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THE NATURAL LEVEL OF CAPITAL FLOWS

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ABSTRACT

We put forward a theory-based time-varying supply-side measure of the natural level of capital flows, KF*, and construct it for 184 countries. Empirical features of KF*are impressive. For the subset of countries that have quarterly time series data of capital flows, we show that KF* is a level to which flows converge in the medium term; greatly improves our ability to model notoriously volatile capital flows; performs well against plausible filtering techniques; and helps predict 6-quarters ahead sudden stop episodes.

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1. Introduction

Unobservable trends in the normal, natural or desired level of key economic indicators—so-called stars—help policymakers see through the noise of period-to-period fluctuations (McDermott 2017; Powell 2018). For example, the natural rate of interest (r^*), the natural rate of unemployment (u^*), core inflation (π^*) and the level of potential GDP (y^*) all guide policy. Each of these stars is an unobserved, estimated construct with definitions that vary across researchers. Nonetheless, by providing a real-time measure against which related macroeconomic variables can be assessed, each aids in our understanding of the economy.

Capital flows are notoriously volatile. See, as examples, the quarterly gross portfolio inflows received by Japan, United Kingdom, Canada, South Africa, Brazil, and Indonesia over the past two decades (Figure 1). While much of the empirical capital flows literature attempts to model the quarter-to-quarter variation depicted in Figure 1—with strikingly little success, as pointed out by Cerutti, Claessens and Rose (2019)—we put forward that it would be useful to have a measure that approximates where one might expect the level of flows to converge to over a medium-term horizon. Such a measure could help policymakers in recipient countries see through the high frequency noise by providing a good gauge of the 'underlying' flows that are expected to persist.

In this paper we introduce such a measure: the natural level of capital flows. We argue that the natural level of capital flows, which we denote KF^*, provides countries with a benchmark that helps gauge the amount of *gross portfolio inflows* they can expect to receive. Our measure of KF^*, which builds on Burger, Warnock and Warnock (2018) and the theory of Tille and van Wincoop (2010) and Devereux and Sutherland (2011), is an easy-to-construct slow-moving supply-side measure that we create for 184 countries starting as early as 2000.[1] Actual flows deviate from KF^*,

[1] KF* is a supply-side measure in that it is derived from the supply of rest-of-world savings.

just as actual GDP differs from potential GDP, headline inflation from core inflation, and the unemployment rate from u*.

For the natural level of capital flows to be a useful measure, these deviations of actual flows from KF* must be informative. And they are. Specifically, tests following the Cogley (2002) assessment of core inflation measures indicate that deviations of actual flows from KF* are transitory, as portfolio inflows, especially for emerging market economies (EMEs) but also for most of the advanced economies (AEs), converge to KF* over a 1-to-2-year horizon. Further, we find the reversion of portfolio flows to KF* can explain roughly 40% of the medium-run variation of flows, which is far more than what is explained by traditional push and pull factors used in the empirical capital flows literature. We also assess other plausible methods and conclude that along many dimensions KF* performs best (although what emerges is that there is some natural level and many plausible measures of it). Finally, we use the current deviation of flows from KF* to predict future sudden stops (6 quarters ahead); KF* proves to be an important predictor of sudden stops and, unlike some other measures, retains its informativeness even in the post-GFC period. The 6-quarters-ahead predictive power is impressive, especially when combined with strong global GDP growth: When both the gap of actual flows from KF* and global growth are one standard deviation above their mean (that is, gap of 3.6% of GDP and global growth of 4.2%) the probability of a sudden stop in six quarters is 40.5%.

The paper proceeds as follows. The next section briefly reviews well-known stars in macroeconomics. Section 3 goes through the many choices one must make when constructing a measure of the natural level of capital flows. Section 4 presents our measure of KF* and tests whether flows converge to it over the medium term. Section 5 briefly compares our measure to various univariate filtering techniques. Section 6 provides a application: Using the gap between actual flows and KF* to predict sudden stops over the medium term. Section 7 concludes.

2. From Macroeconomic Stars to KF*

Before introducing KF*, we briefly review some famous stars in macroeconomics: r*, u*, y* and Π*. While no star is exactly like another, and KF* is not precisely analogous to any particular star, themes from the well-established literatures inform our design decisions.

The notion of a natural rate of interest, r*, goes back to Wicksell's 1898 *Geldzins und Guterpreise*. In the English translation, the natural rate of interest on capital is defined as "a certain rate of interest on loans which is neutral in respect to commodity prices, and tends neither to raise nor to lower them" (Wicksell 1936, page 102). More recently, Williams (2003) defines the natural rate as the real fed funds rate consistent with real GDP equaling potential GDP in the absence of transitory demand shocks, while Laubach and Williams (2003) define it as the real short-term interest rate consistent with output equaling its natural rate and stable inflation. Since definitions vary, methods to measure r* vary too. Orphanides and Williams (2002) note that r* likely varies with trend income growth, fiscal policy and household preferences, themselves not directly observed. Staiger, Stock, and Watson (1997) stress that because the "true" model is unknown there is additional uncertainty around natural rate estimates. In practice, one accepted method (see, for example, Holston, Laubach and Williams 2017) starts from a New Keynesian framework of a Phillips curve and an intertemporal IS curve to find, using Kalman filtering, the real rate that is consistent with zero output gap and stable inflation. As with any latent variable that is a function of other unobservable factors, there are many ways to estimate r* and estimates vary across researchers.

Exact definitions of the natural rate of unemployment (u*) also vary. It can be understood in deceptively simple terms: it is frictional plus structural unemployment, or the actual unemployment rate stripped of cyclical unemployment. It is also often defined as the unemployment rate that, absent supply shocks, is consistent with stable inflation. Efforts to estimate the natural rate of unemployment have used detailed labor market data (see among many others Blanchard and Diamond (1989) and Davis, Faberman, and Haltiwanger (2013)); reduced-form macro models (Staiger, Stock, and Watson (1997); and DSGE models (e.g., Gali, Smets, and Wouters (2012)). Again, with different definitions and fundamentally different approaches that depend on unobservables, there are many ways to estimate u^*.[2]

Another star is potential GDP. While actual GDP is usually measured from the demand side of the economy by summing up spending, potential GDP (y^*)is often estimated from the supply side by using a production function approach that combines the inputs of production—labor and capital—along with total factor productivity.[3] For example, the CBO's estimate of U.S. potential GDP relies on the Solow growth model, creating potential output by focusing on potential inputs and their productivity (Shackleton (2018)). Shocks and frictions can push actual GDP away from potential GDP, but over time actual comes back to potential. A caveat that emerges from the literature on potential GDP is that most existing measures are overly sensitive to transitory shocks and thus lose some usefulness as a structural measure (Coibon, Gorodnichenko, and Ulate forthcoming, henceforth Coibion, et al.).

The case of core inflation (Π^*) is best understood from the perspective of an inflation targeting central bank that wishes to extract the persistent level of inflation from its observation of a volatile headline inflation figure.[4] Ideally, the measure of core inflation eliminates temporary price fluctuations and reveals more fundamental trends in medium-term inflation. There are many ways of estimating core inflation. Some are mechanical, such as the BLS practice of excluding food and energy from the CPI. Others, such as the Bryan and Cecchetti (1993) median core and trimmed

[2] See Crump, Eusepi, Giannoni and Sahin (2019) for an attempt at unifying the u* literature.
[3] See Coibion, Gorodnichenko, and Ulate (forthcoming) for much more on various measures of potential GDP, including those based on filtering techniques.
[4] Note while McDermott (2017) and others refer to core inflation as Π^*, elsewhere in the literature Π^* refers to the policymaker's inflation goal or target.

mean measures, build on theoretical models and at the same time remain quite practical. And still others are purely statistical (for example, the filtering methodology of Cogley (2002) or Stock and Watson (2016)).

This brief review of the literature on stars highlights a number of important points that are relevant for our construction of KF*. First, we think that a star should be simple, intuitive, and grounded in theory. For example, one can (and many do) use univariate filtering to construct an estimate of y*. However, Coibion, et al. emphasize the importance of developing an estimate that is consistent with theory, in part because many statistical measures have a difficult time distinguishing between shorter-term volatility and more fundamental structural changes (and this might be especially true toward the end of the sample). We develop a theory-based supply side (specifically, based on the supply of rest-of-world savings) estimate of the natural level of portfolio flows that is by construction largely shielded from transitory shocks. Second, the literature stresses that there is not necessarily one unique theory that is best suited for constructing any particular star. Stars are often derived from competing theories. We put forward one theory—that of Tille and van Wincoop (2010)—to support the construction of our measure of KF*, but there could be others (an international CAPM, for example). Third, the literature on core inflation makes the point that headline measures can contain a great deal of high frequency noise that makes it difficult for policymakers to discern signals. This suggests a star should provide a time-series reference to pin down low-frequency "fundamental" movements, so that current deviations from the star help forecast a medium-term path. Similar to headline inflation, capital flows have a lot of high frequency noise (Figure 1). Indeed, Meng and van Wincoop (2018) note that "[p]ortfolio flows can be quite volatile at the quarterly frequency, which makes for ugly graphs." The volatility of quarterly flows makes not only for ugly graphs; it makes it difficult to discern what level of flows will likely persist going forward. For our KF* to be successful, deviations from it should help forecast flows over the medium-term.

3. The Theory…and Operationalizing the Theory

3.1 The Underlying Theory

Tille and van Wincoop (2010) (see also Devereux and Sutherland 2011) bring portfolio choice into a DSGE open economy model. The model, with finitely lived agents, is of two countries, although Meng and van Wincoop (2018) show that the insights extend to a multi-country world. The model is simple in many respects, with production driven by an exogenous AR(1) productivity process (which is the only shock in the model), output being paid out as dividends and labor income, consumption home bias a la Warnock (2003), and incomplete financial markets (there are iceberg costs to investing in foreign equity). The model produces a home bias in portfolios, and the only choice agents must make is how to allocate their wealth between home and foreign equities in order to maximize wealth. In forming their optimal portfolio, investors equalize the expected discounted return on each asset.

