycle). Moreover, the use of the term "strength" in this paper is consistent with the notion of "factor strength" in the recent asset-pricing literature (e.g., Pesaran and Smith (2019)).

[3]See also Morrison and White (2009), Bekaert et al. (2011), Ongena et al. (2013), Aiyar et al. (2014), Forbes et al. (2017), Buch and Goldberg (2017), and Ahnert et al. (2020).

financial regulations are tighter now than they were before the 2007-2009 global financial crisis, will the global financial cycle still affect the domestic economy in the same way? Moreover, recent studies on the global financial cycle provide new insights into the cycle itself and point to potential changes in its relationship with other economic variables.[4] In particular, one may wonder how many of these perceived changes can be attributed to differences in the dynamics of the global financial cycle and how many to differences in countries' sensitivities to the cycle. Finally, recent theoretical work on financial frictions has shown that "financial shocks"—i.e., shocks to the relationship between current financial conditions and the amount an agent can borrow—can have important implications for the economy (e.g., Devereux and Sutherland (2011)).[5] Hence, independent of the stage of the global financial cycle, there are shocks that amplify or mitigate the domestic economy's sensitivity to the cycle.

In light of these developments, we make three contributions to the literature. First, to the best of our knowledge, we are the first to document the strength of the global financial cycle consistent with the definition of the cycle in Rey (2013). By estimating a regime-switching factor model for cross-border equity flows on a sample of 61 countries at a weekly frequency, we extract countries' time-varying sensitivities to the global financial cycle. We then propose a new strength measure that aggregates these sensitivities across countries at each point in time. Our second contribution is to use the country-specific and time-varying sensitivities together with local projection methods to assess the impact of the global financial cycle on monetary policy independence in two samples of nine emerging market economies and seven small open advanced economies. We determine the degree of monetary policy independence based on the response of central banks' policy interest rates to exogenous changes in the domestic inflation gap at different degrees of global financial cycle strength. And third, we assess the impact of three different policy tools with respect to their ability to increase monetary policy independence, and discuss their practical relevance.

Our results are as follows. Our analysis of the strength of the global financial cycle delivers two stylized facts. First, we show that the strength of the global financial cycle varies

[4]For example, Kalemli-Özcan (2019) highlights the importance of international risk spillovers, Forbes and Warnock (2019) document a change in the size of capital flow waves, and Avdjiev et al. (2017), Friedrich and Guérin (2019), Forbes and Warnock (2019), and Miranda-Agrippino and Rey (2020a) discuss a change in the relationship between capital flows and the Chicago Board Options Exchange Volatility Index (VIX) and/or US monetary policy.

[5]Related to this, Perri and Quadrini (2018) present a model in which the liquidation value of firms' capital, which serves as a borrowing constraint, contains a stochastic component.

substantially over time, a finding that has not yet been documented in the literature and is consistent with the theoretical literature on financial frictions. Second, we show that not only does the strength of the global financial cycle vary over time but also that this variation exhibits a substantial heterogeneity across countries. Next, our assessment of countries' monetary policy independence at different levels of global financial cycle strength suggests that central banks in emerging market and small open advanced economies experience a lower degree of monetary policy independence when the strength of the global financial cycle is high. In particular, we show that these countries' central banks tighten the policy interest rate in response to an unanticipated increase in the inflation gap during times of low global financial cycle strength. During times of high financial cycle strength, however, the responses of the same central banks to the same unanticipated changes in the inflation gap are muted and do not appear to follow a pattern consistent with the Taylor rule. These effects are not only statistically but also economically significant. For the emerging market sample, for example, we find that the policy rate response of central banks to a 1-percentage point surprise increase in the inflation gap amounts to 18 basis points in times of low comovement but to only 1 basis point during times of high comovement. Finally, our assessment of different policy options to reduce countries' time-varying sensitivities to the financial cycle suggests that the use of (i) capital controls in the form of capital inflow restrictions, (ii) macroprudential policies in the form of the counter-cyclical capital buffer, and (iii) the reliance on a floating exchange rate regime can increase monetary policy independence. While capital controls were the most effective tool overall, they seem to be primarily a tool for emerging market economies and come with potential implementation challenges. Related to this, the positive impact of a flexible exchange rate appears to materialize predominantly for advanced economies. Lastly, while macroprudential policies are the only policy option that shows significant results across both country groups, they seem to be less effective than the other two options (albeit only closely behind flexible exchange rates).

Our paper contributes to two major strands of the literature. First, to a literature that made important contributions to the identification of the global financial cycle. Within this literature, two empirical approaches have emerged. A first approach[6] builds on the findings

[6]Recent examples include Nier et al. (2014); Bruno and Shin (2015); Avdjiev et al. (2017); Habib and

of Rey (2013) that link the global financial cycle to changes in US monetary policy and the VIX. By using selected variables that are both global and observable in nature (e.g., US monetary policy, the VIX, or global leverage) as proxy variables for the global financial cycle and interacting them with proxies for countries' sensitivities to the cycle (e.g., the degree of a country's FX exposure) in a panel data setting, researchers are able to test even complex hypotheses in relatively straightforward ways (e.g., tests for the presence of non-linearities). While this approach is well equipped to identify country-specific impacts of the global financial cycle, its success depends on the appropriate choice of proxy variables. In particular, the link between the global financial cycle proxy and the global financial cycle itself should remain strong and stable over time. However, recent empirical evidence suggests, for example, that the relationship between the VIX and various measures of capital flows has changed substantially since the 2007-2009 global financial crisis (e.g., Avdjiev et al. (2017), Friedrich and Guérin (2019), Forbes and Warnock (2019), and Miranda-Agrippino and Rey (2020a)). Hence, with the relative weight of pre-crisis data in the analysis falling over time, future studies relying on this proxy variable approach will have to take more actively the role of structural breaks into account.

A second approach[7] derives the global financial cycle by estimating a dynamic factor model and extracting a latent common factor from a set of time-series variables (such as capital flow data from a large number of countries). While the reliance on a broader set of financial variables makes this approach more robust to potential changes in some of their underlying relationships, the associated factor loadings, the links between the common factor and the individual time-series variables, are usually assumed to be constant in the estimation process. This in turn implies that countries' sensitivities to the global financial cycle and the strength of the global financial cycle are both considered to be time-invariant according to this approach. As shown earlier, however, several recent developments suggest that countries' sensitivities to the global financial cycle and the cycle's strength should, in fact, vary over time.

By estimating a regime-switching factor model with time-varying factor loadings, we can extract and examine the time variation in countries' sensitivities to the global financial cycle

Venditti (2018); Alstadheim and Blandhol (2018); and Cerutti et al. (2019b).

[7]See, for example, Rey (2013); Miranda-Agrippino and Rey (2020b); Barrot and Serven (2018); Cerutti et al. (2019a); Cerutti et al. (2019b); Habib and Venditti (2019). Although not explicitly referring to the common factor as the global financial cycle, Fratzscher (2012) also uses a comparable empirical methodology.

and thus distill the advantages of both empirical approaches. To the best of our knowledge, the only other paper in the literature that uses a dynamic factor model with time-varying loadings to identify a global financial cycle is Potjagailo and Wolters (2019). The authors examine cyclical comovements in credit, house prices, equity prices, and long-term interest rates across 17 advanced economies using 130 years of annual data since 1880.[8] Their analysis differs from our work in at least two important dimensions. First, their focus is on the evolution of financial variables over a long horizon, similar to the work by Schularick and Taylor (2012). Moreover, possibly as a result of this long time horizon, the frequency of their global financial cycle is much lower and thus more in line with the recent literature that identifies "financial cycles" at the business cycle frequency (Beaudry et al. (2019)) or at even lower frequencies (Drehmann et al. (2012); Borio (2014)).[9] Our work, however, follows Rey (2013), who characterizes the global financial cycle based on correlations in international capital flows at quarterly frequency, and in asset prices at monthly frequency (and possibly, through highlighting the cycle's correlation with the VIX, at even higher frequencies). Hence, the properties and dynamics of global financial cycles extracted at low and high frequencies might differ considerably.

Second, our paper contributes to a literature that describes the relationship between the global financial cycle and monetary policy independence. At the core of this literature is again the work by Rey (2013), who suggests that the classical Mundellian trilemma or "Impossible Trinity"—the fact that an economy cannot simultaneously maintain a fixed exchange rate, free capital movement, and an independent monetary policy—has turned into a dilemma, which leaves policymakers the choice between an open capital account and monetary policy autonomy. Subsequently, a fast-growing literature has evolved that assesses whether the trilemma is still alive. This literature examines, in particular, whether exchange rate flexibility and capital controls can help to reduce countries' sensitivities to the global financial cycle and, thus, increase their monetary policy independence.[10]

[8]They find that for some variables, the importance of global dynamics has increased since the 1980s. Especially for equity prices, global cycles explain more than half of the fluctuations in the data. Global cycles in credit and housing have also become more important, but their relevance has increased only for a subset of countries.

[9]See also Aldasoro et al. (2020) for a recent discussion of different types of financial cycles.

[10]Several studies examine the direct effect of US monetary policy spillovers on foreign variables without a specific focus on monetary policy independence (see, for example, Dedola et al. (2017) for the impact on real variables and Avdjiev et al. (2018) on the impact on banking flows). Moreover, Georgiadis and Mehl (2016) examine the impact of financial globalization on the effectiveness of monetary policy. Related to

Aizenman et al. (2016), for example, provide evidence that countries with more stable exchange rates tend to be more sensitive to changes in foreign monetary policy, leading the authors to conclude that the trilemma is still alive. In doing so, they first determine the sensitivity of domestic financial variables to changes in economic and financial conditions in four major advanced economies. In a second step, they explain these sensitivities with macroeconomic conditions and structural factors. Han and Wei (2018) follow a similar approach, but also estimate a Taylor rule. Their results suggest that a flexible exchange rate allows countries to have some policy independence when the center country tightens its monetary policy. However, when the center country lowers its policy rate, monetary policy independence can be compromised, even if the Taylor rule suggests otherwise. Georgiadis and Zhu (2019) assess the empirical validity of the trilemma by estimating Taylor-rule type monetary policy reaction functions that relate the domestic policy rate to domestic fundamentals and policy rates of their respective base country and find that the trilemma still exists. They note, however, that countries' sensitivities to policy rates of the base country are stronger for economies with negative foreign-currency exposures, even for those economies with flexible exchange rates. Using empirical tests based on an interest parity equation, Klein and Shambaugh (2015) examine whether partial capital controls and limited exchange rate flexibility allow for full monetary policy independence. The authors find that partial capital controls do not help, but a moderate amount of exchange rate flexibility provides some degree of monetary independence, especially for emerging and developing economies. Moreover, Obstfeld (2015) also finds evidence supporting the existence of the trilemma, but he cautions that changes to the exchange rate alone cannot insulate economies from foreign financial and monetary shocks.[11]

By examining the response of a country's domestic policy rate to exogenous inflation gap shocks in Section 3 of our paper, we follow a similar Taylor rule approach as that in Han and Wei (2018) and Georgiadis and Zhu (2019). In particular, our Taylor rule approach accounts for the concern that an observed change in the policy rate, in response to a change in the center country's policy rate, could be a sign of low domestic monetary policy independence or simply the intentional response of both central banks to the same

this, Kalemli-Özcan (2019) finds a positive role for flexible exchange rates in reducing the negative impact of international risk spillovers on domestic monetary policy transmission.

[11]Related to this, Farhi and Werning (2016) show theoretically that under nominal rigidities and financial markets imperfections, there is a role for capital controls even when the exchange rate is flexible.

underlying shock.

Our paper is organized into five sections, as follows. Section 2 presents our new strength measure of the global financial cycle. Section 3 then uses local projection methods to assess the response of emerging market and advanced economies' policy interest rates to unanticipated changes in the inflation gap in times of low and high global financial cycle strength. Section 4 investigates different tools that monetary policymakers could use to increase the degree of monetary policy independence. Finally, Section 5 concludes.

2 Measuring the Strength of the Global Financial Cycle

In this section, we introduce a regime-switching dynamic factor model that simultaneously allows us to estimate a common factor of equity fund inflows into a large set of advanced and emerging market economies—our measure of the global financial cycle—and to capture the strength of this common factor over time. We first describe the data on equity fund flows, followed by a description of the proposed empirical framework, and finally, we discuss our results, with a particular focus on the strength of the global financial cycle.

2.1 Data

As in Friedrich and Guérin (2019), we use data on international equity fund flows from the Emerging Portfolio Fund Research (EPFR) database at weekly frequency (see EPFR (2019)). Fratzscher (2012), for example, refers to this data source as *"[...] the most comprehensive one of international capital flows, in particular at higher frequencies and in terms of its geographic coverage at the fund level."* Moreover, Pant and Miao (2012) present evidence of a strong comovement between data from the EPFR and data from the Balance of Payments (BoP) for emerging markets. A notable difference between both data sources is that the BoP records all types of cross-border equity flows for all types of financial market participants. The EPFR data, however, are limited to international equity flows that are intermediated by equity funds and, to a large extent, originate from non-resident investors. However, since equity funds are important participants in the financial system and financial transactions by non-residents are generally larger in emerging market economies than those by their residents, the timelier EPFR data have become a valuable source in the analysis of capital flows.

We obtain data on equity funds inflows into 61 advanced and emerging market economies at weekly frequency.[12] The country coverage of our sample is broad and spans all major economies in the Americas, Europe, Asia, Africa, and Oceania (for a full list of countries and the regional coverage, see Table 1). The data on equity inflows are expressed as a percentage change in outstanding investments (i.e., the total estimated allocation of money in absolute dollar terms) at the start of the period (i.e., the previous week). In order to reduce the impact of strong outliers, we winsorize the equity flow data at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentile. Our final sample for this exercise ranges from the week of 27 July 2001 to the week of 5 January 2019.

Next, we discuss our choice of conducting the empirical analysis based on equity fund flows, despite the usual focus of the global financial cycle literature on portfolio debt and credit flows. As we highlight below, there are several advantages of using equity flow data at high frequencies to identify the global financial cycle and, in particular, to extract the associated measure of global financial cycle strength.

First, these data are the only ones that are available at high frequency over an extended period of time. Thus, from an econometric perspective, this feature is crucial for increasing the precision of our estimates. In particular, given that one of our objectives is to infer changes in the strength of the common factor, some parameters of the employed model are assumed to evolve over time. Consequently, a large number of observations along the time dimension is required to robustly estimate the time variation in the loadings of the common factor.

Second, equities are a typical example of a risky asset and thus correspond to the original definition of the global financial cycle in Rey (2013), which considers the cycle to be a global comovement in risky assets. Moreover, equities are priced at a high frequency, they can be traded at relatively small costs, and their data are recorded with a high degree of precision.

And third, equity flows are still a good proxy for bond and credit flows. Based on the correlation table shown in Rey (2013), the median correlation across seven world regions—North America, Latin America, Eastern Europe, Western Europe, Emerging Asia, Other Asia, and Africa—amounts to 0.20 between equity and bond flows (with maximum corre-

[12] While the EPFR database contains information for a larger number of countries, our empirical framework requires continuous time-series coverage over the entire sample period.

lations of 0.50 for Eastern Europe and Western Europe, respectively) and to 0.27 between equity and credit flows (with a maximum correlation of 0.34 for Latin America).[13] Moreover, the data shown in Rey (2013) indicate that among the four main asset classes, Equity, FDI, Debt and Credit, equity flows exhibit the highest correlation with the VIX. The corresponding median of the unconditional correlation between equity flows and the VIX across all world regions amounts to -0.29 and the median of the conditional correlation—i.e., after controlling for the world short-term interest rate and the world growth rate—amounts to -0.31. Hence, equity flows can be closely linked to conventional measures of the global financial cycle.