The model leads to two types of flows. Portfolio growth flows are simply the gross flows that would occur if new funds are allocated according to zero-order portfolio weights.[5] A positive productivity shock leads to increased savings that are deployed mostly at home (there is a portfolio home bias) but also abroad. If the productivity shock is persistent, these so-called portfolio growth flows are also persistent. The other type of flows are reallocation flows due to time variation in expected returns and risk. Time variation in expected returns impacts cross-border flows only through the effect of savings, as new home savings is invested mainly at home, pushing up home

[5] The notion of portfolio growth flows appeared first, in a net flow setting, in Kraay and Ventura (2000, 2003).

asset prices and requiring a decrease in expected returns (and, thus, capital outflows) to clear the asset markets. Time variation in second moments (risk) impact optimal portfolio weights through changes in two hedge components: the covariance between excess returns (of home relative to foreign equities) and the real exchange rate and the covariance between excess returns and future expected portfolio returns. It is the change in these covariances that generate reallocation flows so, after a potentially large initial shock, the impact on flows quickly dissipates as future changes become a function of the persistent AR(1) process.

Zero-order portfolio growth flows, essentially the flows that would occur when the volatility of shocks becomes arbitrarily small, are persistent, getting their persistence from the persistence of underlying real-side shocks and hence savings.[6] Reallocation flows can be substantial (and volatile) but, arising primarily from time variation in second moments, ephemeral. The question we address in this paper is: Do zero-order flows provide an approximation of the level of flows likely to persist in the medium-term? Or simply, do portfolio growth flows represent a natural level of capital flows? But first a number of decisions must be made to get from theory to practice.

3.2 Operationalizing the Theory

The Tille and van Wincoop (2010) notion of portfolio growth flows is intuitively appealing, as the flow of new savings is precisely the amount of *new* funds available for foreign (or home) investment. Put another way, new savings is an important source of funds that would be potentially invested, some at home and some abroad. Portfolio growth flows are simply the gross flows that would occur if those new funds are allocated according to zero-order portfolio weights. Intuitively

[6] Ahmed et al. (2017) and Meng and van Wincoop (2018) apply insights from Tille and van Wincoop (2010) to U.S. investors' flows to foreign markets and show that portfolio growth flows can be a substantial component of overall flows.

appealing, but a number of decisions need to be made to proceed from the theory to empirical applications.

3.2.1 Zero-order portfolio weights

What exactly are the zero-order portfolio weights as of time *t*? Theory seems to permit many interpretations. In Devereux and Sutherland (2011, p. 350), zero-order portfolio holdings are "the equilibrium for portfolio holdings in a world with an arbitrarily small amount of stochastic noise". Similarly, in Tille and van Wincoop (2010) the zero-order component is the value when the volatility of shocks becomes arbitrarily small. In these and other papers optimal portfolio weights are a function of things like financial frictions and hedge terms such as the covariance of returns with the real exchange rate, consumption, or future expected portfolio returns. A problem with operationalizing zero-order portfolio weights is that it generally requires assuming substantial frictions (for which there is no good measure) to get close to the sizeable home bias observed in actual data.

In practical applications of the Tille and van Wincoop (2010) model, researchers resort to using actual (lagged) portfolio weights. For example, Meng and van Wincoop (2018) employ a simple one-quarter lag to construct zero-order weights. Burger, Warnock and Warnock (2018) take a longer view and use a trailing 5-year moving average of portfolio weights (and also explore 1-year and 3-year lagged moving averages). If one wants changes in markets to enter KF* quickly, a short lag for weights would be appropriate. We prefer our measure to be less sensitive to current conditions—on this point in a potential GDP setting see Coibion, et al.—and thus use a lagging 5-year moving average of actual weights in forming KF*.[7]

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[7] Note that we are not applying a filter to flows themselves, just to portfolio weights. That is akin to the CBO's approach to estimating potential GDP, as it applies a filter to the capital share rather than allowing the volatility in the capital-share series to create volatile estimates of potential GDP (Shackleton 2018).

3.2.2 Bilateral or ROW Approach?

Another choice is whether to use a bilateral or rest-of-the-world (ROW) approach. The bilateral approach utilizes data on the new amount of savings in each origin country o as well as on each origin country's portfolio weights in each destination country d. Specifically, denote the period t zero-order weight (however constructed) of destination country d in origin country o's portfolio as $\omega_{od,t}$.

Portfolio growth gross capital flows from o to d in period t, denoted by $KF^*_{od,t}$, are the new savings generated in o in the current period ($S_{o,t}$) allocated according to its zero-order portfolio weights ($\omega_{od,t}$). That is,

$$KF^*_{od,t} = \omega_{od,t} S_{o,t} \qquad (1)$$

And summing across all O origin countries provides destination country d's total benchmark inflows, we have

$$KF^*_{d,t} = \sum_{o=1}^{o=O} \omega_{od,t} S_{o,t} \qquad (\textit{for } o \neq d) \qquad (2)$$

In (1) and (2) $\omega_{od,t}$, the bilateral portfolio weight between o and d (specifically, the weight of d in o's portfolio), can be formed using holdings data from the IMF's CPIS, which reports bilateral portfolio (bond and equity) holdings of about 60-80 origin countries starting in 2001.

The alternative is to use aggregate ROW data to estimate country d's total benchmark inflows, where the weights are $\omega_{ROW,d,t}$, or the weight of destination country d in ROW portfolios:

$$KF^{*}_{d,t} = \omega_{ROW,d,t} S_{ROW,t} \quad (3)$$

Portfolio weights in (3) can be formed using Lane and Milesi-Ferretti (2018) data on the stock of portfolio equity and portfolio debt liabilities, available annually for over 100 countries starting in roughly 1995.[8]

The bilateral approach, which attributes savings to origin countries according to each country's exposure to a destination country, requires high quality *bilateral* portfolio holdings data. Such data, even if the statistical authorities use best practices, is unfortunately confounded by the use of tax havens and more generally by any country whose residents tend to utilize third-country custodians and/or invest through third-country vehicles (such as Luxembourg-based mutual funds). This pushes us toward a ROW approach, which is both consistent with BOP capital flows data (which are also ROW) and is likely less sensitive to the use of third-country investment vehicles. In addition, we consider the euro area as a whole to alleviate, to the extent possible, its substantial inter-area financial center bias.[9]

3.2.3 How to Scale Portfolios?

Forming portfolio weights requires data on a scale factor. Taking a broad view, we scale by all financial assets, domestic and foreign. Specifically, to scale origin countries' portfolios, we use two complementary measures. One is a measure of household wealth at year end, which is available from 2000 to 2017 for 212 countries. This measure, used in (and created by) Davies, Lluberas, and

[8] The Lane and Milesi-Ferretti (2018) data start earlier than 1995, but prior to 1995 there is dramatically reduced country coverage (in particular for portfolio debt liabilities).
[9] See Warnock and Cleaver (2003) on the financial center bias in portfolio flows and Felettigh and Monti (2008) on the intra-eurozone bias.

Shorrocks (2018) is built wherever possible from household balance sheet data or household survey data (or, if those sources are not available, by estimation) and seems to align well with the notion of portfolio size in Tille and van Wincoop (2010) and Devereux and Sutherland (2011).

The other source for a scale factor is the country's stock of total financial assets (TFA), which is available from McKinsey Global Institute (MGI) for a wide range of countries from 1995-2016; see McKinsey Global Institute (2018) for a description of the data. Pulling primarily from publicly available sources, MGI calculates total financial assets as the sum of a country's equities, bonds and loans. To be sure, residents of other countries hold some of those equities, bonds, and loans, and the country's residents hold foreign assets. Thus, to create the size of a country's portfolio using MGI data, we add its net foreign assets to its TFA, effectively subtracting out foreigners' claims on the country's TFA and adding the country's claims on other countries' TFA.[10]

With the ROW approach (equation 3), we need a measure of ROW wealth, which is simply global wealth minus the country's wealth. Since we use a 5-year lagged weight, for our first data point (2000) we need data on ROW wealth starting in 1995. While the Davies et al. and MGI measures are quite similar—for the years both measures are available (2000-2016), the correlation is 0.985—the Davies et al. measure seems better aligned with the notion of portfolio size in the theory. So in practice we use the Davies et al. measure for the 2000 to 2017 period and, because we need a scale factor back to 1995, splice in the MGI data for 1995 to 1999.

3.2.4 Measures of ROW Savings

[10] For example, the ROW weight on Philippine equities equals the stock of Philippine portfolio equity liabilities (that is, ROW holdings of Philippine equities) divided by ROW wealth, whether wealth is from Davies et al. (in which case ROW household wealth is global wealth less the Philippine wealth) or MGI (ROW TFA is global financial assets less the sum of Philippine financial assets and Philippine net foreign assets).

There can be many concepts of savings within any particular country, but for savings (in billions of US$) across a wide range of origin countries we turn to the IMF WEO dataset and construct private savings as national savings rates less fiscal savings rates, multiplied by country-level nominal GDP to convert to US dollars.[11] Savings, then, in the ROW approach is just ROW savings (i.e., world savings minus the recipient country's savings).