2.2 Empirical Methodology

In this section, we propose a dynamic factor model that simultaneously allows us to (i) estimate the latent common factor driving equity fund inflows across countries, and (ii) measure the strength of this common factor over time. We define the strength of the common factor as the degree of comovement between countries' equity inflows and the common factor.

In particular, we assume that equity fund flows into country i at time t, denoted by $y_{i,t}$, can be decomposed into a common and an idiosyncratic component.

$$y_{i,t} \quad = \quad \gamma_{i,S_{i,t}} f_t + \sigma_{i,S_{i,t}} e_{i,t}, \tag{1}$$

for $i = 1, ..., n$, where f_t denotes the latent common factor, which gauges the overall comovement associated with equity fund flows into countries. As a result, f_t is a measure of the evolution of the global financial cycle. The common factor is assumed to evolve according to an autoregressive process of order L, and $u_t \sim N(0,1)$.[14]

$$f_t \quad = \quad \phi(L) f_{t-1} + u_t. \tag{2}$$

Also, the idiosyncratic terms, $e_{i,t}$, are assumed to be normally distributed, $e_{i,t} \sim N(0,1)$.[15]

[13] The correlations in Rey (2013) are based on quarterly data over the period 1990Q1 to 2012Q4.

[14] For our benchmark specification, we assume $L = 1$, due to the low persistence typically found in high-frequency data. However, results remain qualitatively similar when employing a specification with a larger number of lags.

[15] We also employed alternative specifications for the idiosyncratic terms, such as autoregressive processes. The results are similar to the benchmark specification, which we prefer to use because it is more parsimonious

The key parameters that capture the strength of the relationship between equity fund flows into individual countries and the common factor are the factor loadings, denoted by $\gamma_{i,S_{i,t}}$. Since we are interested in inferring changes in the strength of these relationships over time, we allow the factor loadings to evolve over time as well. To model the time variation in factor loadings, the econometric literature has previously relied on random walk specifications (see, e.g., Del Negro and Otrok (2008)). With a random walk specification, the time variation obtained implies gradual changes in factor loadings. However, relying on gradual changes in factor loadings is less appealing in our empirical application because financial data are often volatile at high frequencies and can exhibit sudden breaks in the dynamics (e.g., substantial shifts in the level).

To account for these features, we follow Guérin et al. (2019) and allow factor loadings to evolve according to idiosyncratic Markovian dynamics. Accordingly, the factor loading associated with country i is defined as

$$\gamma_{i,S_{i,t}} \quad = \quad \gamma_{i,0} + \gamma_{i,1} S_{i,t}, \tag{3}$$

where $S_{i,t} = \{0, 1\}$ denotes a latent state variable. We use two regimes to model the time variation in factor loadings. Hence, provided that $\gamma_{i,1} > 0$, a sequence of periods when $S_{i,t} = 0$ can be interpreted as a "low-comovement" regime, with a factor loading of $\gamma_{i,0}$, while consecutive periods when $S_{i,t} = 1$ can be interpreted as a "high-comovement" regime, with a relationship between country-specific portfolio investment flows into equity and the global factor given by $\gamma_{i,0} + \gamma_{i,1}$. Each latent state is assumed to be driven by a first-order Markov chain with constant transition probabilities,

$$Pr(S_{i,t} = m | S_{i,t-1} = l) \quad = \quad p_{lm}. \tag{4}$$

This feature allows us to model the persistence associated with the regimes of high and low comovement. In addition, the two latent states are assumed to be independent from each other.

Notice that in a low- (high-) comovement regime, the correlation between country i and the global factor is weak (strong), and therefore, the variability captured by the idiosyncratic component is higher (lower). To take this feature into account, we also allow the variance

given the large number of countries involved in the model.

of the idiosyncratic innovations to vary across the two regimes, and define it as

$$\sigma^2_{i,S_{i,t}} \quad = \quad \sigma^2_{i,0}(1 - S_{i,t}) + \sigma^2_{i,1} S_{i,t}. \tag{5}$$

Moreover, we do not impose any restriction on $\sigma_{i,0}$ or $\sigma_{i,1}$.

The model described in Equations (1)-(5) is estimated with Bayesian methods by relying on Gibbs sampling procedures, which are described in Guérin and Leiva-León (2019). We run the Bayesian algorithm 8,000 times (after an initial burn-in period of 2,000 iterations). Appendix A.1 provides further details on the estimation algorithm. Notice that since the regimes, $S_{i,t}$, are not observed, what the model retrieves are probability assessments about the occurrence of the regimes; that is, $Pr(S_{i,t} = m)$, for $m = 0, 1$.

2.3 Results

In this section, we introduce our new measure of global financial cycle strength. After briefly presenting the global financial cycle itself, we discuss the development of the aggregated strength measure over time. Next, we examine the heterogeneity of this measure across countries by assessing countries' average sensitivities to the global financial cycle—the other side of the same coin. Finally, we combine both pieces of information and present evidence for selected case studies on countries' sensitivities to the global financial cycle at different points in time.

2.3.1 The Dynamics of the Global Financial Cycle

In line with the focus of the previous literature, we first discuss the dynamics of the global financial cycle itself. The global financial cycle corresponds to the common factor of equity fund flows across our sample countries, described in the previous section, and is shown in Panel (a) of Figure 1. This figure depicts the common factor at weekly frequency with a solid blue line and a smoothed version of the same factor with a dashed black line.[16] The light blue bands around the factor represent credible sets that correspond to the 5^{th} and the 95^{th} percentiles of 8,000 replications of the Bayesian estimation algorithm, respectively.

Because it is extracted from weekly data, our factor represents changing financial conditions at a high frequency. Moreover, our focus on equity fund flow data reflects the absence

[16] The smoothed version of the common factor has been computed based on a Hodrick-Prescott filter with a lambda value of 100,000.

of potential diversification benefits that are present in a factor extracted from data covering different asset classes. As such, our factor is characterized by a higher volatility than a factor extracted from data at lower frequencies (e.g., quarterly or annual) or from a broader set of asset classes (e.g., equity, debt, and credit flows).

The smoothed version of our factor shares considerable similarities with the common factor presented in Rey (2013)—presumably the most commonly used measure of the global financial cycle in the literature.[17] Both factors experience a gradual build-up in the first half of the 2000s, a steep drop following the 2007-2009 global financial crisis, and a substantial post-crisis recovery.[18] Appendix Figure A1 plots our measure of the global financial cycle and the one presented in Rey (2013) in the same figure. It appears that four of the five most prominently visible turning points in the factor of Rey (2013) match well the turning points of our smoothed factor, as indicated by relatively narrow shaded areas (yellow for troughs, green for peaks) representing the timing differences between these turning points. The main difference between both series emerges over the 2006-2008 period, where our factor shows a flatter trajectory than the factor of Rey (2013). The reason behind this flatter trajectory is that emerging market equities already experienced a notable correction in mid-2006, which did not spill over to most other country groups and asset classes, however.[19] Hence, since we extract our factor from equity fund flow data, this event features more prominently in our measure of the global financial cycle than in the one of Rey (2013), for example, which is based on over 400 different asset prices.

Moreover, we show in Appendix Figure A2 that when we apply a conventional dynamic factor model with constant factor loadings to our own data, the resulting global financial cycle measure exhibits very similar dynamics to the one obtained using our regime-switching dynamic factor model with time-varying loadings. This is the case when using equity fund flow data at weekly frequency in Panel (a) and becomes even more visible when aggregating

[17] E.g. Figure 3 on PDF-Page 9 in Rey (2013).

[18] When moving beyond the overlapping sample, there appears to be evidence that the amplitudes of the global financial cycle have become smaller for both the smoothed and the unsmoothed version of our factor since around 2011. While this observation could be taken as a loss of the global factor's relevance, we show below that this can only be part of the story.

[19] The IMF Financial Market Update from June 2006 states that *"[...] cyclical challenges and the accompanying monetary policy response have had a powerful impact on investor positioning in risky asset markets, such as carry trade currencies and equities, especially in emerging markets."* Moreover, Figure 25 of this report indicates that the drop in equity prices amounted to close to 18 percent, while the correction in debt markets (external and local currency debt) amounted to less than 3 percent. Source: https://www.imf.org/External/Pubs/FT/fmu/eng/2006/0606.PDF.

the weekly factors to monthly frequency in Panel (b).

Taken together, evidence presented in this section suggests that our measure of the global financial cycle (i.e., the common factor) shares a considerable overlap with global financial cycle measures in the previous literature, and thus, our analysis has the same starting point. The remaining differences in the appearance of our (unsmoothed) factor and other estimates from the literature exist primarily because of differences in the data frequency, occur to some extent due to our focus on equity flows, and are largely unrelated to our choice of the empirical model.

2.3.2 The Strength of the Global Financial Cycle Over Time

In this section, we introduce our new measure, which captures the strength of the global financial cycle. To facilitate the transition from the previous section to our strength measure of the global financial cycle, note that Table 2 reports the correlation between country-specific equity fund flows and the common factor during the regimes of (i) high comovement ($Pr(S_{i,t} = 1) > 0.5$), and (ii) low comovement ($Pr(S_{i,t} = 1) \leq 0.5$). These correlations are closely related to the estimated factor loadings, which play a crucial role in identifying the common factor of capital flows.[20] Turning to the results, most notably, there are substantial differences between the correlations across regimes of high and low comovement. While correlations in the high-comovement regime range from around 0.60 to 0.95, correlations in the low-comovement regime are substantially lower and reach values of -0.25. Within both comovement regimes, it appears that emerging market economies experience generally higher correlations while advanced economies experience lower correlations or, in the case of the low-comovement regime, even negative ones. This heterogeneous pattern regarding countries' exposures to the global financial cycle is consistent with previous studies.

Next, Panel (b) of Figure 1 presents the new measure of global financial cycle strength over our sample period. The measure of global financial cycle strength is defined as the share of countries facing a high-comovement regime at each point in time, and thus ranges between 0 and 1. The measure describes, depending on the view point, the (aggregate) strength of the global financial cycle or countries' sensitivities to the global financial cycle.

[20] The factor loadings are essentially regression coefficients that can be interpreted as partial correlations. Moreover, they are endogenously estimated without prior knowledge of the timing of the comovement regimes. Instead, the correlations shown in Table 2 are obtained by dividing the sample into subsamples of high- and low-comovement regimes based on the exogenously defined threshold of ($Pr(S_{i,t} = 1) > 0.5$, for $i = 1, ..., n$).

Since the model is estimated in a Bayesian fashion, we are able to simulate the entire distribution of the strength measure, and therefore construct the associated credible sets, which are represented by the light blue bands around the median of the distribution. The close fit of these credible sets around the solid blue line indicates that the strength measure is tightly estimated.

Most importantly, the strength measure shows that the strength of the global financial cycle varies substantially over time, confirming the earlier hypothesis that countries' sensitivities to the global financial cycle should vary over time. The importance of this time variation can be seen when relating the strength measure's standard deviation of 0.17 to its mean of 0.57, which results in a coefficient of variation of around 0.3. In our sample, the strength measure peaks at 0.91—i.e., when over 90 percent of our sample countries were in a high-comovement regime—in August 2006, a period that marks the last stages of the run-up to the 2007-2009 global financial crisis. Moreover, taking on values between 0.80 and 0.90, the strength measure remains highly elevated during the financial crisis itself. The trough of the measure is located at 0.13 in May 2011, when the economic recovery was ongoing elsewhere in the world but Europe was experiencing the sovereign debt crisis.

It also appears that the persistence of the strength measure has increased over time. While its persistence is particularly low between 2002 and 2009, with frequent changes in the share of sample countries in a high-comovement regime, the measure shows a smoother trajectory with more gradual changes after 2009. Further, while it appears that the large amplitudes of the strength measure during the crisis have fallen somewhat in recent years, the amplitudes of the strength measure still seem sizable and, thus, do not appear to suggest that the global financial cycle is losing relevance, as possibly opposed to the dynamics of the factor itself.

Finally, we conduct a robustness check on the composition of our country sample. As around 40 percent of our sample countries are associated with the geographical region of Europe (see Table 1), and thus, are likely to share close political, economic, or financial ties, one could be concerned that these observations may not be independent from each other. While our analysis is based on a relatively large and heterogeneous sample of 61 advanced and emerging market economies, which mitigates this concern considerably, we present additional evidence illustrating that our key results are not driven by the composition of our sample. In particular, we re-estimate the regime-switching factor model and include, in addition to the 35 non-European countries, only the largest five countries from the European region, namely France, Germany, Italy, Spain, and the United Kingdom. Figure A3 in Appendix A.3 presents the resulting global financial cycle and its corresponding strength measure. Despite covering only two-thirds of the countries in our original sample, we still observe a very close alignment of the two global financial cycle measures (comparison of Panels (a) across Figure A3 and Figure 1). We also observe a close alignment of the two strength measures, which is supported by the almost identical locations and the often comparable magnitudes of their respective turning points (comparison of Panels (b) across Figure A3 and Figure 1). Hence, this evidence suggests that our results are not driven by the inclusion of a potentially large number of European economies or the specific composition of our sample.

Overall, this subsection has shown that the strength of the common factor, and thus the strength of the global financial cycle, varies substantially over time. Going forward, we refer to this finding as our first stylized fact.

2.3.3 The Sensitivity to the Global Financial Cycle Across Countries

After having established the stylized fact that the strength of the global financial cycle varies substantially over time, we focus on the other side of the same coin: the time-varying sensitivity of countries to the global financial cycle.

We start this assessment based on Figure 2, where we decompose the strength measure into a partial strength measure for advanced economies in Panel (a) and for emerging market economies in Panel (b). The corresponding means and standard deviations of the partial strength measure amount to 0.53 and 0.33 for advanced economies and to 0.60 and 0.18 for emerging market economies, respectively. Hence, these numbers suggest that the strength of the global financial cycle shows a stronger time variation for advanced economies than for emerging markets, but emerging market economies generally experience a higher average level of strength.

Next, we zoom in to the country level. Figure 3 presents the dynamics of the underlying regime probabilities for all our 61 sample countries over time. It appears that our first stylized fact, the strong time variation in the average strength over time, carries over to the time-varying sensitivities at the country level. Moreover, as is evident from the patterns of these regime probabilities, the degree of time variation is highly heterogenous across countries. While regimes in some countries, such as Colombia, Hong Kong and Lithuania, seem to have a low persistence, regimes in other countries, such as Egypt, Indonesia and South Africa, appear to switch less often.

Hence, not only does the strength of the global financial cycle vary over time, but the variation in the strength also points to a substantial heterogeneity across countries, as reflected by countries' time-varying sensitivities to the global financial cycle. This finding constitutes our second stylized fact.

2.3.4 Selected Case Studies

We then combine the two stylized facts established in the previous subsections and present selected case studies that illustrate the importance of the strength concept when discussing the impact of the global financial cycle. We visualize countries' sensitivity to the global financial cycle based on world maps, whose coloring scheme reflects the sensitivity that ranges from 0 (yellow) to 1 (red).

Figure 4 presents the average of the sensitivity for each country over the period from 2001 to 2019. As discussed in the context of Table 2 in Section 2.3.2, the pattern shown on this map would be related to that obtained with traditional factor approaches that assume time-invariant loadings. While we observe relatively high exposures for emerging market economies, such as South Africa, Egypt, Pakistan and Indonesia, we observe generally lower exposures for advanced economies, such as Canada, various countries in Western Europe, and Australia. Interestingly, the United States, the country frequently considered to be at the center of the global financial cycle, appears to exhibit average correlations at the lower end of the distribution. This observation might be explained by the fact that this exercise captures only contemporaneous correlations, whereas the financial cycle of the United States is likely to predate the global financial cycle.

To illustrate the importance of the strength dimension of the global financial cycle, we examine the correlation pattern on this map for three distinct weeks in our sample, shown in Figure 5. Each time, the resulting color pattern should be compared against the sample average in Figure 4.