3.2.5 China's Savings

One limitation of the ROW approach is that it assumes that all ROW savings are allocated in the same way across countries—specifically, according to ROW portfolio weights. China however differs in that while it creates a large portion of world savings (27% in 2015) it has comparatively little outbound international portfolio investment. This disconnect between the importance of China in world savings and its (limited) propensity to invest internationally necessitates excluding China from ROW savings and, for the seven reserve currency countries identified in IMF COFER data (US, UK, Eurozone, Japan, Switzerland, Australia, and Canada), from flows and ROW portfolio weights. While removing China from ROW savings is straightforward, removing its bond flows and bond holdings requires estimation. To do so we assume China's reserve holdings are distributed across countries as global reserves are distributed across currencies in the IMF COFER data (and we then equate countries with currencies). To construct implied China bond flows we then multiply this period's reserve accumulation by China by last period's IMF COFER currency weights. Similarly, implied China bond holdings is simply the stock of China's reserves multiplied by the COFER currency weights. We can construct this adjustment for our entire annual sample; for quarterly data the adjustment can be done starting in 2005 (when China began to report quarterly flow data, including reserve accumulation).

[11] In the WEO data, fiscal savings is the variable "General government net lending/borrowing".

3.2.6 Summary

To summarize, our measure of KF* relies on the theory of Tille and van Wincoop (2010) and Devereux and Sutherland (2011); uses a 5-year lagged moving average to approximate zero-order portfolio weights, the Davies et al. (2018) measure of household wealth for 2000 to 2017, spliced with MGI's data for 1995 to 1999, and private savings from the IMF WEO; is built from ROW data; and makes an adjustment to deal with the disconnect between China's savings (sizeable) and its outward portfolio investment (small).[12]

We made these decisions after careful consideration, but other choices are possible. Some choices might naturally be revisited in time as data quality improves (e.g., the bilateral holdings data might improve so as to make the bilateral approach a plausible alternative). Others, such as what theory to use, are more philosophical and so of course other researchers might make different choices.[13] That others will make different choices to construct a measure of the natural level of capital flows makes KF* much like other stars in macroeconomics such as u*, y*, Π*, and r*.

4. KF*

4.1 Descriptive Analysis

Based on the choices laid out in the previous section, we construct KF* for the period 2000 to 2018. The number of countries for which we can do this is limited primarily by Lane and Milesi-Ferretti (2018) data on portfolio liabilities; if a country has portfolio liabilities data, we can create its

[12] Note that KF* looks very much like a Bartik (1991) instrument, as used in different settings in Nakamura and Steinsson (2014), among many others. As current ROW savings is exogenous to the recipient country and the lagged zero-order weights are pre-determined, KF* could prove to be a useful instrument when assessing the impact of capital flows on various indicators of interest.

[13] For example, one might use the theory of Mendoza et al. (2009) or an international CAPM to form weights, although the well-known and pervasive home bias in portfolios would likely limit the practical usefulness of the resulting measures.

KF* even if the country does not itself publish flow data.[14] Ninety-one countries have portfolio liabilities data starting in 1995; for these we can form a five-year lagged rest-of-the-world portfolio weight ($\omega_{ROW,d,t}$) starting in 2000 (i.e., the average weight from 1995 through 1999).[15] For another 90 countries we can form KF* beginning later. In all, we create KF* for 184 countries (see Table A1 in the Appendix). We also form a quarterly version of KF* by linearly interpolating between year-end values.[16]

We show annual KF* since 2000 by region in Figure 2. In each region KF* increases through 2011 and especially in the period starting in 2005. Examining the general trends in KF* highlights the importance of a theory-based measure. Based on the underlying theory, there can be two possible reasons for this increase in KF* (see equation 3): increased ROW private savings, which is largely common to all regions, or foreigners' increased weights on a region's stocks and bonds, which can vary substantially across regions. Indeed, global (excluding China) private savings increased 8.4% per year over the period from 2005 to 2011, so all else equal each region should have experienced a commensurate increase in KF*. But all else was not equal. In particular, the weight of foreign bonds and equities in investors' portfolios increased strongly as there was a general increase in financial globalization (a reduction in home bias). So, for example, EME Asia's KF* increased 30% per year between 2005 and 2011, as the 8.4% annual increase in ROW savings combined with a tripling of the weight of its equities and bonds in foreigners' portfolios. Other regions did not

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[14] Note that once the decision is made to use the ROW approach, KF* can be created even for small countries that do not have savings or wealth data, as long as one is willing to assume their savings or wealth are negligible relative to ROW savings or wealth.

[15] We also create year 2000 lagged weights for countries for which Lane and Milesi-Ferretti portfolio liabilities data begin after 1995 but by 1999; for these (the eurozone and five other countries) the weight in the year 2000 uses a shorter lag. We only implement this fix for countries that have year 2000 flow data.

[16] We are limited in ways to create quarterly values of our measure. For many countries positions data are only available annually, and even quarterly nominal GDP (which would allow us to get closer to a quarterly savings series) is available for surprisingly few countries. That said, we are not overly concerned by this as our measure is slow moving.

experience the same magnitude of change, but all had increased KF* over the 2005-2011 period, with annual increases of 14% in Latin America, 21% in EME Europe, 23% in Africa, 17% in the euro area, 11% in the US, and 14% in AE Other.

After 2011 things changed. Global (excluding China) private savings has been essentially flat since 2011—this is due to relatively stagnant global (excluding China) GDP rather than changes in savings rates—so any increase in KF* would have to come from increased foreign weights. Foreign weights did continue to increase in all regions except the euro area (where the weights were flat from 2011 to 2017) and CIS (where the weights fell). Thus, in all regions annual increases in KF* slowed over the period 2011-2018 (compared to 2005-2011) because the tailwind of strong increases in ROW savings was removed. Most regions still experienced increases in KF* because of the continued internationalization of portfolios (i.e., foreign weights increased), but the increases have slowed.

Quarterly gross portfolio inflows and KF* are plotted in Figure 3 for the same six countries from Figure 1.[17] To be a useful measure, KF*—built, recall, from the supply of ROW funds—must help us see through the noise of the volatile quarter-to-quarter flows. For many countries, the graphs clearly show actual flows fluctuating around KF*. There are some persistent deviations, for example: Brazilian inflows have been below the natural level for the past three years (Figure 3), and for Switzerland there appears to be a fundamental disconnect between KF* and actual flows (Figure A1).[18] But for most countries KF* appears to be a level around which volatile quarterly flows fluctuate. We turn next to more formal analysis.

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[17] See the Appendix for similar graphs for all 59 countries for which we have quarterly flow data in Figure A1.

[18] The Switzerland disconnect owes to a stark disconnect in its reported data on positions and flows, specifically for equities. Reported portfolio equity inflows have been slightly negative over the past two decades, whereas the reported positions have increased by about $700 billion. While valuation adjustments can explain part of the difference, using reasonably returns measures (e.g., the MSCI Switzerland index) there is still a gap of over $200 billion. Careful analysis in Stoffels and Tille (2018) suggests this gap—which in their

4.2 Predicting Flows over the Medium-Term

Identifying the natural level of portfolio flows is analogous to the objective of an inflation targeting central bank looking for a way to extract the "true" inflation signal from the noise of period-to-period inflation fluctuations. Cogley (2002) noted that there are many candidate methods to reveal the persistent component of inflation, including measures of core inflation formed by excluding some volatile components and various filtering methods. In each case the goal, as specified by Bryan and Cecchitti (1994), is to eliminate transient price variation and identify "the component of price changes that is expected to persist over medium-run horizons of several years."

In our setting, a policymaker looking at volatile quarterly flows series (such as those in Figure 1) might want to gauge the persistent or natural level of flows that the country will receive in the next periods. For our measure of KF* to be of practical use, it should provide a reasonable approximation of where one should expect the level of portfolio flows to converge in the future:

$$KF_t^* = E[flows_{t+h}] \tag{4}$$

where E[.] is the expectations operator and h is the medium-run horizon over which flows are expected to converge to their natural level. Subtracting current flows from both sides of (4) yields

$$E[flows_{t+h}] - flows_t = -(flows_t - KF_t^*) \tag{5}$$

paper sums to US$224 billion from 2000 to 2017—is due to unreported flows. While $224 billion in additional flows would improve our KF* graph for Switzerland, because the gap is due to infrequent improvements in positions data there is no way to distribute it across particular time periods. So we keep Switzerland in our dataset as is and just note that there is a well-documented disconnect between Swiss reported flows and positions, and such a disconnect adversely impacts the relationship between KF* and flows (and this affects our AE results in the next section).

Equation (5), the capital flow equivalent of the Cogley (2002) analysis of inflation, states that if (4) holds then the difference between expected h-period ahead flows and current flows is the negative of today's gap between flows and KF^*. Following Cogley (2002), to assess whether our estimate of KF^* fulfills the objective in equations (4) and (5) we test the hypothesis that deviations of current flows from the natural level are inversely related to subsequent changes in flows. That is, we estimate:

$$flows_{t+h} - flows_t = \alpha_h + \beta_h(flows_t - KF_t^*) + \varepsilon_t \qquad (6)$$

Cogley noted that α_h should equal zero, else KF^* would be biased, but focused on β_h. If KF^* satisfies equations (4) and (5), we expect to estimate β_h=-1 in equation (6) for medium-run horizons. An estimate of β_h=-1 would suggest that the gap between current flows and KF^* represents the transient component of portfolio flows, and flows can be expected to converge to KF^* in h periods. For horizons of 1 to 12 quarters (h=1,…,12), we implement the Cogley (2002) test by estimating equation (6) separately for each country.[19]

Figure 4 (left column) presents box plots for the estimates of β_h from equation (6) for the 17 AEs and 30 EMEs that have portfolio flows and KF^* over the entire 2001Q1-2018Q4 sample. From left to right the box plots display β_h estimates for horizons of 1 to 12 quarters. The top and bottom of each box indicate the 75th and 25th percentile estimates of β_h, the line inside a box indicates the median, while the whiskers indicate upper/lower adjacent values (within 1.5 times the

[19] Note that the Cogley (2002) technique is used by some central banks to gauge the informativeness of various measures of core inflation. See, for example, the Kamber and Wong (2016) application on various inflation measures in New Zealand.

length of the box from the upper/lower quartile) and dots indicate outside values. For both the AE and EME subsamples we find β_h estimates are generally less than one in absolute value for short time horizons but approach -1 at intermediate horizons. For example, the median value for β_h is -0.88 at a 7-quarter horizon for AEs and -0.99 at a 9-quarter horizon for EMEs. Wald tests indicate failure to reject the null hypothesis of β_h=-1 for 12 of the 17 AEs at a 6-quarter horizon, and more impressively, we fail to reject the null of β_h=-1 for 25 of the 30 EMEs at a 9-quarter horizon.[20]

The tests suggest that, especially for EMEs, our KF* cuts through the noise of volatile quarterly flows and provides guidance for the level of portfolio inflows a country should expect to receive in one to two years. To be clear, KF* is also informative for next quarter's flows—for h=1 the median β_h is roughly -0.7 for both EMEs and AEs, suggesting deviations from KF* are typically short lived—but it is most informative for predicting one-to–two-year-ahead flows. The Cogley tests support the notion that over the medium-term portfolio flows converge to a natural level that is well approximated by KF*.

4.3 On the Explanatory Power of KF*

Cerutti, Claessens and Rose (2019) pushes the empirical capital flows literature to think about the amount of variation in flows explained by various measures, rather than just whether a particular variable is statistically significant, and at the same time notes (as others have) that the literature is not explaining much of the variation in flows. Indeed, the R^2 in a typical quarterly capital flows regression is quite low (roughly 0.10 and often even lower). On this we note that the gap between current flows and KF* explains a substantial portion of the variation in subsequent flows.

[20] Wald test results vary somewhat by horizon but we generally fail to reject β_h =-1 for 10-12 of the 17 AEs and 20-25 of the EMEs over intermediate horizons. Wald tests also fail to reject the null hypothesis of a_h=0 for the vast majority of AEs and EMEs.

The right column of Figure 4 displays box plots for the adjusted R^2 from equation (6) for the 17 AEs and 30 EMEs with complete data on KF* and flows. The median R^2 peaks at over 0.40 for a 7-quarter horizon in both the EME and AE samples.

Of course, the literature Cerutti et al. is speaking to is attempting to model the quarter-to-quarter variation in flows. While the goal of creating a measure of the natural level of capital flows is to help gauge what the level of flows will be in the *medium term*, even for a 1-quarter horizon the explanatory power of KF* is substantial, with median R^2 of 0.39 (for EMEs) and 0.32 (for AEs). This is not an artefact of our sample, as we show by conducting a similar exercise without KF* but with a few prominent push and pull factors. For push factors we include changes in VIX and long-term interest rates, two variables that are commonly used in the empirical capital flows literature (Koepcke (2018)). As a pull factor we add local MSCI equity returns.[21] To give the push and pull factors maximum potential explanatory power we essentially give them perfect foresight, allowing them to enter contemporaneously with the change in flows over the estimated horizon as in equation (7):

$$flows_{t+h} - flows_t = \alpha_h + \beta_{1,h}\left(VIX_{t+h} - VIX_t\ \right) + \beta_{2,h}\left(i_{t+h} - i_t\ \right) + \beta_{3,h}\left(\left[\frac{msci_{t+h}}{msci_t}\right]^{1/h} - 1\right) + \varepsilon_t \qquad (7)$$

Figure 5 (middle row) displays box plots for the adjusted R^2 from regression equation (7) estimated across 1 to 12 quarter horizons for 17 AEs and the 18 EMEs that in addition to having complete data on KF* and quarterly flows also have complete MSCI data. We find that push and pull factors explain much less of the variation in flows, with adjusted R^2 peaking at a median of 0.17 for the 7-quarter EME regressions and 0.14 for the 4-quarter AE regressions. For this sample, the R^2 in

[21] MSCI equity returns, because they are based on U.S. dollar returns, is a nice summary measure that matters to both equity and bond investors. In particular, MSCI equity returns combine a local growth factor that should matter to equity investors (local equity returns are likely higher when local GDP growth is stronger) and a currency factor that should matter to international bond investors (as global investors' return on a local bond is a combination of the currency and bond returns).

regressions containing just the gap between flows and KF* peaks just above 0.40 (top row of Figure 5). Finally, and not surprisingly, adding push and pull factors to our KF* regressions increases the R^2 but not by much; peak R^2 (at 7 quarters) increases to about 0.50 for both EMEs and AEs (bottom row of Figure 5). Deviations from our slow-moving structural measure, KF*, explain much more of the variation in subsequent flows than traditional push and pull factors.

4.4 KF* *in a Nutshell*

How does KF* perform? Quarterly flows, which are quite volatile, oscillate around KF* as evident in the graphs. This is further supported by the Cogley regressions, which indicate that deviations of actual flows from their natural level (approximated by KF*) are transitory; portfolio flows, especially for EMEs, revert to KF* over a 1-to-2-year horizon. Remarkably, the tendency of the transitory element in quarterly portfolio flows to dissipate over time grants KF* significant explanatory power for the change in flows over the medium-run. The reversion of portfolio flows to KF* can explain roughly 40% of the medium-run variation, while contemporaneous push and pull factors have far less explanatory power.

5. Comparison to Other Plausible Natural Levels

As we discussed in some detail, many choices must be made when forming any star, including KF*, and other researchers could choose a different method. It is certainly possible, for example, to create another version of KF* using univariate statistical filtering methods, such as creating a measure based solely on a moving average of past flows. Along some dimensions such a measure would perform well enough but would not lend itself well to an explanation of why deviations from it are likely to be transitory.

There are at least two relevant examples in the literature. Coibion, et al. note that many measures of potential GDP adjust too quickly to transitory shocks, and thus potentially send the wrong signal. (In the y* setting, if slow economic growth feeds quickly into downward revisions of y*, a policymaker might think there is less slack than otherwise.) Williams (2003), in the context of r*, notes that while "averaging methods tend to work well at estimating the natural rate of interest when inflation and output growth are relatively stable, they do not work so well during periods of significant increases or declines in inflation when real interest rates may deviate from the natural rate for several years." Williams points to the late 1960s and the 1970s when real rates were low because inflation increased sharply (and hence real rates were below the natural rate for a long period), but an averaging approach would falsely ascribe the low real rates to a low natural rate.

5.1 Descriptive Comparison

Similar dynamics play out with capital flows. In Figure 6a we show, for Colombia, Chile and Norway, quarterly portfolio flows (the most volatile line in each graph), our measure of KF* (the smoothest line), and a 12-quarter moving average of portfolio flows. The graphs on the left end early—in 2015q2 for Colombia and Chile, in 2008q2 for Norway—just to highlight a particular point. Filters like a 12-quarter moving average are sensitive to recent flows and can be misleading. For example, in mid-2015, for both Colombia and Chile the 12-quarter moving average had increased substantially, suggesting the then-current flows were normal. In contrast, KF* was quite a bit lower, suggesting that those flows were abnormally high. The full sample graphs (on the right) show that flows did indeed come back to KF*. The same dynamics were apparent in Norway in 2008q2, when flows and the 12-quarter moving average were quite high, but KF* suggested they were abnormally high. And flows did subsequently return to KF* (and beyond, as flows into Norway have been low the past few years).

Two current examples are included Figure 6b. In the case of Mexico, a moving average proxy for the natural rate of flows would have likely overreacted to the transitory boom in capital flows experienced from 2011 to 2014. And more recently, the depressed inflows experienced by euro area and Mexico bring the moving average measure down rather quickly. In contrast, our measure of KF* makes it clear that 2018 inflows into both are well below the natural rate (and thus are expected to bounce back). Indeed, Figure 6b (and 6a) looks strikingly similar to Figure 4 in Laubach and Williams (2003), which depicts their measure of r* along with an actual real interest rate and measures based on univariate filtering.[22]

5.2 Empirical Comparisons to Various Filter-based Measures

For a more concrete test of alternative statistical proxies for the natural rate of flows we re-estimate equation (6) replacing KF* with three univariate filters: (1) a twelve-quarter moving average of portfolio flows, (2) a one-sided HP filter of portfolio flows, and (3) the Hamilton (2018) linear projection.[23] Focusing on Cogley regressions with a seven-quarter horizon, for which each measure performs best, Table 1 provides a comparison of beta estimates and R^2 for KF* relative to the alternative benchmarks.[24]

[22] More generally, our construction of KF* clearly indicates that capital flows to many countries have faced headwinds since 2011 because global savings have not increased much since then (because global GDP growth has slowed), thus holding back the growth in KF*. Yes, in many countries (especially those AEs that have implemented UMP) flows have slowed even more than the slowing of KF*, but some slowing of flows is natural until more savings are created in the global economy.

[23] Hamilton (2018) argues forcefully against the use of an HP filter and proposes a simple alternative whereby an OLS regression of a variable at date *t* is regressed upon the four most recent values as of date t-h in order to isolate the structural and cyclical components. Hamilton recommends a medium-run horizon of 8 quarters, which in our case implies a regression of current quarterly flows on flows in periods t-8, t-9, t-10, and t-11. The fitted values from this regression become an estimate of trend flows and the residual is the gap used in Cogley regressions.

[24] For each of the four candidates considered, average adjusted R^2 for Cogley regressions peaks at the seven-quarter horizon.

For EMEs, KF* performs best in Cogley regressions, in that it produces beta estimates that have the smallest absolute deviation from negative 1 (0.151, on average) and the highest mean R^2 (average of 0.437). Along both dimensions, the Hamilton (2018) procedure is second best for EMEs.