Panel (a) of Figure 5 displays the period with the strongest comovement in our sample, which is observed during the week following Wednesday, 8 January 2006.[21] During this

[21] Note that the weeks in the EPFR data set start on Wednesdays.

week, the world map shows a deep red color scheme, indicating that almost all our sample countries are in a high-comovement regime. A potential explanation behind this pattern is that strong growth expectations[22] and a rising interest rate[23] facilitated the inflow of foreign capital into the United States. Inflows originated, in particular, from Asia,[24] from European surplus countries, such as Germany, and from oil exporters in the Middle East due to the high oil prices at that time. Correspondingly, the United States recorded a record high current account deficit of -5.8 percent of GDP in 2006.[25]

Panel (b) of Figure 5 shows that countries experienced the lowest comovement in the week following Wednesday, 5 January 2011. The world map shows a yellow color scheme, representing the presence of a low-comovement regime, in almost all our sample countries. A potential explanation of this observation is that economic developments in the world were unevenly distributed across countries at this point in time, and thus the comovement of capital flows, and in particular of equity fund flows, was relatively low. This is mirrored in the economic commentaries at that time.[26]

While Panels (a) and (b) of Figure 5 demonstrate the strong time variation in the strength of the global financial cycle, they might suggest that all countries experience the same strength patterns. To substantiate our second stylized fact from Section 2.3.3, which stated that the strength of the global financial cycle varies not only over time but also that this variation is highly heterogeneous across countries, we present in Panel (c) of Figure 5 data for the week with the highest cross-country heterogeneity in our sample. We define the degree of heterogeneity based on the cross-sectional standard deviation of the comovement in equity fund flows at each point in time. The period with the strongest cross-country heterogeneity was the week following Wednesday, 17 December 2008. While most advanced economies show a yellow color scheme in this figure, representing very low levels of comovement, most of the emerging market economies of our sample show a red color scheme, suggesting a high degree of comovement instead. A WEO Update from January 2009 states

[22] For example, the World Economic Outlook (WEO) in September 2006 states about this period, *"The global expansion remained buoyant in the first half of 2006"* and *"Growth was particularly strong in the United States in the first quarter of 2006."*

[23] The US Federal Reserve steadily increased the interest rate, which, in January 2008, was only 75 basis points away from its peak of 5.25 percent in June 2006.

[24] See Bernanke (2005) on the "Global Savings Glut" hypothesis.

[25] See WEO Database 2019 October.

[26] On 25 January 2011, for example, the International Monetary Fund (IMF) published a WEO Update that states, *"The two-speed recovery continues. In advanced economies, activity has moderated less than expected, but growth remains subdued [...]. In many emerging economies, activity remains buoyant [...]."*

that global growth expectations experienced a downward revision of 1.75 percentage points relative to November 2008.[27] Against this backdrop, the US Federal Reserve lowered the interest rate between 75 and 100 basis point to a level of 0 to 0.25 percent on 16 December. As capital flows across country groups reacted differently to this announcement, the corresponding comovement pattern is highly diverse.

To conclude, in this section, we have identified a new measure of strength for the global financial cycle. Based on this measure, we have documented that the strength of the global financial cycle varies substantially over time, and also, that this variation is highly heterogeneous across countries, especially, between advanced and emerging economies.

3 Implications for Monetary Policy Independence

In this section, we go one step further and relate the concept of global financial cycle strength to the seminal question of monetary policy independence. In particular, we estimate a panel of Taylor rules for nine emerging market economies and seven small open advanced economies,[28] and assess how monetary policy independence in these economies relates to the extent of their sensitivities to the global financial cycle—the key inputs into our measure of global financial cycle strength. Moreover, our definition of monetary policy independence in this section refers to central banks' macroeconomic stabilization objectives, and in particular, to the ability of domestic monetary policy to respond to unexpected changes in domestic inflation.[29] We start this section by introducing our data and explaining how we extract exogenous shocks from estimated inflation gaps. We then present our

[27] Moreover, the publication states, *"[...] output in the advanced economies is now expected to contract by 2 percent in 2009."* and *"Growth in emerging and developing economies is expected to slow sharply from 6 percent in 2008 to 3 percent in 2009."*

[28] The emerging market sample includes Brazil, Chile, Hong Kong, India, Malaysia, Mexico, South Africa, Thailand, and Turkey. The small open advanced economy sample includes Australia, Canada, Japan, Korea, New Zealand, Norway and the United Kingdom. Our selection of emerging market economies is governed by the availability of long-enough time series on inflation and industrial production. For the sample of small open advanced economies, we exclude Denmark, Israel, Switzerland and Sweden, since their policy interest rates hit the zero lower bound for part of our sample period, and shadow short-term interest rates are not readily available for these countries.

[29] This focus is different from an assessment of the ability of domestic monetary policy to affect inflation or the output gap (i.e., the effectiveness of monetary policy). Moreover, our definition of monetary policy independence does not refer to the operational independence of the central bank that is required to fulfill its legal mandate.

empirical strategy to obtain impulse responses using a local projections approach. Finally, we present our results.

3.1 Data

We rely on the notion of a Taylor rule where the central bank's policy rate can be expressed as a function of (i) the inflation gap, π_t^{gap}, defined as the difference between the annual inflation rate, π_t, and its medium- to long-term trend, π_t^*, and (ii) the output gap, x_t^{gap}, defined as the deviations of the level of output, x_t, from its potential, x_t^*. In our empirical analysis, we focus on how the central bank's policy interest rate reacts to unexpected movements, or shocks, in the inflation gap, $\epsilon_{\pi,t}^{gap}$. Our data come from the following sources.

Central Banks' Policy Interest Rates: We obtain data on central banks' policy interest rates from the Bank for International Settlements (BIS). For the United Kingdom and Japan, we use the monthly average of the shadow short rate calculated by Krippner (2013) when the policy interest rate is at the zero lower bound.

Inflation Gap Shocks: A central challenge in the estimation of the response of central banks' policy interest rates to changes in inflation is to overcome the underlying endogeneity problem. Since an increase in the policy interest rate, for example, is expected to lead to a fall in inflation, the measured effects that inflation has on the policy rate would be biased. We tackle this reverse causality challenge by extracting a series of exogenous "shocks" from our inflation gap series, which correspond to the residuals of a trend-cycle decomposition.

To decompose inflation into trend and cyclical components, we rely on an unobserved component (UC) model.[30] Our specification assumes that the trend component follows a random walk with a time-varying drift, and that the cyclical component follows an autoregressive process. We then interpret the error term associated with the autoregressive process as our measures of inflation gap shocks. Appendix A.2 provides more details on the unobserved components model.

[30] A variety of methods that can be used to decompose inflation into trend and cyclical components, the Hodrick-Prescott (HP) filter being probably the most common method. However, due to its non-parametric nature, the HP filter is not able to separately identify expected and unexpected movements of the extracted cycles and trends.

Our data on inflation come from the IMF's International Financial Statistics (IFS).[31] To better distinguish the trend from the cycle, we start our sample for the identification of inflation shocks in 1990 and employ all data available.

To illustrate the performance of the unobserved component model in extracting inflation gap shocks, we present the corresponding trend, cycle, and shock estimates for one emerging market (India) and one advanced economy (United Kingdom) from our sample in Figure A4 of Appendix A.3.[32] These figures also compare the inflation gap estimates obtained from the unobserved component model to an inflation gap extracted with the Hodrick-Prescott (HP) filter. Reassuringly, the two gaps follow a similar pattern. Moreover, the resulting inflation gap shocks are centered on a value of zero and show the typical low persistence of a macroeconomic shock series.

3.2 Empirical Methodology

Our baseline regression to evaluate the degree of monetary policy independence follows a Taylor rule approach, whereby we evaluate the response of the central bank interest rate to inflation gap shocks at different levels of financial cycle strength. We derive our impulse responses based on a regime-dependent version of Jordà's local projection approach (Jordà (2005)) in a panel setting. Our model is similar to the regime-dependent model in Ramey and Zubairy (2018), who estimate the effects of fiscal policy in different phases of the business cycle. A key feature of our impulse response analysis is that we capture the strength of the global financial cycle by relying on the simulated regimes of high and low comovement in equity fund flows obtained in Section 2. In the absence of a "true" benchmark for high- and low-comovement regimes, this choice allows us to better account for estimation uncertainty.[33] The regime-dependent model is

$$\begin{aligned} irs_{i,t+h} = I^j_{i,t-1}[\alpha^h_{i,A} + \gamma^h_t + \psi^h_A(L)z_{i,t-1} + \beta^h_A shock_{i,t}] \\ +(1 - I^j_{i,t-1})[\alpha^h_{i,B} + \gamma^h_t + \psi^h_B(L)z_{i,t-1} + \beta^h_B shock_{i,t}] + \omega_{i,t+h} \end{aligned} \tag{6}$$

for $h = \{0, 1, 2, ...\}$

where subscripts i and t denote the country and the time dimension, respectively, and

[31] The time series were seasonally adjusted using the Census X-12 method.

[32] The results corresponding to the remaining countries are available upon request.

[33] Other than in the world of business cycle analysis, there is no official committee that "dates" such regimes in the context of international capital flows.

superscript h represents the projection horizon. $irs_{i,t+h}$ is the central bank's policy interest rate in country i at time t over horizon h. $\alpha_{i,A}$ and $\alpha_{i,B}$ are regime-specific country fixed effects that capture all time-invariant differences across countries and γ_t represents time fixed effects that control for the effect of all common shocks across countries. Moreover, z is a vector of control variables, ψ is a polynomial of order 4, and $shock$ is the inflation gap shock variable. The vector of control variables $z_{i,t-1}$ includes lagged values of the policy interest rate, the output gap, the effective exchange rate, and lags of the shock variable to control for any serial correlation.[34] $I^j_{i,t-1}$ is a dummy variable that takes on the value of 1 in the "high-comovement regime" (i.e., during times when countries' sensitivity to the global financial cycle is high) according to the Bayesian estimation output in replication j at time $t-1$, as estimated in Sections 2.2 and 2.3. We thus estimate Equation (6) 8,000 times, each time using a different dummy variable $I^j_{i,t-1}$ associated with replication j.

Impulse responses are constructed as the sequence of the regression coefficients, which gives the response of irs at time $t+h$. The parameter β^h_A will capture the average reaction of the monetary policy authorities at horizon h to an inflation gap shock whenever capital flows comove strongly with the global financial cycle. In contrast, the parameter β^h_B will capture the average reaction of the monetary policy authorities at horizon h to this shock whenever capital flows tend to be relatively disconnected from the global financial cycle. The confidence bands around these parameter estimates are obtained from the 16$^{\text{th}}$ and the 84$^{\text{th}}$ percentiles of the 8,000 estimations. We conduct our estimation at monthly frequency and our sample extends from January 2002 to December 2017.[35]

3.3 Results

Figure 6 contains the results of estimating the two regime-dependent models on our two panels of nine emerging market central banks and seven small open advanced economy central banks. In both panels, we present the response of central banks' policy interest rates to a positive inflation gap shock during the "low-comovement" regime (blue lines) and during the "high-comovement" regime (red lines), representing times of low and high global financial cycle strength, respectively. In each case, the solid lines show the estimated

[34] Our results are qualitatively unchanged when expanding the set of controls to commodity prices (the Global Price Index of All Commodities from the IMF) or US industrial production.

[35] The frequency of the analysis is monthly, since the data on inflation were not available at a high frequency.

point response over a period of 24 months and the dotted lines indicate the corresponding 68 percent confidence intervals.

We start by discussing the impact of inflation gap shocks on emerging market central banks' policy rates during low-comovement times. The blue line in Panel (a) shows that there is a positive and significant relationship between inflation gap shocks and central banks' policy rates in the low-comovement regime. In particular, the policy rate response to the inflation gap shock is most pronounced 3 to 17 months after the shock, peaking after 14 months. At this peak, the increase in the policy rate in response to a 1-percentage point surprise increase in the inflation gap is statistically significant and amounts to 18 basis points. Hence, these results suggest that emerging market central banks respond to an unexpected increase in inflation in low-comovement times with a policy rate tightening—a response that is consistent with the Taylor rule.

We then turn to the response of emerging market central banks during high-comovement times. The red line in Panel (a) shows that the corresponding impulse response is flatter or even negative across all horizons, and we do not observe, at any point, a significantly positive response of central banks' policy interest rates to an unexpected increase in the inflation gap. Moreover, the (positive) peak response of the policy rate, which now occurs after one month, amounts to only 1 basis point and is thus substantially smaller than during low-comovement times.

It is also worth noting that the lower confidence band of the low-comovement case and the higher confidence band of the high-comovement case do not overlap for the vast majority of horizons.[36] This suggests that the impulse response functions in the low- and in the high-comovement regimes are statistically different from each other.

Next, we turn to the description of the interest rate responses to inflation gap shocks of small open advanced economy central banks in Panel (b). While the interest rate responses for advanced economies appear to be shorter and less pronounced than for emerging market economies, their patterns are very similar.[37] Again, the blue line represents the impulse response in the low-comovement regime. This time, the response is most pronounced in the first four months after the shock, which is earlier than in the emerging market economy

[36] The only exceptions are the four horizons of one, two, seven, and eight months.

[37] Candidate explanations for this finding are that central bank policy rates in advanced economies are lower and their inflation shocks are smaller than in emerging market economies. Moreover, advanced economy central banks might be more likely to "look through" commodity price shocks when setting their policy rates than emerging market economy central banks.

sample. Similarly, the peak response in the low-comovement regime for advanced economies is located at the three-month horizon, again earlier than before. Moreover, the peak response amounts to 9 basis points, which is less than half the strength of the emerging market sample.

Finally, the red line in Panel (b) represents the impulse response of small open advanced economies' policy rates to inflation gap shocks in the high-comovement regime. The response appears to be overwhelmingly negative, with a positive and significant response only in the second and the third months. Related to this, the peak response in month three amounts to only 5 basis points and thus to approximately half the value of the response in the low-comovement regime. However, again the two sets of responses are significantly different from each other over most of the sample period, in particular during the first month as well as during months 6 to 20. This suggests that also the policy rate responses of small open economy central banks differ depending on the comovement regime.

Overall, the analysis in this section appears to suggest that monetary policy in emerging market and small open advanced economies becomes less responsive to domestic inflationary pressures in the presence of high sensitivity to the global financial cycle. However, the weak response of the policy rate to an inflation gap shock does not necessarily imply that central banks do not react at all in times of high global financial cycle strength. Most likely, central banks will set their policy rates in a way that ensures a smooth passage for the domestic economy through this period by especially considering the role of domestic and international financial conditions and the dynamics of the exchange rate in their decisions. While such a strategy appears to be dominant from the central bank's perspective in times of high global financial cycle strength, it might come at the cost of deviating from the central bank's macroeconomic objectives by potentially neglecting the stabilization of inflation during this period. We refer to this situation as one in which the independence of domestic monetary policy is potentially constrained.

A potential concern in this context is that the differential response of central banks in the high- and in the low-comovement regime could be caused by differences in the size of the inflation gap shocks across the two regimes. Consider, for example, a central bank that "looks through" small inflation shocks but tightens its policy interest rate in response to larger ones. If the high-comovement regime was systematically associated with small inflation gap shocks and the low-comovement regime with large ones, then it would be reasonable to expect a stronger policy rate response from such a central bank in the low-comovement regime. We show, however, that this is not the case, as the size of the inflation gap shocks does not differ notably across regimes. Appendix Figure A5 presents the standard deviations of the inflation gap shocks in the low- and in the high-comovement regime for all sample countries in this exercise. The figure shows that the standard deviations of the shocks are almost identical across the two regimes in 13 of the 16 countries in our sample (potential exceptions are Turkey, where the standard deviation of the low-comovement regime dominates, and Malaysia and Thailand, where those of the high-comovement regime dominate) and there is no evidence for a systematic difference in shock size across the two regimes. Hence, the differential response of central banks across the two regimes is not related to the size of the underlying inflation gap shocks.