For AEs, KF* performs less well, with a large deviation from beta=-1 and a relatively low (but still quite high) R^2. But even where KF* does not perform as well is instructive. KF* performs well for almost all countries in our sample, but the notable exception is in recent years for the AEs that have implemented unconventional monetary policies (defined here as QE or negative policy rates). For example, for the 30 EMEs and 10 non-UMP AEs, beta deviates from one on average only by 0.141 and R2 averages 0.436. In contrast, for the 7 UMP AEs, beta deviates from one on average by 0.343 and R2 averages 0.336. Filtering methods, which by nature adjust to substantial changes in actual flows, perform better for UMP countries, but KF* points more definitively to a reason behind the deviation: The large deviations of actual flows from KF* in UMP countries are due primarily to much lower than benchmark bond inflows, suggesting a beggar-thy-neighbor aspect of UMP.

Overall, KF* performs quite well—by some measures, best—against plausible alternatives, with the Hamilton (2018) method also performing well. A useful characteristic of KF* is that being structural and not constructed as a filter, deviations from it are informative.

6. An Application: Predicting Extreme Capital Flow Episodes Using KF*

In the previous sections we established that KF* helps identify the component in gross portfolio flows that are expected to persist over medium-run horizons. Given the boom-bust nature of international flows, policymakers may find the KF* benchmark particularly useful when trying to identify whether the current level of portfolio inflows is sustainable, or whether a dramatic change in flows is imminent. In this section we test whether a policymaker armed with KF* might be able to forecast extreme capital flow episodes at a medium-run horizon.

Specifically, in this section we test whether portfolio flows that are well above (below) KF* predict an upcoming sharp decline (increase) in flows. That is, does the gap between actual flows and KF* help predict extreme capital flow episodes (defined as the sudden stops and surges of Forbes and Warnock (2012, 2020)? For sudden stops we estimate models of the form:

$$Prob(STOP_{i,t+h} = 1) = F(KF^{*}gap_{i,t}, Global\ Growth_t, Global\ Risk_t) \quad (8)$$

where $STOP_{i,t+h}$ is an indicator variable that takes the value of 1 if country i is experiencing a sudden stop in capital flows at time *t+h*; $KF^{*}gap_{i,t}$ is the gap between current flows and KF* scaled by GDP, averaged over the last 4 quarters; Global Growth is year-over-year global GDP growth from the IMF's World Economic Outlook dataset; and Global Risk is the change in VXO. For this analysis, we take from Forbes and Warnock (2020) all variables (except KF*gap) and the estimation technique: because extreme capital flow episodes are rare we estimate equation (8) using the complementary logarithmic (or cloglog) framework, which assumes F(·) is the cumulative distribution function of the extreme value distribution.

Results from panel estimation of equation (8) at a 6-quarter forecast horizon are presented in Table 2. Merging our KF* dataset with the Forbes and Warnock (2020) capital flows episodes leaves us with a sample of 32 countries (15 AEs and 17 EMEs). For the full sample of 2098 quarterly observations we find that flows above KF*, strong global growth, and rising global risk are each associated with an increased likelihood of a sudden stop in capital inflows in 6 quarters.[25,26]

To get a sense for economic magnitudes we calculate the model's estimated probability of a future stop when KF*gap = 0 (approximately the sample mean) v. positive KF*gaps of 3.6% of GDP and 7.2% of GDP (which represent KF*gaps that are one and two standard deviations above the mean). When current flows are equal to KF* there is a 7.7% probability of experiencing a stop episode six quarters in the future. But when KF*gap is one or two standard deviations above its mean the probability of a stop increases significantly to 13.1% and 21.9% respectively (holding all other variables at their means). We also find evidence that faster current global growth portends future capital flows stops. For example, if global growth climbs one standard deviation above its sample mean (of 2.6%) to 4.2%, the model predicts a 23.7% probability of a stop episode six quarters hence.

The combination of strong global growth and a large positive KF*gap is a particularly powerful predictor of a coming sudden stop: When KF*gap and global growth are each one standard deviation above their mean the probability of a future stop climbs to 40.5%.

The story that emerges is similar to the 'gap' analysis that the BIS uses to predict banking crises; see Aldasoro, Borio and Drehmann (2018). For example, the BIS uses two 'gaps' as predictors, each defined as an underlying—corporate debt-to-GDP or debt-service ratio—growing faster than trend, where trend for the BIS credit gap is estimated by an HP-filter and for the debt-

[25] It is thought that after the GFC extreme capital flow episodes have become more idiosyncratic (i.e., more difficult to model) and that risk's importance has diminished (e.g., Forbes and Warnock 2020). But we find in column (2) of Table 2 that for the post-GFC sample (2010Q1-2018Q4) KF*gap remains highly statistically significant with very stable predicted probabilities. Consistent with other research, global variables fall to marginal levels of statistical and economic significance.

[26] In column (3) we present results for surge episodes and find that they are very difficult to predict at a six-quarter horizon. Although KF* provides an early warning indicator for stops, it provides less information about the likelihood of a future surge, suggesting that stops are often preceded by periods of booming flows but surges do not necessarily begin from periods of depressed flows.

service ratio is a 20-year moving average. The BIS indicators are not based on whether debt levels or debt servicing burdens are high, but whether they are growing faster than in the past.

A similar 'gaps' analysis seems at work with predicting sudden stops. When KF* is growing (because global growth and hence global savings are growing) and actual flows are growing even faster (i.e., both global growth and KF*gap are above their sample means), a sudden stop is very likely in 6 quarters. One difference from the BIS indicators: Our 'trend' is not a mechanical trend but KF*.

7. Conclusion

Capital flows are quite volatile, plotting them does not seem to offer insights further than their gyrations, and yet researchers try to model them and policymakers must try to discern the signal hidden amongst the noise. We put forward a theoretically motivated candidate for the natural level of capital flows, KF*. In the DSGE model of Tille and van Wincoop (2010), savings provides a persistent source of gross portfolio flows allocated according to steady state portfolio weights. These portfolio growth flows provide an intuitive foundation for KF*. Although high frequency flows will be influenced by shocks to risk (i.e., time varying second moments), flows should return to their natural level over time.

Our empirical work provides support for the notion of a natural rate of capital flows that is well approximated by KF*. Tests indicate that deviations from KF* are transitory, as flows revert to KF* over the medium term (1 to 2 years). Further, the reversion of flows to KF* explains a significant fraction of the medium-run variation in flows, performs well in tests against various filtering methods, and the current deviation of flows to KF* helps predict future (6-quarters-ahead) sudden stops.

While empirical tests suggest KF* is a useful construct by helping to identify the underlying persistent component in gross portfolio inflows by differentiating between longer-term structural flows and short-term cyclical noise, another useful characteristic is that it is structural and not based on the filtering of actual flows. Since KF* is structural—built from components that are suggested by theory—we can do better than saying flows are lower than (a potentially dynamic) trend and instead understand root drivers. For example, KF* highlights that capital flows all over the world faced headwinds from 2011 to 2017 because global private savings was flat. And even where KF* does not perform as well is instructive. It performs less well for AEs that have implemented unconventional monetary policies, but this is just a realization of one intent of such policies: to greatly reduce the amount of bond inflows so the domestic currency depreciates.

We close by urging others to conduct similar analysis of other types of capital flows, along two dimensions. First, the reader might note that we focus on inflows rather than outflows, but our measure can certainly be used to create benchmark outflows. Specifically, in equation (1), instead of summing across all O origin countries to calculate destination country *d*'s total benchmark inflows, one could sum across all D destination countries to form origin country o's total benchmark outflows; indeed, Ahmed et al. (2017) and Meng and van Wincoop (2018) do just that for a single origin country (the US). Second, we focus on portfolio flows, because those flows line up most directly with the underlying theory. But future work could extend this to other types of flows. For direct investment, applying our basic notion seems feasible. New funds available for DI are corporate earnings—yes, companies can borrow to fund M&A activity, but new funds come from the flow of corporate earnings—and thus to create benchmark DI flows one just needs to decide on a pre-determined allocation rule. For banking flows, it is less clear how to think about a benchmark (or even what BOP-based banking flows represent), but a step might be found in McCauley et al. (2017).

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Figure 1. Gross Portfolio Inflows (2000q1-2018q4, billions of USD)