To sum up, in this section we have provided empirical evidence for the hypothesis that central banks respond less to unexpected movements in the inflation gap when their country's sensitivity to the global financial cycle (and thus the strength of the global financial cycle) is high. Hence, the conduct of counter-cyclical monetary policy, as suggested by a Taylor rule, appears to be potentially constrained in such situations, which we interpret as a lower degree in central banks' monetary policy independence. Our findings provide support to the arguments made in Rey (2013), which suggest that central banks in small open economies with open capital accounts experience a reduction in monetary policy independence regardless of their exchange rate regime—and, hence, the traditional trilemma turns into a dilemma between monetary policy independence and a restricted capital account. However, we also show that monetary policy independence appears unaffected in times of a low sensitivity to the global financial cycle. During these times, the central banks of our sample showed the expected counter-cyclical monetary policy response to an unexpected increase in inflation and, thus, they should be able to fulfill their domestic stabilization mandates as expected.

4 Policy Options

In this section, we examine a wide range of policy options available to policymakers to increase the degree of monetary policy independence by reducing the time-varying sensitivity of their economies to the global financial cycle. We conduct this analysis based on the large sample of advanced and emerging market economies from Section 2.

4.1 Empirical Methodology and Data

We run annual panel regressions in the following form:

$$prob_{i,t} = \alpha + \alpha_i[+\alpha_t] + \beta policy_{i,t-1} + \delta controls_{i,t-1} + \epsilon_{i,t} \tag{7}$$

where $prob_{i,t}$ represents the probability of country i in year t to be in a high-comovement regime (henceforth referred to as "regime probability"), obtained from our dynamic factor model in Section 2.2. The weekly regime probabilities are aggregated at an annual frequency using a simple arithmetic mean. The variable $policy_{i,t}$ varies across countries and over time and represents policies that can reduce the impact of the global financial cycle. To mitigate endogeneity concerns, we lag the policy variables by one period. We discuss the full set of policies toward the end of this section. Further, α is the intercept term and α_i represents country fixed effects that account for all country-specific factors that do not vary over time. In selected specifications, we also include time fixed effects, α_t, which account for all common factors that do not vary across countries. Moreover, we include two additional controls for institutional quality and political stability that vary across countries and over time into all specifications. These controls allow us to take the impact of idiosyncratic non-economic shocks into account, which otherwise could affect the degree of comovement in the regime probabilities.[38] Finally, $\epsilon_{i,t}$ is the error term. Standard errors are heteroskedasticity-robust and clustered at the country level.

Next, we briefly discuss the three policy options. The first two are the use of capital inflow controls and macroprudential policies based on Rey (2013).[39] As the third policy option, we consider the frequently cited role of exchange rate flexibility to cushion the impact of global financial shocks on the domestic economy (e.g., Obstfeld et al. (2018)).

[38] The two variables are "Rule of Law" and "Political Stability and Absence of Violence" from the Worldbank's Worldwide Governance Indicators (WGI) data set. The variables are defined as follows. *Rule of Law* "captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence." *Political Stability and Absence of Violence/Terrorism* "measures perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism."

[39] Rey (2013) also references the internalization of spillovers from US monetary policy as a policy tool. However, we do not consider this tool in our analysis, since US monetary policy has a domestic mandate, and thus, this policy option appears to be outside of the control of policymakers in affected economies.

- **Capital Controls:** We use data on capital controls from Fernández et al. (2016). In particular, we use their overall inflow restrictions index *kai*, which ranges between zero and one.

- **Macroprudential Policies:** We measure macroprudential policies by announced rates of the counter-cyclical capital buffer (CCyB). We select the CCyB as it varies over the cycle and specifically relates to the banks' holdings of capital—two central features of the macroprudential policies discussed in Rey (2013).[40] As the CCyB has been introduced only recently, we use data on announced CCyB rates instead of effective CCyB rates in order to increase the variation in our sample (it usually takes about one year until announced rate increases become effective; announced decreases are effective immediately).[41] Data on CCyB rates come from the BIS and the European Systemic Risk Board (ESRB).[42]

- **Flexible Exchange Rates:** We measure exchange rate flexibility based on an indicator variable that takes on the value of 1 when a country is considered to have a freely floating exchange rate, and 0 otherwise. Our data on exchange rate classifications stem from the database provided by Ilzetzki et al. (2019).[43]

Table A1 in the appendix contains the summary statistics for these three policy measures as well as for the other variables of our analysis. Finally, we exclude the United States from our analysis in this section, since we also examine the impact of US monetary policy spillovers. Moreover, five countries in our sample from Section 2 do not have data on all

[40] Rey (2013) discusses two types of macroprudential policies that are able to mute the transmission mechanism of the global financial cycle: *"cyclical measures to limit excessive credit growth"* and *"dampening the amplification capacity of financial intermediaries."* As such, the CCyB captures the "cyclicality" aspect of the former (moreover, Rey (2013) mentions explicitly the CCyB as one of the corresponding policy tools in this context) and the "capital" aspect of the latter (the corresponding policy tool in Rey (2013) is the leverage ratio, which, according to its definition under Basel III, relates banks' assets to their Tier 1 capital). Since a full-fledged analysis of the effectiveness of macroprudential policies that covers a broad range of policy tools is beyond the scope of this paper, there is a possibility that other macroprudential tools could potentially serve as complements to the CCyB and render our findings as a lower bound of the effects.

[41] However, our results also hold with effective CCyB rates.

[42] See Bank for International Settlements (BIS), 2020. "Countercyclical Capital Buffer (CCyB)," `https://www.bis.org/bcbs/ccyb/`, and European Systemic Risk Board (ESRB), 2020. "Countercyclical Capital Buffer," `https://www.esrb.europa.eu/national_policy/ccb/html/index.en.html`, for details.

[43] We use the database "Exchange rate regime classification, annual, 1946-2016." and opt for the "Fine Classification." We use the classifications "13 = Freely floating" and "14 = Freely falling" as measures of a freely floating exchange rate. We include the freely falling category in addition to extend our measure of flexible exchange rates to emerging market economies as well.

three policies and are thus missing from some of our specifications.[44]

4.2 Results and Discussion

Table 3 presents the results from estimating Equation (7) on our sample of up to 60 economies at annual frequency from 2001 to 2016. We examine the individual impact of all three policy options on the regime probabilities before including them jointly in the regression. Moreover, we report the results separately with (even numbered specifications) and without (uneven numbered specifications) time fixed effects.

First, we focus on capital controls as a policy tool. Capital controls can be used to insulate the domestic economy from the global financial cycle by taxing or restricting the inflow and outflow of foreign capital.[45] Specifications (1) and (2) in Table 3 show that our measure of inflow controls carries a negative sign and is highly significant in both cases. This suggests that a tightening of capital inflows controls could reduce countries' sensitivities to the global financial cycle. While the literature specialized in the analysis of capital controls conducts a more comprehensive assessment of their effectiveness,[46] our findings that capital controls are able to reduce countries' sensitivities to the global financial cycle, and thus, increase their monetary policy independence, are fully consistent with the overall message of this literature. Evaluating close to 40 studies on the effectiveness of capital controls in a meta-analysis, Magud et al. (2018) summarize this literature by stating *"[...] more often than not, in practice they [capital controls] do not work."* However, the authors qualify this statement by also noting that *"capital controls on inflows seem to make monetary policy more independent and alter the composition of capital flows."* Hence, even if capital controls are not able to reduce the volume of capital flows or meaningfully affect exchange rate dynamics, their ability to favorably affect the composition of capital flows (e.g., by encouraging more stable FDI flows) may be sufficient to reduce countries' sensitivities to the global financial cycle.

However, the use of capital controls is associated with a number of challenges. First, the previous literature has shown that capital controls require specific country characteristics

[44] These countries are Croatia, Estonia, Lithuania, Taiwan, and Zimbabwe.

[45] See Davis and Presno (2017) for a theoretical discussion of the relationship between capital controls and monetary policy autonomy in small open economies.

[46] For example, Forbes et al. (2015) use a propensity score matching technique to account for selection bias, Fernández et al. (2016) and Pasricha et al. (2018) examine the role of different types of capital controls, and Forbes et al. (2016) distinguish between direct and spillover effects.

to work (e.g., Magud et al. (2018)). For example, they appear to be less effective in low- and middle-income countries, especially for debt flows (e.g., Binici et al. (2010)).[47] Second, the costs associated with capital controls, in particular their allocational impacts, appear to be substantial. Forbes (2007), for example, finds that capital controls distort the decision-making by firms and households, reduce market discipline for governments, raise the cost of financing for smaller firms, and are difficult to enforce.[48] And third, current legislation in the European Union prohibits the use of capital controls for its member states, including that of controls targeted at non-EU countries (e.g., Article 63 of the Treaty on the Functioning of the European Union (TFEU) states that *"[...] all restrictions on the movement of capital between Member States and between Member States and third countries shall be prohibited."*) Hence, for policymakers in most advanced economies, capital controls are usually not part of the tool set.

Our second policy tool consists of macroprudential policies. Macroprudential policies are an appealing policy tool from a theoretical view point as they are able to address the underlying financial frictions directly (e.g., Bianchi and Mendoza (2018)). Thus, as opposed to capital controls, macroprudential policies can be applied in a more targeted way and have a better chance of meeting their objectives without overly distorting the economic allocation. Moreover, their use is subject to fewer legal restrictions compared with capital controls. Specifications (3) and (4) present the impact of tightening the CCyB, our measure of macroprudential policies in this exercise, on the regime probabilities. We find that the coefficient on the use of the CCyB is negative and highly significant, suggesting that macroprudential polices can also be an effective policy tool to reduce countries' sensitivity to the global financial cycle.[49] Moreover, the finding that macroprudential policies can be effective in mitigating financial vulnerabilities is further supported by rich evidence from the empirical literature (e.g., IMF (2011); Cerutti et al. (2017); Alam et al. (2019)). In particular, it appears that their distortionary effects on inflation and output are small (e.g., Richter et al. (2019)). However, a word of caution is required, as an insufficient design of

[47] A potential explanation for our results, which suggest that a capital control tightening does reduce the sensitivity of countries to the global financial cycle, could relate to the fact that we examine their effect on equity fund flows instead of debt or credit flows.

[48] Related to this, Alfaro et al. (2017) find evidence consistent with an increase in the cost of capital for firms after announcements of capital controls in Brazil.

[49] Moreover, it should be noted that we are derived our measure of the global financial cycle from equity fund flows and thus macroprudential policies that are primarily focused on the banking system could be even more effective in the context of bank flows.

macroprudential policies can create leakages and spillovers across sectors or across countries, which could reduce their effectiveness (e.g., Buch and Goldberg (2017); Ostry et al. (2012); Ahnert et al. (2020)). Moreover, macroprudential policy frameworks vary substantially across countries, as well as the type of authority that controls them (e.g., Friedrich et al. (2019); Correa et al. (2017)). This, in turn, could create additional challenges for their implementation.

Our third policy option is the reliance on a flexible exchange rate. A flexible exchange rate can help countries to buffer global financial shocks and thus mitigate the impact of the global financial cycle. As pointed out in the introduction, the previous literature has been somewhat inconclusive as to whether a floating exchange rate regime is a sufficient condition to isolate a country from the global financial cycle or not. Specifications (5) and (6) present the impact of our measure of flexible exchange rates on the regime probabilities. As evident from the table, the coefficient is negative (albeit insignificant) in Specification (5) but becomes significant at the 5-percent level in Specification (6), when time fixed effects are included. Moreover, there appears to be one important advantage of exchange rate flexibility over the other two policy tools. Once a floating exchange rate regime has been established, the exchange rate works as a shock absorber without requiring any policy interventions. This, in turn, reduces potential implementation challenges present for the other policies that could arise as a result of political considerations.

In Specifications (7) and (8), we include all three policies jointly in the regression. Again, we observe that the coefficients associated with all three policies are negative and highly significant regardless of whether time fixed effects are included in the specification or not. In order to get a better idea of the relative effectiveness of all three policies, we examine their quantitative impact based on Specification (7) (which we refer to as our "baseline specification" in the remainder of this section). Specification (7) indicates that (i) a 1-unit increase in the measure of capital controls (a change from the lowest to the highest possible value) reduces the regime probabilities by 60.56 percentage points, (ii) a 1-percentage point increase in the CCyB reduces the regime probabilities by 31.11 percentage points, and (iii) the movement from a non-flexible to a flexible exchange rate regime reduces the regime probabilities by 18.5 percentage points. In order to make these numbers more comparable across policy measures, we multiply them with the standard deviation of their respective policy measures (obtained from Table A1 in the Appendix). Hence, a 1-standard deviation tightening for the capital control variable leads to a probability reduction of 18.17 percentage points, a corresponding CCyB tightening to a reduction of 4.04 percentage points, and the move to a flexible exchange rate regime to a reduction of 5.74 percentage points. Hence, it appears that the most effective policy tool is the capital control policy, followed with some distance by the flexible exchange rate regime and the macroprudential policy.

Next, in Table 4, we conduct a range of checks that demonstrate the robustness of our results. Specification (1) in this table corresponds to our baseline specification and is added as a benchmark. Specification (2) in Table 4 provides results for emerging market economies only (we base this definition on Table 1). While the impact of capital controls and macroprudential policies remains of similar significance as in our baseline specification, the effect of flexible exchange rates becomes insignificant. This could suggest that the impact of flexible exchange rates is weaker in emerging market economies and thus closer to the interpretation that the traditional trilemma has turned into a dilemma, regardless of the exchange rate regime, as put forward in Rey (2013). This finding is potentially also in line with Obstfeld (2015), who suggests emerging market economies with flexible exchange rates are better off than those with fixed exchange rates but that exchange rate changes alone do not insulate countries from foreign financial and monetary shocks. Specification (3) limits the sample to advanced economies. This time, the coefficient on capital controls becomes insignificant, while the coefficients on macroprudential polices and the flexible exchange rate remain significant. While the former shows that flexible exchange rates still help mitigate shocks in advanced economies, the latter could reflect the fact that advanced economies use capital controls less frequently and thus the variation behind this variable is less strong. Finally, in Specifications (4)-(7), we explore the impact of the policy tools on four alternative dependent variables that were obtained from the dynamic factor model in Section 2.2. Specification (4) still relies on regime probabilities but uses a winsorized version that replaces the tail values with the values of the 10^{th} and the 90^{th} percentile, respectively. Specification (5) assesses the effect of the three policies on the factor loadings and Specifications (6) and (7) on the regimes themselves. Specification (6) uses the annual averages of the weekly regime values and Specification (7) rounds these averages to either zero or one (thus, establishing the binary nature of the regime variable again). Overall, it turns out that the impact of all three policies remains highly significant regardless of the dependent variable employed, which, in turn, confirms the results of our baseline specification.

We then go one step further and explore in Table 5 the role of potential transmission mechanisms for the three policy options. Specifications (1), (4) and (7) present for each policy option an interaction term specification between the policy and a variable that captures a country's US dollar exposure over the period 1990 to 1999 (which is the last full decade before our sample starts).[50] We obtain the US dollar exposure by summing up for each country the variables "total assets in USD as % of GDP" and "total liabilities in USD as % of GDP" from Lane and Shambaugh (2010).[51] The results in Table 5 are structured as follows. The coefficients "L.Inflow Restr.," "L.CCyB," and "L.Flex. Ex. Rate" capture the direct effect of these policies on the regime probabilities, regardless of a country's US dollar exposure. The corresponding interaction terms then capture the differential effect that these policies have in the presence of US dollar exposures. Hence, a negative interaction term coefficient suggests that a tightening of the policies is more effective in reducing the regime probabilities in the presence of a substantial US dollar exposure. It turns out that this is particularly the case for the flexible exchange rate in Specification (7), where the interaction term coefficient is highly significant, and for the macroprudential policies in Specification (4), where the interaction term coefficient is significant at the 10-percent level. The effect for capital controls in Specification (1) is insignificant. The remaining six specifications limit the sample to two environments that are closely associated with the elevated presence of US monetary policy spillovers. Specifications (2), (5) and (8) present the results for a sample where the annual standard deviation of the US shadow rate is above the sample average,[52] and Specifications (3), (6) and (9) for a sample where US monetary policy uncertainty is above the sample average.[53] As can be seen across all three policy instruments, the interaction term coefficients become larger and more significant in the presence of these shocks. This suggests that the three policies are particularly effective in reducing the impact of US monetary policy spillovers when they are high. Thus, these

[50] This is equivalent to adding the interaction term "$policy_{i,t-1} \times USDexposure_i$" to Equation (7), where $USDexposure_i$ is the US dollar exposure variable. Since $USDexposure_i$ does not vary over time, its direct effect is absorbed by the country fixed effects and thus is not included separately in the specification.

[51] The results are qualitatively robust to using the more general version of this variable that captures all foreign-currency exposure, regardless of the currency denomination.

[52] We use the US shadow short rate from Krippner (2013) for this exercise.

[53] We obtain the data on US monetary policy uncertainty from Husted et al. (2019).

results provide additional evidence on how the three policy options can mitigate the impact of the global financial cycle.

To sum up, our assessment of three frequently discussed policy options has shown that all three tools appear to be effective in reducing countries' sensitivities to the global financial cycle. However, the results and the associated discussion have shown that none of them comes without challenges. While it appears that exchange rate flexibility could be the first line of defense, as it does not require any specific actions by policymakers, we found signs that it might not be sufficiently strong in emerging market economies. Capital controls appeared to be the most effective policy tool in the entire sample when judged by the impact of a 1-standard deviation change, but they did not appear to be effective in advanced economies. This could possibly be related to the fact that their implementation may pose legal challenges in certain economies. Moreover, there is evidence in the literature that capital controls can create allocational distortions, such as raising financing costs for small firms. Finally, there are macroprudential policies that can address the underlying financial frictions that give rise to the global financial cycle more directly. Macroprudential policies were also the only policy tool in our analysis that appeared equally feasible for advanced economies and emerging markets. At the same time, macroprudential policies exhibited the lowest effectiveness among all three policy options (although only slightly lower than that of flexible exchange rates). However, their effectiveness could possibly be strengthened once more robust macroprudential frameworks are deployed and their design better incorporates leakages and possible spillover effects.

5 Conclusion

In this paper, we have made three contributions to the literature. First, we have proposed a new measure that captures the strength dimension of the global financial cycle by extracting time-varying regime probabilities from a common factor in cross-border equity flows for 61 countries. We have shown that the strength of the global financial cycle varies substantially over time and, moreover, that this variation exhibits a substantial heterogeneity across countries.

Next, we have used this new measure to assess how the strength of the global financial cycle affects monetary policy independence, defined as the response of central banks' policy interest rates to exogenous shocks in inflation. Based on evidence from nine emerging markets and seven small open advanced economies, we have shown that central banks tighten their policy rates in response to an unanticipated increase in the inflation gap during times of low global financial cycle strength. During times of high financial cycle strength, however, the response of the same central banks to the same unanticipated change in the inflation gap is muted and does not appear to follow a pattern consistent with the Taylor rule. These effects are not only statistically but also economically significant. For example, we find in our emerging market sample that the policy rate response of central banks to an unexpected 1-percentage point inflation gap increase amounts to 18 basis points in times of low comovement but to only 1 basis point during times of high comovement. We interpret this difference as a potential reduction of central banks' monetary policy independence in times of high financial cycle strength.

Finally, we have assessed the effectiveness of three frequently cited policy options, namely the implementation of capital controls in the form of inflow restrictions, the use of macroprudential policies in the form of the counter-cyclical capital buffer, and the presence of a flexible exchange rate regime to reduce a given country's sensitivity to the global financial cycle. Our results suggests that all three policy options can potentially increase the degree of monetary policy independence. While capital controls were most effective overall, they seem to be primarily a tool for emerging market economies. Related to this, the impact of a flexible exchange rate was present mainly for advanced economies. Only macroprudential policies showed significant results across both country groups but were overall the weakest policy. This suggests that more work is needed to devise appropriate macroprudential policy strategies.

Future work could build on our analysis along three avenues. First, we have identified the strength of the global financial cycle in data on equity fund flows at a high frequency. Since most of the previous literature on the global financial cycle has focused on bond and credit flows instead, future research could extend our analysis to these alternative asset classes. A central challenge in this process is the availability of appropriate data sets that comprise a wider range of asset classes, have global coverage, and feature a sufficiently high frequency.

Second, we conducted our assessment of monetary policy independence for a subset of our broad country sample and for inflation shocks only. We focus on a selection of nine emerging market economies and seven advanced economies, two country groups that the literature frequently associates with a strong exposure to the global financial cycle. However, broadening this analysis to a wider range of countries could deliver additional insights on how monetary and macroprudential policy frameworks could affect monetary policy independence. Moreover, we did not consider a potential role of output shocks and financial shocks in our Taylor rule analysis. One could think of a situation, for example, in which the central bank addresses such shocks more proactively by changing its policy rate. In particular, assessing how a "leaning against the wind" behavior would interact with the strength of the global financial cycle could help broaden our understanding of the benefits and costs of such policies.

And third, especially the implementation of macroprudential policies will require a better understanding of their intended transmission channels, as well as their unintended leakages and spillovers. With a steadily rising availability of data on macroprudential policies and the accumulation of experience with their implementation, however, researchers and policymakers appear increasingly better equipped to make significant progress on these questions.

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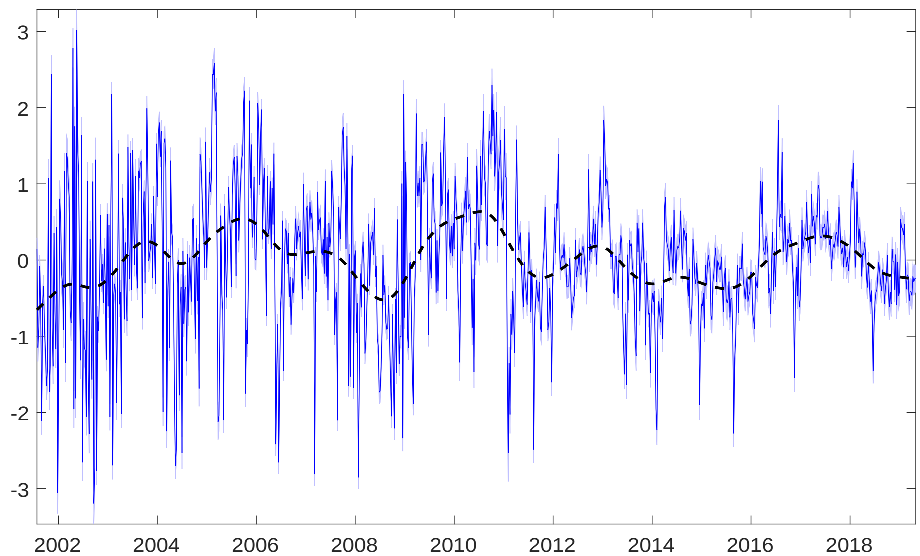
6 Figures and Tables

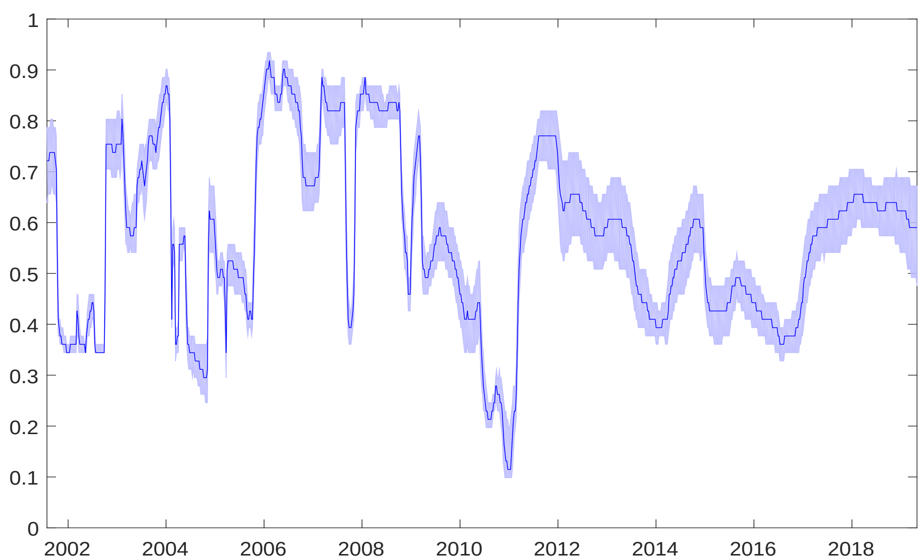
6.1 Figures

Figure 1: The Global Financial Cycle

(a) The Global Financial Cycle (Common Factor)



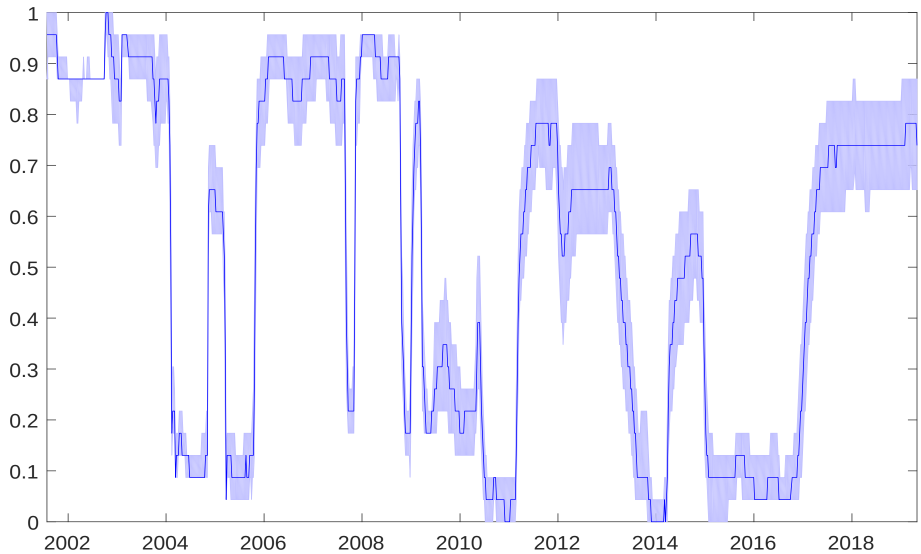
(b) Strength of the Global Financial Cycle



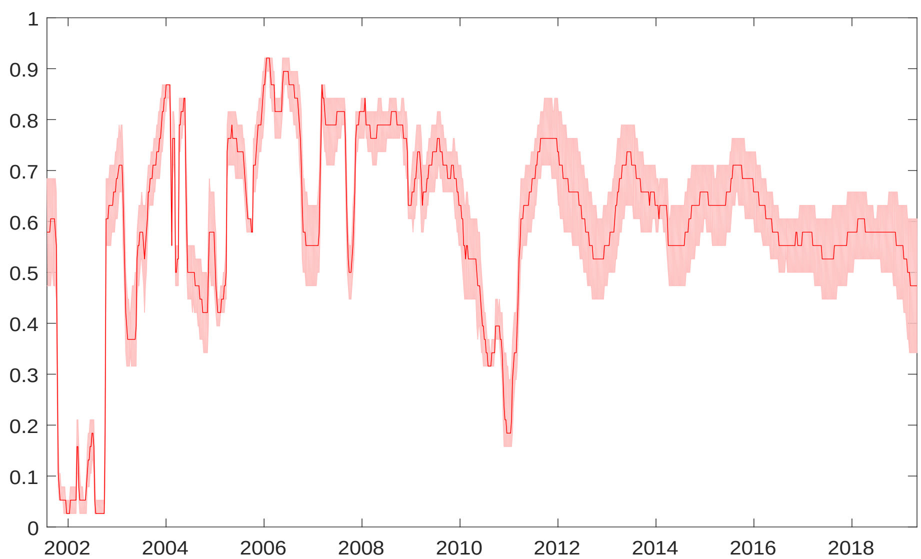
Note: Panel (a) plots the common factor (blue solid line), f_t, extracted from equity fund inflows into our 61 sample countries listed in Table 1. The dashed black line is an HP-filtered smoothed version of the factor. Panel (b) plots the strength of the common factor, χ_t, defined as the share of countries in a high-comovement regime; that is, $\chi_t = \frac{1}{n}\sum_{i=1}^{n} S_{i,t}$. For both panels, the shaded area represents the 5^{th} and 95^{th} percentiles of the posterior distribution, while the solid blue line plots the median.