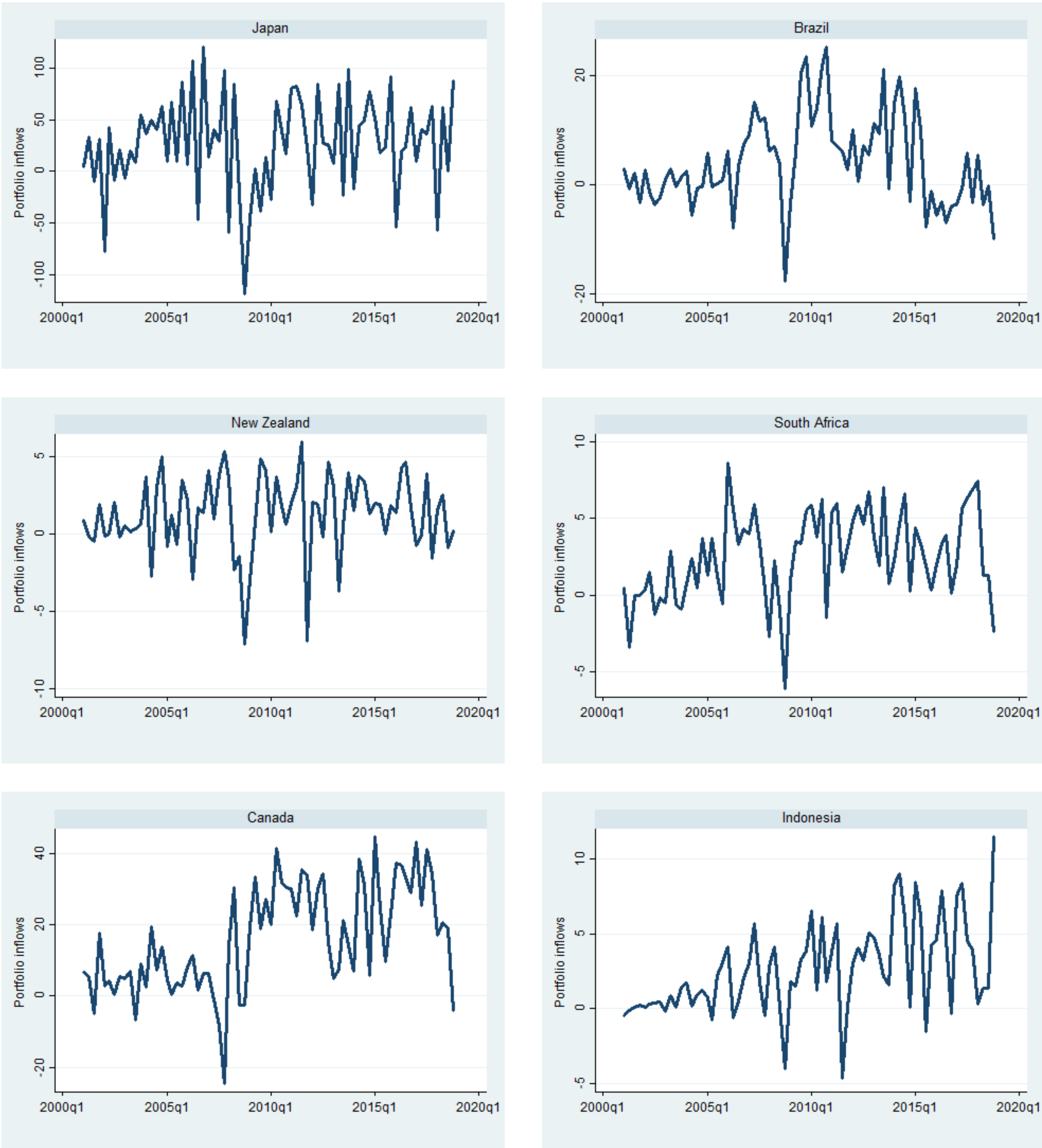


Figure 2. KF* by Region (annual data, $US billions)
Note that only countries with KF* for the entire sample are included in the below graphs.

A. Emerging Market Economies

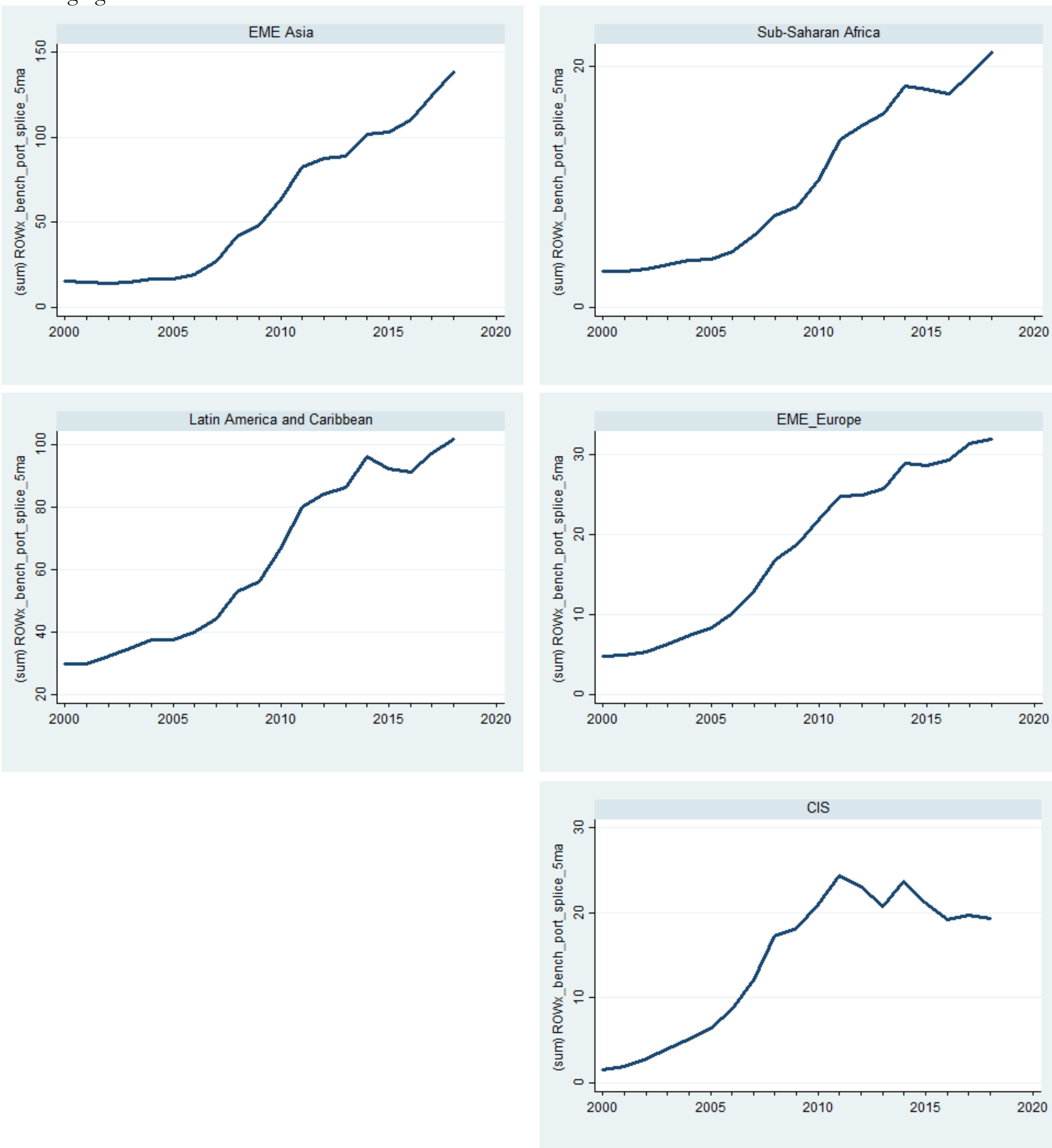
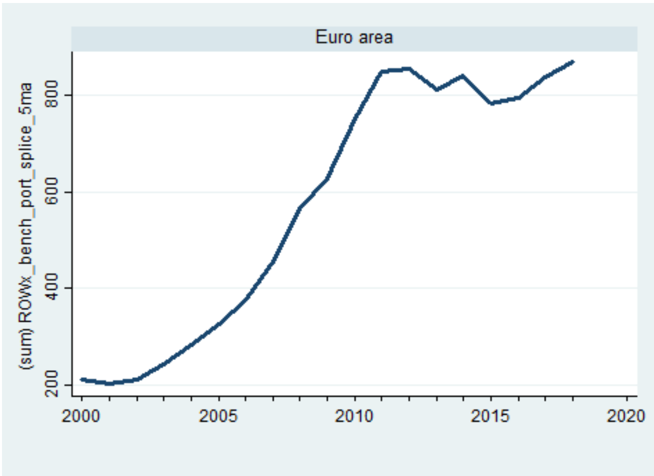
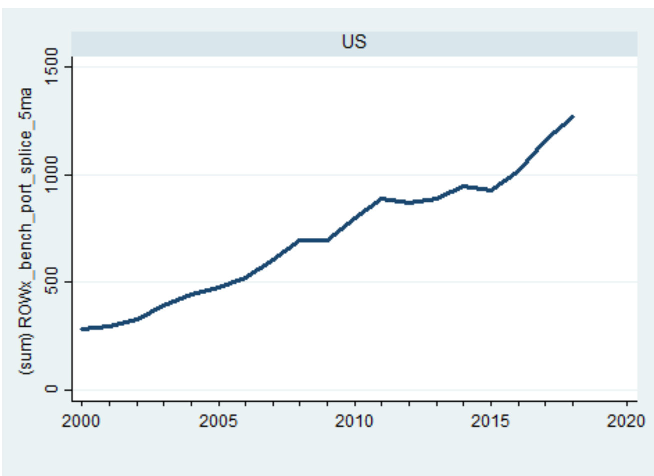


Figure 2. KF* by Region (cont.)

B. Advanced Economies





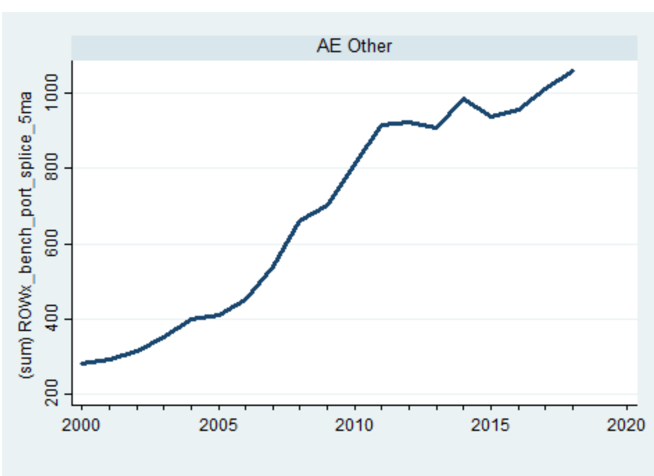


Figure 3. KF* and Gross Portfolio Inflows (2000q1-2018q4, billions of USD)