Figure 2: Partial Strength for Different Country Groupings

(a) Advanced Economies

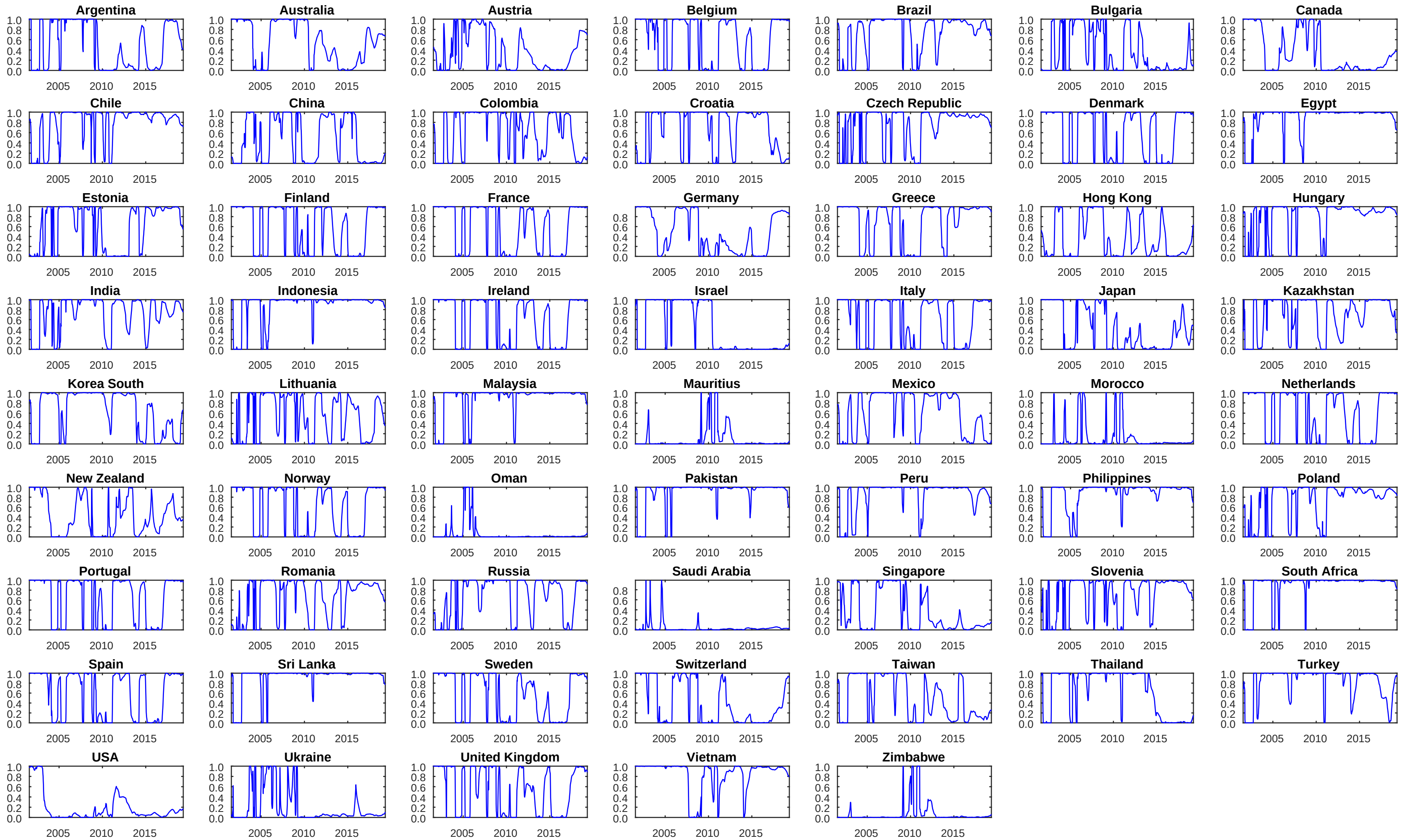


(b) Emerging Economies



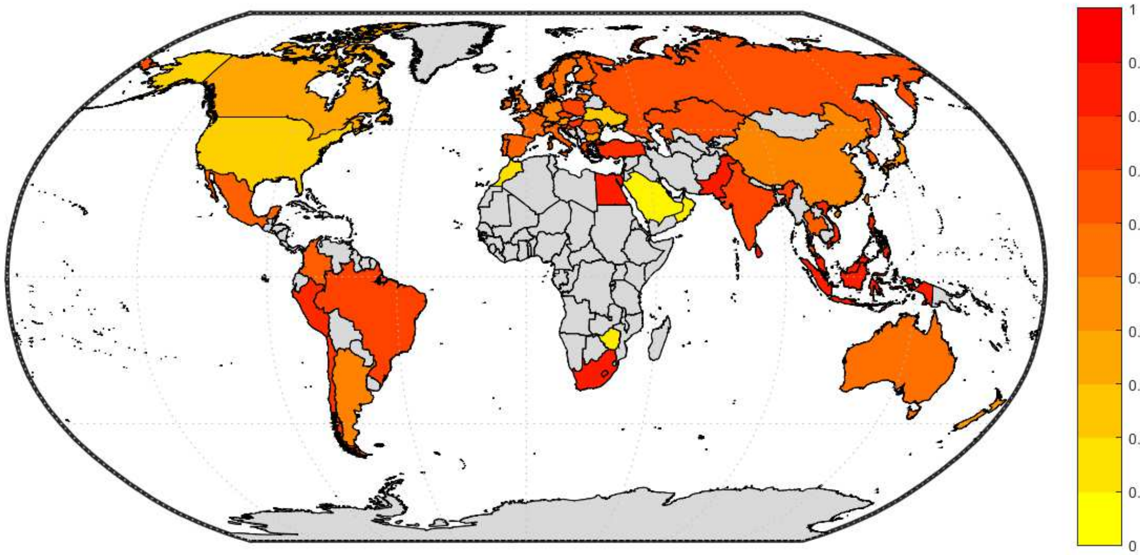
Note: Panel (a) plots the partial strength of the common factor associated with advanced economies, defined as the share of advanced economies in a high-comovement regime. Panel (b) presents the same statistic for emerging market economies. Hence, for advanced economies, the partial strength can be expressed as $\chi_{adv,t} = \frac{1}{n}\sum_{i=1}^{n} S_{i,t_{I[i=adv]}}$, while for emerging economies, it is given by $\chi_{eme,t} = \frac{1}{n}\sum_{i=1}^{n} S_{i,t_{I[i=eme]}}$. For both panels, the shaded area represents the 5^{th} and 95^{th} percentiles of the posterior distribution, while the solid blue line plots its median.

Figure 3: Regime Probabilities Across Countries



Note: The figure plots the country-specific probability of being in a high-comovement regime; that is, $Pr(S_{i,t} = 1)$.

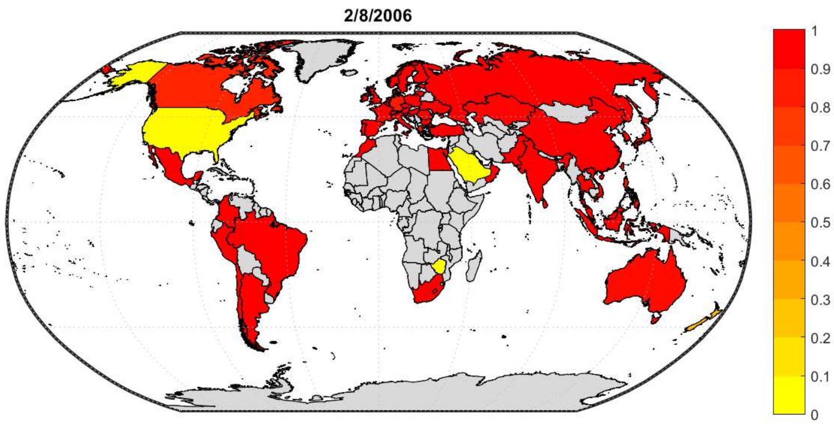
Figure 4: Average Comovements Across Countries: 2001-2019



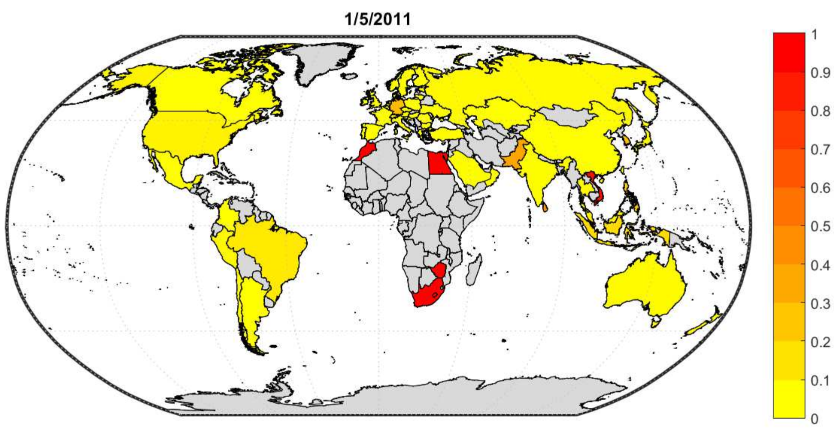
Note: The figure shows the average country-specific degree of comovement with the global factor over the period 2001-2009. The degree of comovement of country i is given by the associated regime probability from the factor model; that is, $Pr(S_{i,t} = 1)$. The darker (lighter) the corresponding area, the stronger (weaker) the degree of comovement with the global factor.

Figure 5: Selected Case Studies

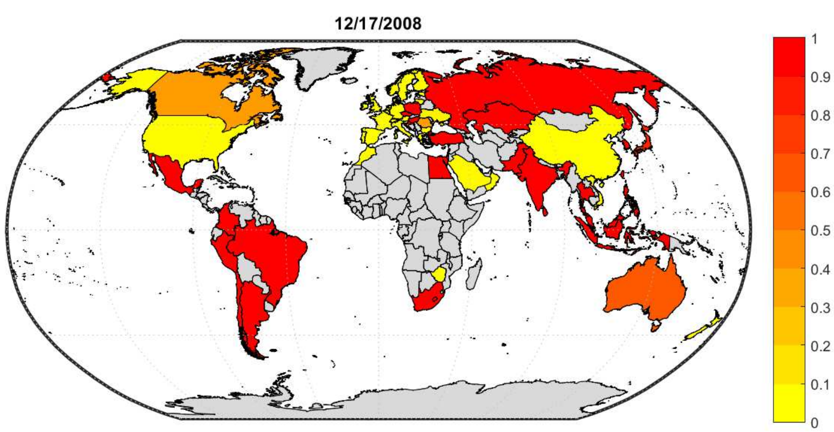
(a) Week of Strongest Comovement Across Countries



(b) Week of Weakest Comovement Across Countries



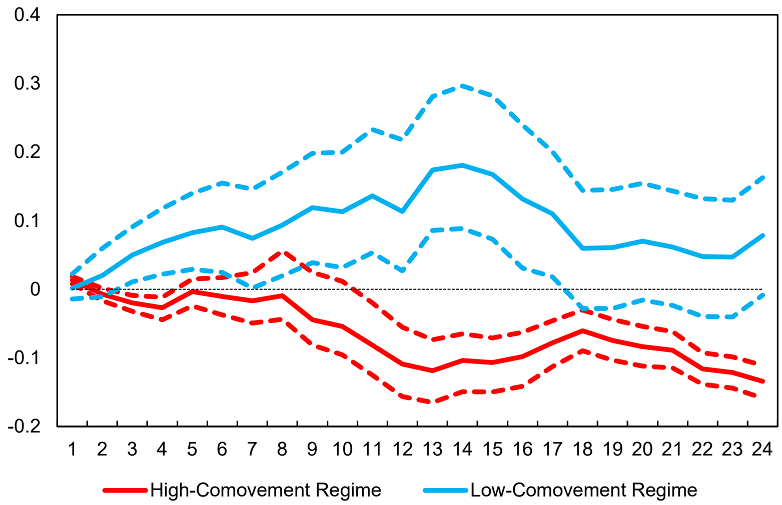
(c) Week of Most Heterogeneous Comovement Across Countries



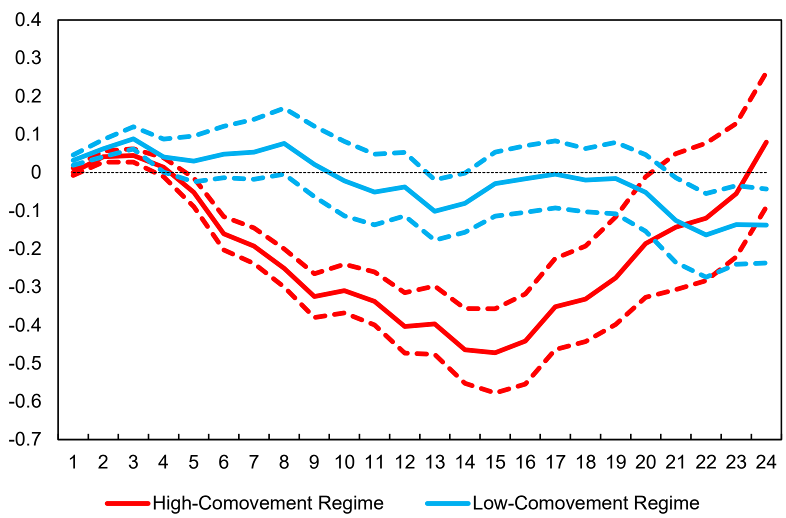
Note: The charts show the country-specific degree of comovement with the global factor for selected time periods. The degree of comovement of country i is given by the associated regime probability from the factor model; that is, $Pr(S_{i,t} = 1)$. The darker (lighter) the corresponding area, the stronger (weaker) the degree of comovement with the global factor.

Figure 6: Policy Interest Rate Response to Inflation Gap Shocks

(a) Emerging Market Economies



(b) Advanced Economies



Note: The figure shows the response of the policy interest rate to a positive inflation gap shock (scaled as a 1-standard deviation increase in the inflation gap shock). Results are shown for two regime-dependent models—one with low- and one with high-comovement regimes—using the local projections approach from Jordà (2005) (see Equation (6)). The control variables include the policy interest rate, lagged inflation, the lagged output gap and the lagged nominal effective exchange rate. The solid red line is the point response and the dotted blue lines correspond to 68 percent confidence intervals. The emerging market economies sample includes Brazil, Chile, Hong Kong, India, Malaysia, Mexico, South Africa, Thailand, and Turkey. The advanced economies sample includes Australia, Canada, Japan, Korea, New Zealand, Norway and the United Kingdom.

6.2 Tables

Table 1: List of Sample Countries for the Global Financial Cycle

America	Europe			Asia			Africa	Oceania
Argentina*	Austria	Germany	Portugal	China*	Oman*	Turkey*	Egypt*	Australia
Brazil*	Belgium	Greece	Romania*	Hong Kong*	Pakistan*	Vietnam*	Mauritius*	New Zealand
Canada	Bulgaria*	Hungary*	Slovenia*	India*	Philippines*		Morocco*	
Chile*	Croatia*	Ireland	Spain	Indonesia*	Russia*		South Africa*	
Colombia*	Czech Rep.*	Italy	Sweden	Israel	Saudi Arabia*		Zimbabwe*	
Mexico*	Denmark	Lithuania*	Switzerland	Japan	Singapore*			
Peru*	Estonia*	Netherlands	United K'dm	Kazakhstan*	Sri Lanka*			
USA	Finland	Norway	Ukraine*	South Korea	Taiwan*			
	France	Poland*		Malaysia*	Thailand*			

Note: The table reports the list of countries used in the empirical analysis along with their corresponding geographic region. Economies marked with a star (*) are part of our emerging market sample in Sections 2 and 4.

Table 2: Regime-dependent Correlations With the Global Financial Cycle

Country	High Comovement	Low Comovement	Country	High Comovement	Low Comovement
Argentina	0.94	0.85	Mauritius	0.83	0.57
Australia	0.74	0.22	Mexico	0.84	0.59
Austria	0.69	0.06	Morocco	0.91	0.52
Belgium	0.75	-0.25	Netherlands	0.78	-0.23
Brazil	0.90	0.79	New Zealand	0.76	0.25
Bulgaria	0.88	0.29	Norway	0.78	-0.17
Canada	0.70	0.04	Oman	0.77	0.47
Chile	0.89	0.64	Pakistan	0.92	0.73
China	0.82	0.70	Peru	0.87	0.36
Colombia	0.89	0.58	Philippines	0.92	0.90
Croatia	0.92	0.51	Poland	0.87	0.40
Czech Republic	0.90	0.35	Portugal	0.77	-0.24
Denmark	0.79	-0.24	Romania	0.87	0.31
Egypt	0.87	0.37	Russia	0.89	0.57
Estonia	0.85	0.35	Saudi Arabia	0.61	0.08
Finland	0.78	-0.24	Singapore	0.84	0.68
France	0.75	-0.24	Slovenia	0.84	-0.11
Germany	0.65	0.04	South Africa	0.91	0.60
Greece	0.73	-0.12	Spain	0.74	-0.25
Hong Kong	0.86	0.69	Sri Lanka	0.94	0.72
Hungary	0.92	0.53	Sweden	0.77	-0.08
India	0.87	0.58	Switzerland	0.75	0.07
Indonesia	0.93	0.78	Taiwan	0.93	0.69
Ireland	0.79	-0.21	Thailand	0.92	0.61
Israel	0.92	0.59	Turkey	0.91	0.60
Italy	0.73	-0.28	USA	0.61	0.13
Japan	0.76	-0.18	Ukraine	0.90	0.60
Kazakhstan	0.94	0.78	United Kingdom	0.79	-0.20
South Korea	0.91	0.60	Vietnam	0.71	-0.15
Lithuania	0.83	0.00	Zimbabwe	0.79	0.51
Malaysia	0.89	0.75			

Note: The table reports the correlation between country-specific portfolio investment flows into equity funds and the global factor during regimes of (i) high comovement, and (ii) low comovement. The country-specific regimes of comovement, $R_{i,t}$, are defined as a dummy variable that is a function of the estimated regime probabilities from the factor model; that is, $R_{i,t} = \mathbf{1}[Pr(S_{i,t} > 0.5)]$.

Table 3: Policy Options to Reduce Countries' Sensitivities to the Global Financial Cycle

Dependent Variable: Probabilities	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.Inflow Restr.	-0.5285***	-0.3882***					-0.6056***	-0.4676***
	(0.138)	(0.136)					(0.144)	(0.137)
L.CCyB			-0.3103***	-0.2116***			-0.3111***	-0.2149***
			(0.061)	(0.066)			(0.075)	(0.076)
L.Flex. Ex. Rate					-0.0899	-0.1344**	-0.1850***	-0.1792**
					(0.072)	(0.063)	(0.068)	(0.072)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.04	0.26	0.02	0.24	0.02	0.24	0.06	0.27
Observations	825	825	900	900	900	900	825	825
Countries	55	55	60	60	60	60	55	55

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The sample includes up to 60 economies at annual frequency from 2001 to 2016. "Prob'ties" (Probabilities) corresponds to the regime probabilities estimated in Section 2.3; "Inflow Restr." (Inflow Restrictions) is a measure of capital controls; "CCyB" (Counter-Cyclical Capital Buffer) is a measure of the announced counter-cyclical capital buffer rate; "Flex. Ex. Rate" is an indicator variable for a flexible exchange rate regime. For more details on data and methodology, see 4.1. Heteroskedasticity-robust standard errors, clustered at the country level, are shown in parentheses.

Table 4: Robustness Checks for Policy Options

Dependent Variable (1)-(3): Probabilities	(1) Baseline	(2) Emerg. Mkts.	(3) Adv. Econs.	(4) Prob'ties, wins.	(5) Loadings	(6) Regimes	(7) Regimes, 0-1
L.Inflow Restr.	-0.6056***	-0.4710***	-0.9968	-0.6033***	-0.4782***	-0.6454***	-0.6034***
	(0.144)	(0.134)	(0.636)	(0.143)	(0.125)	(0.152)	(0.161)
L.CCyB	-0.3111***	-0.3732***	-0.2108***	-0.3093***	-0.3120***	-0.3291***	-0.2607**
	(0.075)	(0.128)	(0.061)	(0.073)	(0.068)	(0.083)	(0.120)
L.Flex. Ex. Rate	-0.1850***	-0.1189	-0.2121**	-0.1851***	-0.1671***	-0.1921***	-0.2055**
	(0.068)	(0.071)	(0.100)	(0.067)	(0.051)	(0.063)	(0.091)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	No	No	No
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.06	0.03	0.20	0.06	0.06	0.05	0.03
Observations	825	495	330	825	825	825	825
Countries	55	33	22	55	55	55	55

Note: Specification (1) presents the baseline specification—Specification (7) of Table 3—for comparison. Specifications (2) and (3) restrict the sample to advanced economies and emerging market economies, respectively. Specifications (4)-(7) repeat the baseline specification for alternative dependent variables. Specification (4): probabilities winsorized at the 10^{th} percentile on each side of the distribution; Specification (5): the underlying factor loadings; Specification (6): the regimes averaged to the annual frequency; Specification (7): the regimes, averaged to the annual frequency and rounded to 0 or 1 (binary variable). Heteroskedasticity-robust standard errors, clustered at the country level, are shown in parentheses. For additional details, see the notes to Table 3.

Table 5: Transmission Mechanism for Policy Options

Dependent Variable: Probabilities	(1) Full Sample	(2) High Std.	(3) High Unc.	(4) Full Sample	(5) High Std.	(6) High Unc.	(7) Full Sample	(8) High Std.	(9) High Unc.
L.Inflow Restr.	-0.2614	-0.7638*	0.6615						
	(0.327)	(0.387)	(0.589)						
L.Inflow Restr. × USD Exp.	-0.0073	0.0018	-0.0300**						
	(0.009)	(0.010)	(0.012)						
L.CCyB				-0.2004**	1.1249***	-0.3723***			
				(0.077)	(0.046)	(0.063)			
L.CCyB × USD Exp.				-0.0017*	-0.0237***	-0.0000			
				(0.001)	(0.001)	(0.001)			
L.Flex. Ex. Rate							0.0896	-0.0087	0.2377
							(0.108)	(0.107)	(0.259)
L.Flex. Ex. Rate × USD Exp.							-0.0024***	-0.0013*	-0.0051***
							(0.001)	(0.001)	(0.002)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	No	No	No	No	No
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.05	0.05	0.14	0.03	0.02	0.11	0.02	0.01	0.11
Observations	780	520	208	825	550	220	825	550	220
Countries	52	52	52	55	55	55	55	55	55

Note: "USD Exp." (US Dollar Exposure) is the average sum of each country's US dollar denominated assets and liabilities in percent of GDP over the period 1990 to 1999. Specifications (1), (4) and (7) present the results for the full sample. Specifications (2), (5) and (8) present the results for a sample where the annual standard deviation of the US shadow rate is above the sample average. Specifications (3), (6) and (9) present the results for a sample where US monetary policy uncertainty is above the sample average. Heteroskedasticity-robust standard errors, clustered at the country level, are shown in parentheses. For additional details, see the notes to Table 3.

A Appendix

A.1 Estimation of the Factor Model with Time-Varying Strength

We use regime-switching dynamics to model the time variation in the factor loadings, as described by the following equations,

$$Y_t = \Gamma_{S_t} F_t + \Omega_{S_t} e_t, \tag{8}$$

$$F_t = \Phi(L) F_{t-1} + u_t, \tag{9}$$

where $Y_t = (y_{1,t}, ..., y_{n,t})'$, and F_t contain the underlying q latent factors. The idiosyncratic components, $e_t = (e_{1,t}, ..., e_{n,t})'$, are assumed to be normally distributed, $e_t \sim N(0, I)$, and cross-sectionally uncorrelated, with Ω being a diagonal matrix, and $u_t \sim N(0, I)$. Hence, Equation (8) is the measurement equation of the state-space system and Equation (9) is its transition equation. When there is one factor, $q = 1$, we define it as $F_t = f_t$. In this case, the regime-dependent loadings and standard errors are given by $\Gamma_m = (\gamma_{1,m}, ..., \gamma_{n,m})'$, $\Omega_m = (\sigma_{1,m}, ..., \sigma_{n,m})'$, respectively, for $m = \{0, 1\}$. And the Markovian variables, and corresponding transition probabilities are collected in $\mathbf{S}_t = (S_{1,t}, ..., S_{n,t})'$, and $P = (p_{1,lm}, ..., p_{n,lm})'$, respectively.

Notice that in the case of two regimes, Equation (8) can be alternatively expressed as

$$Y_t = (\Gamma_0^* \odot (\mathbf{1} - \iota' \otimes \mathbf{S}_t) + \Gamma_1^* \odot (\iota' \otimes \mathbf{S}_t)) \odot F_t + (\Omega_0^* \odot (\mathbf{1} - \iota' \otimes \mathbf{S}_t) + \Omega_1^* \odot (\iota' \otimes \mathbf{S}_t)) \odot e_t, \tag{10}$$

where ι is a vector of ones of size q, $\mathbf{1}$ is a $n \times q$ matrix of ones, $\odot$ represents the Hadamard product, $\otimes$ represents the Kronecker product, and the matrices of regime-dependent loadings and standard errors are defined as

$$\Gamma_0^* = \begin{bmatrix} \gamma_{1,0} \\ \gamma_{2,0} \\ \vdots \\ \gamma_{n,0} \end{bmatrix}, \Gamma_1^* = \begin{bmatrix} \gamma_{1,0} + \gamma_{1,1} \\ \gamma_{2,0} + \gamma_{2,1} \\ \vdots \\ \gamma_{n,0} + \gamma_{n,1} \end{bmatrix}, \Omega_0^* = \begin{bmatrix} \sigma_{1,0} & & & [\mathbf{0}] \\ & \sigma_{2,0} & & \\ & & \ddots & \\ [\mathbf{0}] & & & \sigma_{n,0} \end{bmatrix}, \Omega_1^* = \begin{bmatrix} \sigma_{1,1} & & & [\mathbf{0}] \\ & \sigma_{2,1} & & \\ & & \ddots & \\ [\mathbf{0}] & & & \sigma_{n,1} \end{bmatrix}.$$

The approach to estimate the model (9)-(10) relies on a multi-move Gibbs sampling procedure, where (i) the parameters, $\theta = \{\Gamma_0, \Gamma_1, \Omega_0, \Omega_1, \Phi, P\}$, (ii) the Markov-switching variables, $\tilde{S}_T = \{\mathbf{S}_t\}_{t=1}^T$, and (iii) the factors, $\tilde{F}_T = \{F_t\}_{t=1}^T$, are treated as random variables given the data in $\tilde{y}_T = \{Y_t\}_{t=1}^T$. The algorithm used to approximate the corresponding posterior distributions is given by the following steps:

Step 1: Generate $\tilde{S}_T$ conditional on $\tilde{F}_T$ and θ, and $\tilde{y}_T$.

Step 2: Generate P conditional on $\tilde{S}_T$ and $\tilde{y}_T$.

Step 3: Generate Γ_0, Γ_1 conditional on Ω_0, Ω_1, $\tilde{S}_T$, $\tilde{F}_T$ and $\tilde{y}_T$.

Step 4: Generate Ω_0, Ω_1 conditional on Γ_0, Γ_1, $\tilde{S}_T$, $\tilde{F}_T$ and $\tilde{y}_T$.

Step 5: Generate Φ conditional on $\tilde{F}_T$, and $\tilde{y}_T$.

Step 6: Generate $\tilde{F}_T$ conditional on $\theta, \tilde{S}_T$ and $\tilde{y}_T$.

Steps 1 through 6 can be iterated $M^* + M$ times, where M is large enough to ensure that the Gibbs sampler has converged. For our empirical application, we use a burn-in period of $M = 2,000$ iterations to converge to the ergodic distribution, and run $M^* = 8,000$ additional iterations. To assess convergence, we examine the recursive means of the retained draws. Recursive means are relatively constant, suggesting evidence in favor of convergence.

From Equation (10) it can be noticed that since the covariance matrix Ω is diagonal, steps 1 to 4 can be straightforwardly performed by sampling, one subequation at a time, draws of the parameters associated to univariate Markov-switching regressions following the approach of Kim and Nelson (1999). Next, conditional on the factor, $\tilde{F}_T$, step 5 can be performed using a standard Gibbs sampling approach. Also, conditional on the configuration of states, or dummies, the model becomes a linear state-space and the Carter and Kohn (1994) algorithm can be readily applied to conduct inference on the factor F_t. This is an important feature of the algorithm, since it greatly simplifies the estimation of the model by dealing with the proliferation of states in an efficient manner. For further details about the estimation algorithm, see Guérin and Leiva-León (2019).

Regarding the priors distributions employed, for the regime-switching factor loadings, we use a Normal prior, $\lambda_i \sim N(\underline{\lambda}, \underline{V}_\lambda)$, with $\underline{\lambda} = (\lambda_{low}, \lambda_{high})'$, $\underline{V}_\lambda = I_2/c$, and where $\lambda_{low} = 0.1$, and $\lambda_{high} = 1$. We use an inverse Gamma distribution as prior for the variances $\sigma_{i0}^2 \sim IG(\underline{v}_0, \underline{s})$, with $\underline{v} = 10$ and $\underline{s}_0 = (\underline{v} - 1) \times \lambda_{high}$, and $\sigma_{i1}^2 \sim IG(\underline{v}_1, \underline{s})$, with $\underline{s}_1 = (\underline{v} - 1) \times \lambda_{low}$. For the autoregressive coefficients, a Normal prior is used, $\Phi \sim N(0, I_q)$. And for the transition probabilities associated to the i-th state variable, we use Beta distributions as conjugate priors, $p_{i,00} \sim Be(u_{i,11}, u_{i,10})$, $p_{i,11} \sim Be(u_{i,00}, u_{i,01})$, with the hyperparameters given by $u_{i,01} = 0.1/c$, $u_{i,00} = 9.9/c$, $u_{i,10} = 0.1/c$ and $u_{i,11} = 9.9/c$, for $i = 1, 2, ..., n$, where $c = 100$ denotes a scaling factor, which is used to ensure regimes with relatively high persistence in an environment involving data at the weekly frequency.

A.2 The Unobserved Component (UC) Model

The relationships described in Section 3, regarding the decomposition of inflation, can be expressed with the following equations:

$$\begin{aligned}
\pi_t &= \pi_t^{trend} + \pi_t^{gap}, &(11)\\
\pi_t^{trend} &= \pi_{t-1}^{drift} + \pi_{t-1}^{trend} + \epsilon_{\pi,t}^{trend}, &(12)\\
\pi_t^{drift} &= \pi_{t-1}^{drift} + \epsilon_{\pi,t}^{drift}, &(13)\\
\pi_t^{gap} &= \phi_1 \pi_{t-1}^{gap} + \phi_2 \pi_{t-2}^{gap} + \epsilon_{\pi,t}^{gap}, &(14)
\end{aligned}$$

where π_t is the observed inflation rate, while π_t^{trend} and π_t^{gap} denote the corresponding trend and cyclical components, respectively. In addition, the trend component is assumed to contain a drift, π_t^{drift}, which evolves according to a random walk. This feature provides enough flexibility to the framework for capturing the time trends in hyperinflation episodes. The model is estimated with Bayesian methods by employing the Gibbs sampler, following Kim and Nelson (1999).

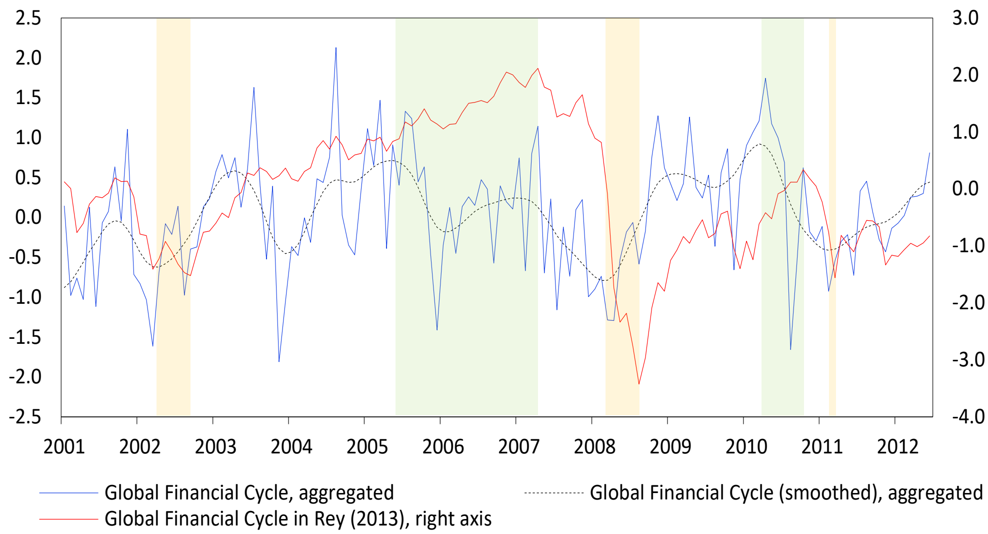
A.3 Additional Tables and Figures (ONLINE APPENDIX)

Table A1: Summary Statistics for Policy Options Analysis

Variable	**Obs.**	**Mean**	**Std.**	**Min.**	**Max.**
Dependent Variables:					
Prob'ties	825	0.58	0.37	0.00	1.00
Prob'ties, wins.	825	0.58	0.37	0.02	1.00
Loadings	825	0.68	0.38	-0.23	1.56
Regimes	825	0.58	0.40	0.00	1.00
Regimes, 0-1	825	0.59	0.49	0.00	1.00
Explanatory Variables:					
Inflow Restr.	825	0.32	0.30	0.00	1.00
CCyB	825	0.01	0.13	0.00	2.00
Flex. Ex. Rate	825	0.11	0.31	0.00	1.00
USD Exp.	780	59.69	43.68	23.79	181.66
US SSR, Std.	825	0.55	0.31	0.10	1.05
US MP Uncertainty	825	106.08	28.38	54.86	174.36
Rule of Law	825	0.64	0.95	-1.14	2.10
Pol. Stab. and Viol.	825	0.19	0.95	-2.81	1.76

Note: The table reports the summary statistics for the analysis of policy options in Section 4.