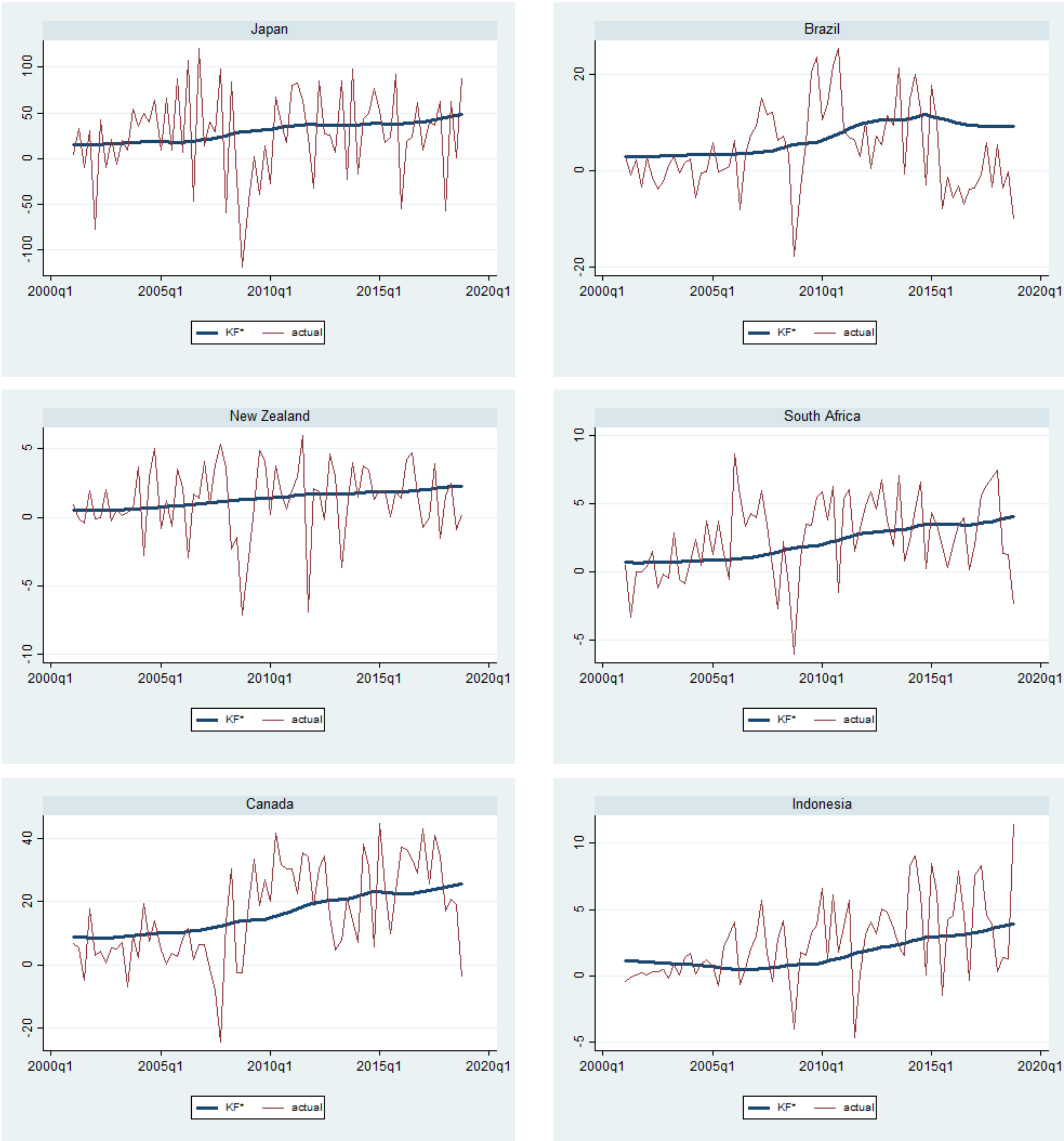


Figure 4. Cogley Results

Note that only countries with KF* and flows for the entire sample are included in the below. In all graphs, going from left to right, the horizon increases (starting at 1-quarter ahead and ending with 12-quarters ahead). The top and bottom of each box indicate the 75th and 25th percentile estimates of β_h (left column) or the adjusted R^2 (right column), the line inside a box indicates the median, while the whiskers indicate upper/lower adjacent values (within 1.5 times the length of the box from the upper/lower quartile) and dots indicate outside values.

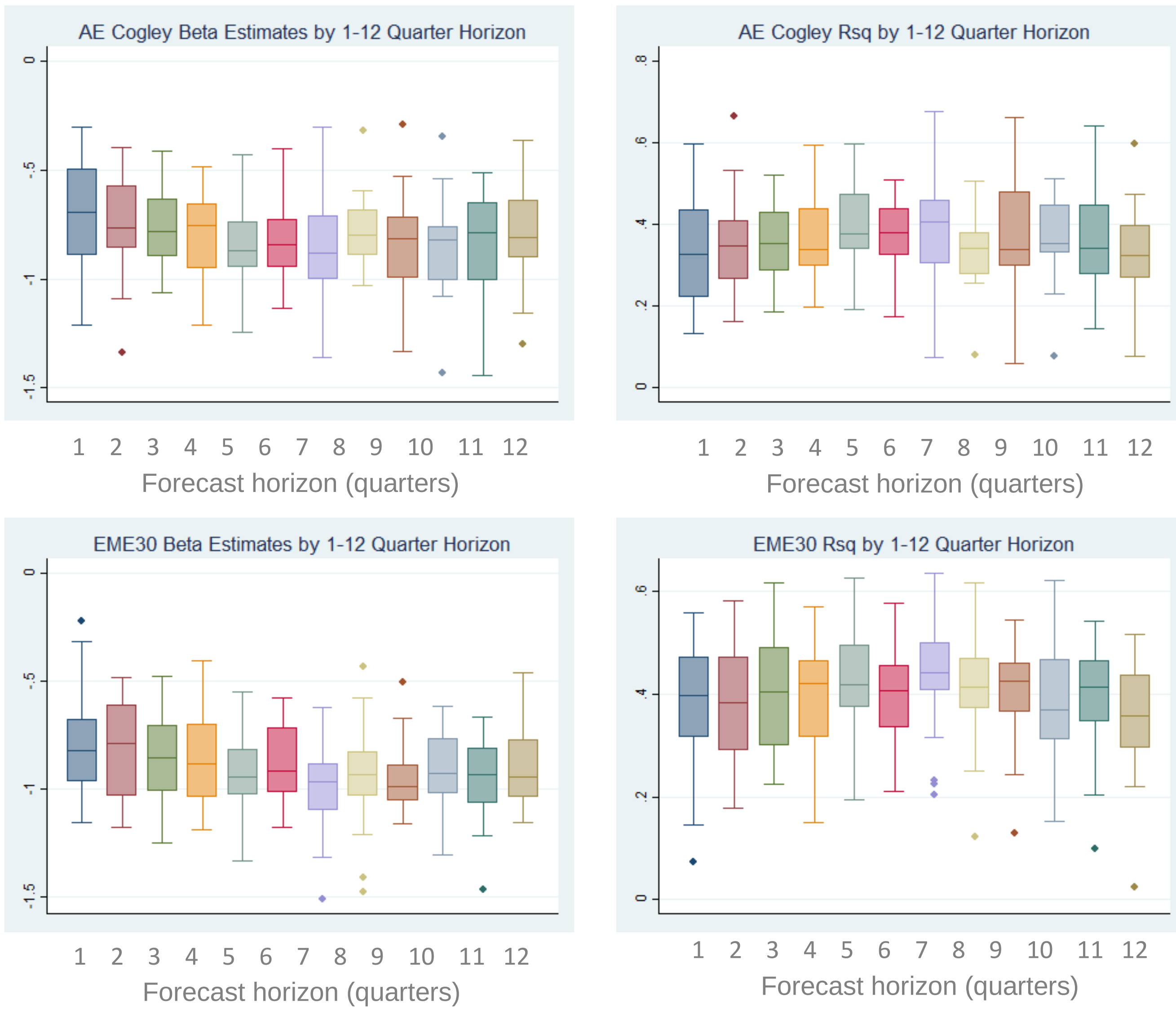


Figure 5. Cogley R^2 Comparison

Note that only countries with KF*, flows, and MSCI equity returns for the entire sample are included in the below. See note to Figure 4 for details on how to interpret the graphs.

Figure 6a.KF* and a Moving Average Measure

In this figure, the smooth line is KF*, the most volatile is actual portfolio inflows, and the other line is a 12-quarter moving average of portfolio inflows. Graphs on the right side include the full sample through 2018q4; graphs on the left side end in 2015q2 (for Colombia and Chile) and 2008q2 (for Norway). All series are quarterly and in billions of USD.