Figure A1: Comparison of the Global Financial Cycle to the Literature

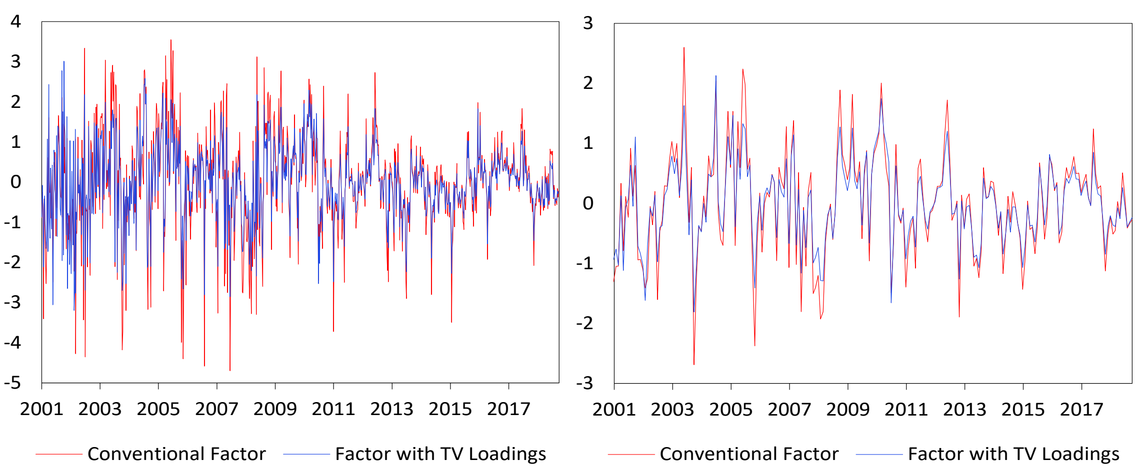


Note: The figure compares the unsmoothed and the smoothed version of the global financial cycle (common factor) obtained from our regime-switching dynamic factor model with time-varying (TV) loadings (i.e., the same global financial cycle measures as shown in Panel (a) of Figure 1 in this paper), aggregated to monthly frequency, to the original global financial cycle measure used in Rey (2013). The shaded areas represent the timing differences between the turning points of our smoothed global financial cycle (dashed black line) and the original global financial cycle measure from Rey (2013) (red solid line). Trough comparisons are shown in yellow and peak comparisons are shown in green. Data for the global financial cycle in Rey (2013) has been obtained from `http://silviamirandaagrippino.com/code-data` and corresponds to the series "Global Factor Paper Version 1990:2012, standardized."

Figure A2: Comparison of the Global Financial Cycle across Different Factor Models

(a) Comparison at Weekly Frequency

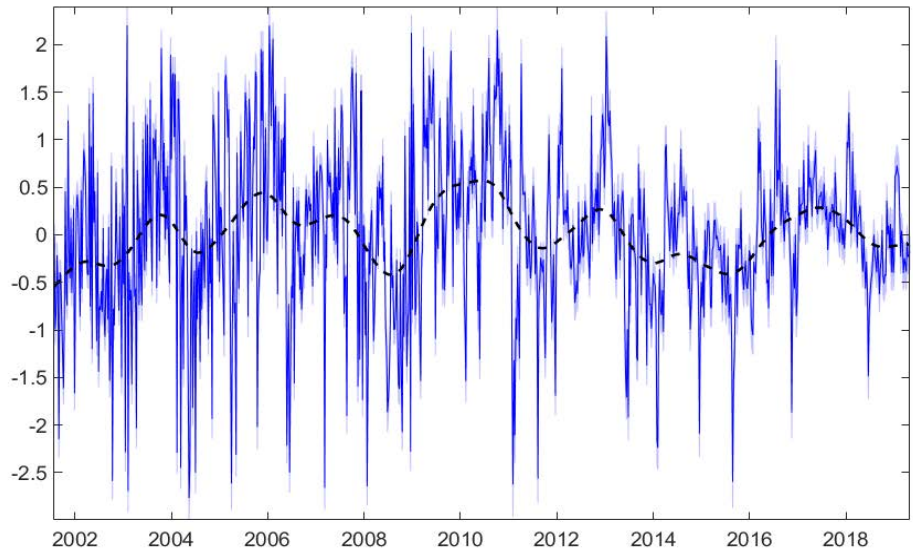
(b) Comparison at Monthly Frequency



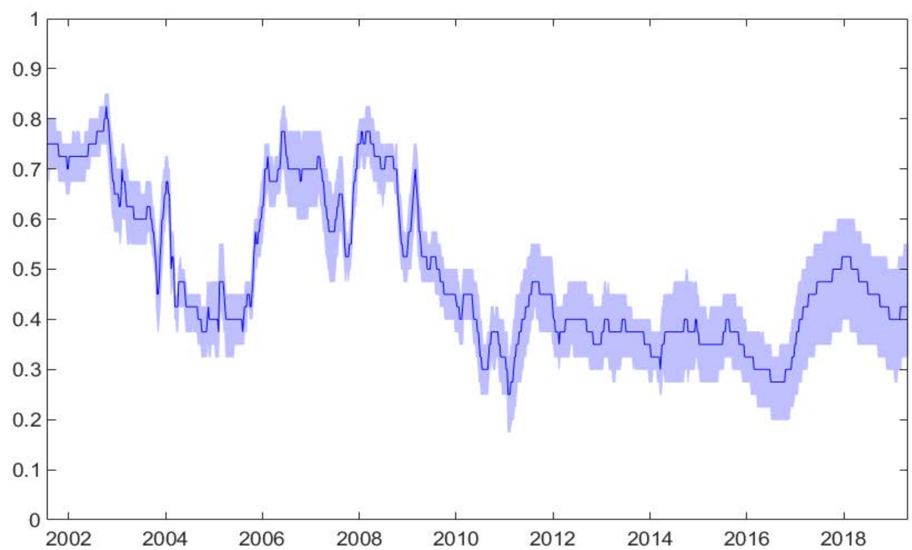
Note: Panels (a) and (b) compare the global financial cycle (common factor) obtained from our regime-switching dynamic factor model with time-varying (TV) loadings (i.e., the same global financial cycle as shown in Panel (a) of Figure 1 in this paper) to a global financial cycle obtained from a conventional dynamic factor model with constant factor loadings—both computed on the same data set. Panel (a) displays the results at weekly frequency, as obtained from the models. Panel (b) presents the same results aggregated to monthly frequency for an easier comparison.

Figure A3: The Global Financial Cycle – Robustness with a Smaller European Sample

(a) The Global Financial Cycle (Common Factor)



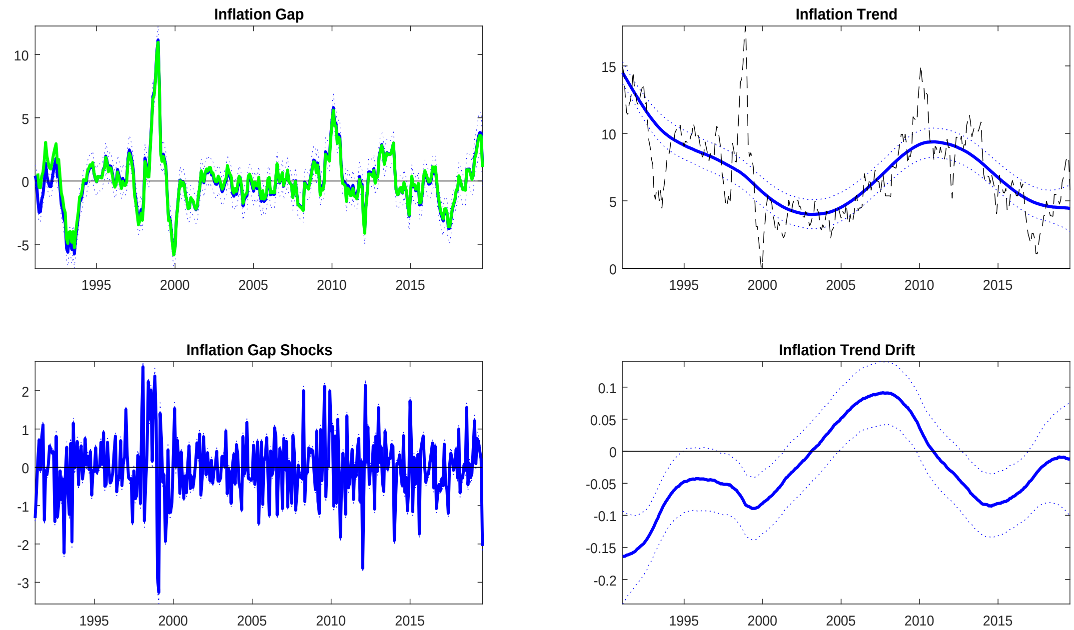
(b) Strength of the Global Financial Cycle



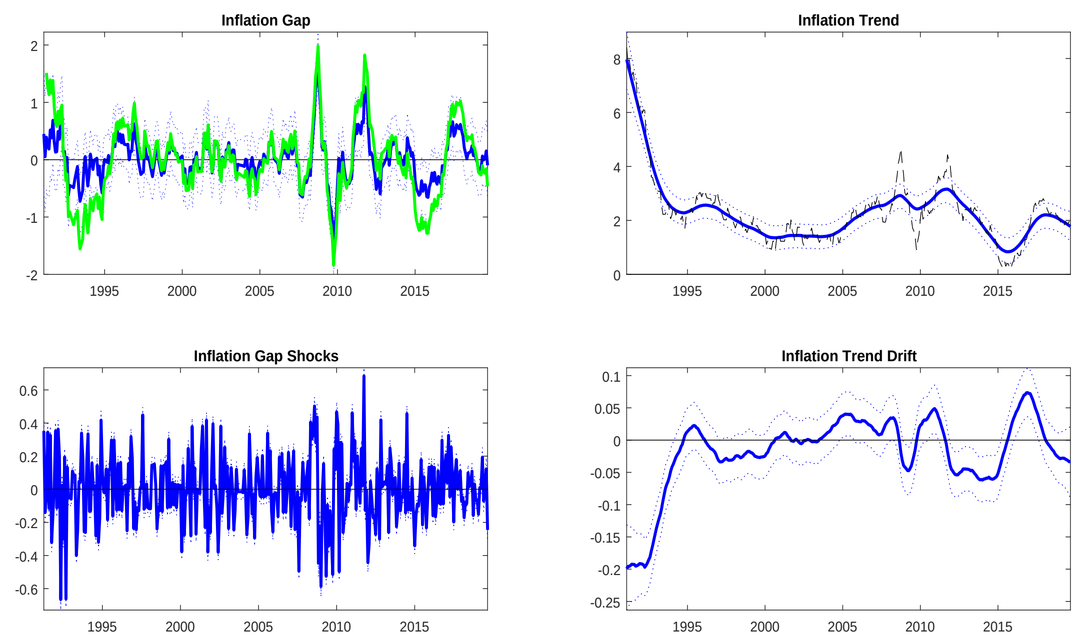
Note: This figure corresponds to Figure 1 but relies on a smaller sample that excludes all European countries except for France, Germany, Italy, Spain, and the United Kingdom. Panel (a) plots the common factor (blue solid line) together with a smoothed version of the common factor (black dashed line). Panel (b) plots the strength of the common factor, where the solid blue line represents the median and the shaded area the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles of the posterior distribution.

Figure A4: Extraction of Inflation Gap Shocks in India and the United Kingdom

(a) India



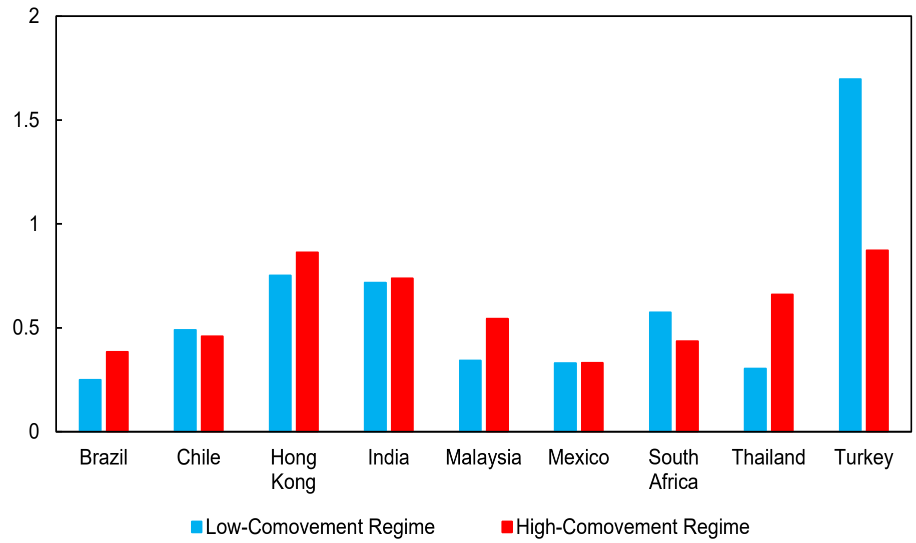
(b) United Kingdom



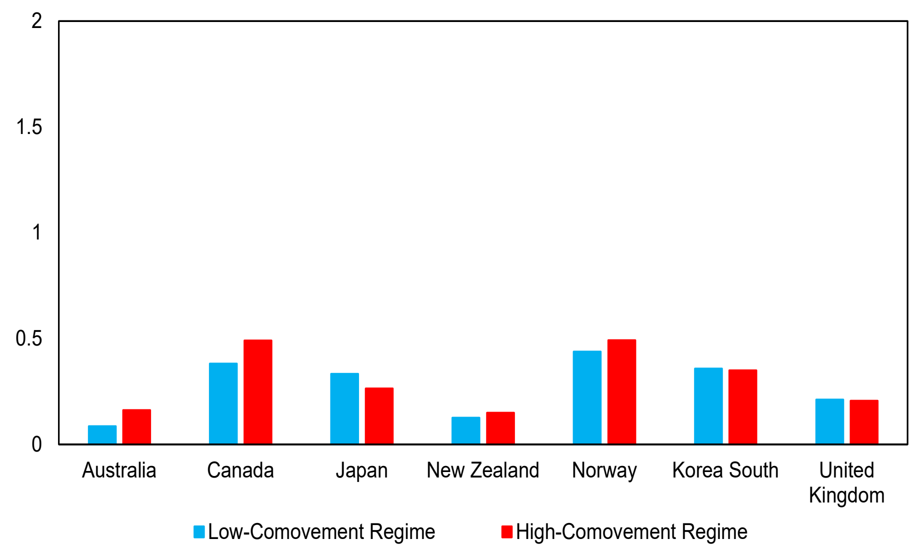
Note: Panels (a) and (b) plot the estimates of the inflation gap shocks ($\epsilon^{gap}_{\pi,t}$) of India and the United Kingdom, respectively. The estimates are obtained using the unobserved components model described in Equations (12)-(14) of Appendix A.2. The panels also include information on the inflation gap (π^{gap}_t), the inflation trend (π^{trend}_t), and the inflation trend drift (π^{drift}_t). While the solid blue lines denote the median of the posterior distribution, the dotted blue lines denote the distribution's 16$^{\text{th}}$ and 84$^{\text{th}}$ percentiles. The dashed black lines in the top-right plots display the annual inflation rates. The solid green lines in the top-left plots show the inflation gap obtained with an HP-filter for comparison.

Figure A5: Comparison of Inflation Gap Shocks across the Two Regimes

(a) Emerging Market Sample



(b) Advanced Economy Sample



Note: This figure presents the standard deviations of inflation gap shocks in the low- and in the high-comovement regime for each sample country. Panel (a) displays the standard deviations for the countries included in the emerging market economy sample and Panel (b) for those included in the small open advanced economy sample.