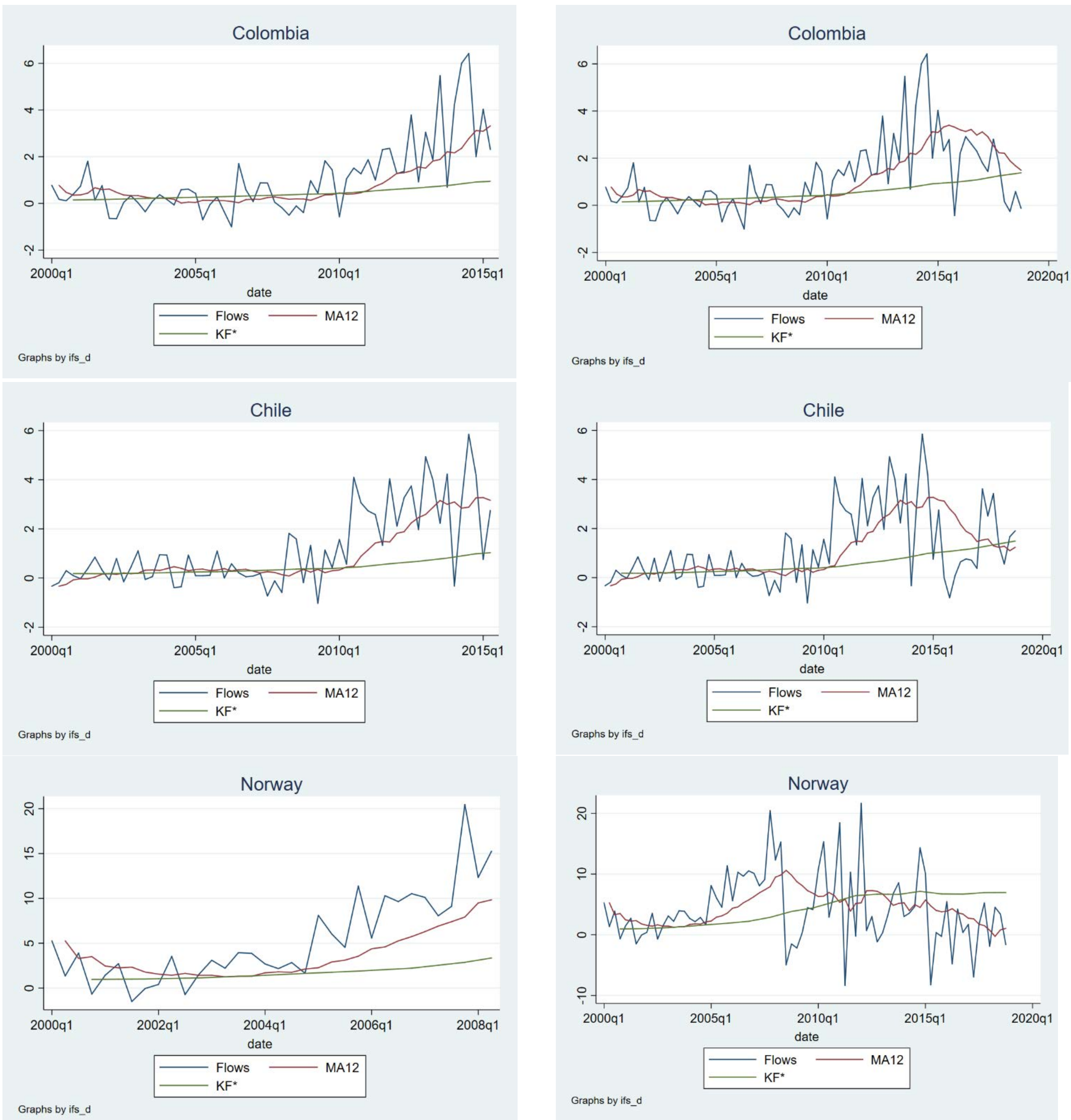
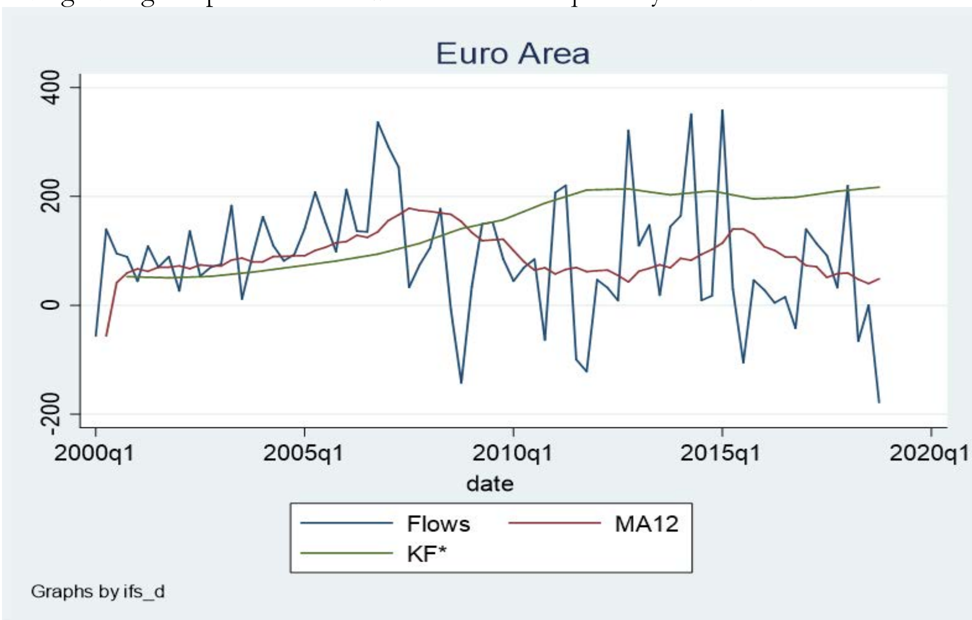


Figure 6b. KF* and a Moving Average Measure

In this figure, the smooth line is KF*, the most volatile is actual portfolio inflows, and the other line is a 12-quarter moving average of portfolio inflows. All series are quarterly and in billions of USD.



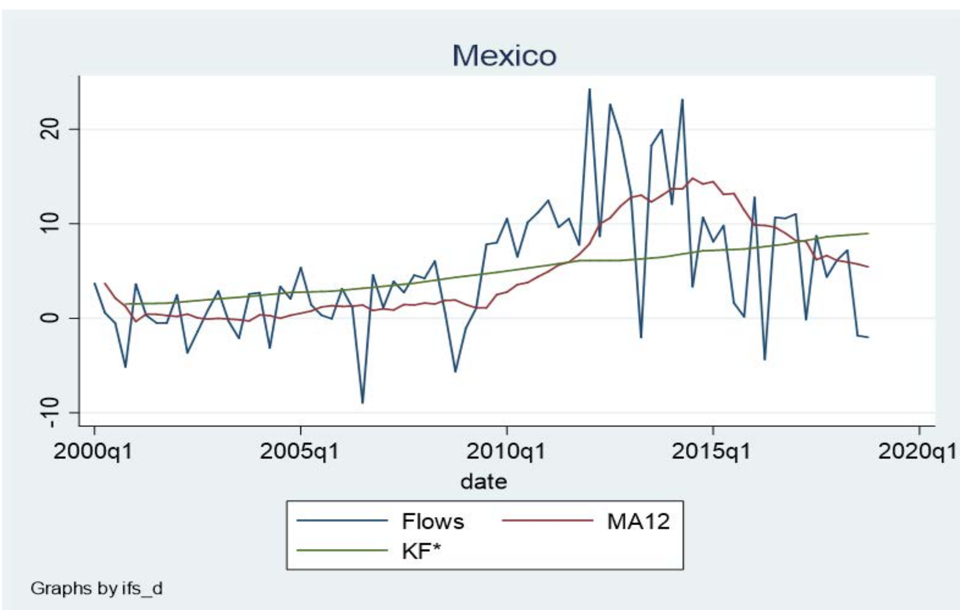


Table 1. KF* and Other Methods

The table presents the average deviation (in absolute value) of beta from negative 1 and the mean Rsq for a sample of 30 EMEs and 17 AEs for the period 2000Q4-2017Q1. The forecast horizon is 7 quarters, the horizon at which each method performs best, thus the last quarter in the forecast period is 2018Q4. MA is a 12-quarter moving average; HP is a one-sided HP filter; and Hamilton is as described in the text. UMP is defined here as quantitative easing and/or negative policy rates.

	KF*	**MA**	**HP**	**Hamilton**
	Average Deviation from beta=-1			
EME (30)	0.151	0.163	0.188	0.160
AE (17)	0.206	0.122	0.142	0.136
nonUMP	0.111	0.099	0.140	0.131
UMP	0.343	0.154	0.144	0.144
	Mean Rsq			
EME (30)	0.437	0.373	0.328	0.419
AE (17)	0.395	0.416	0.371	0.450
nonUMP	0.435	0.439	0.385	0.477
UMP	0.336	0.384	0.351	0.412

Table 2. KF* and Extreme Capital Flow Episodes

Panel A presents regressions of period *t* KF*gap/GDP (the deviation of actual flows from KF*, expressed as a share of GDP), global GDP growth, and the change in the VIX on period *t+6* sudden stops and surges. Using marginal effects from those regressions, Panel B shows the probability of a period *t+6* sudden stop when (i) KF*gap/GDP is at its mean (0%) and 1 and 2 standard deviations above its mean (3.6% and 7.2%), holding all other variables at their mean, and (ii) both KF*gap/GDP and global GDP growth are 1 standard deviations above their means. See text for more details.

Panel A	**Prob(Stop) t+ 6 quarters**		**Prob(Surge) t+ 6 quarters**
	Full Sample	2010-2018	Full Sample
KF* gap/GDP	15.74***	17.1***	0.460
	(4.59)	(5.07)	(3.00)
Global Growth	0.798***	0.23*	0.054
	(0.18)	(0.08)	(0.087)
VXO_ch	0.093***	0.021**	0.002
	(0.016)	(0.008)	(0.008)
Observations	2098	1149	2098
Countries	32	32	32

Panel B	**Prob (Stop) t+6 quarters**
KF* gap/GDP = 0%	7.7%
KF* gap/GDP = 3.6%	13.1%
KF* gap/GDP = 7.2%	21.9%
KF* gap/GDP = 3.6% & growth = 4.2%	40.5%

Appendix

Table A1. Country Coverage for **KF***

Countries are listed in alphabetical order within regions, which are primarily from the IMF's Classification of Countries.

code		Start	End
111	United States	2000	2018
163	Euro Area	2000	2018
	Other Advanced Economies		
193	Australia	2000	2018
156	Canada	2000	2018
546	China,P.R.:Macao	2000	2018
935	Czech Republic	2000	2018
128	Denmark	2000	2018
532	Hong Kong	2000	2018
176	Iceland	2000	2018
436	Israel	2000	2018
158	Japan	2000	2018
542	Korea	2000	2018
196	New Zealand	2000	2018
142	Norway	2000	2018
135	San Marino	2006	2018
576	Singapore	2000	2018
144	Sweden	2000	2018
146	Switzerland	2000	2018
528	Taiwan	2000	2018
112	United Kingdom	2000	2018
	Commonwealth of Independent States		
911	Armenia	2000	2018
912	Azerbaijan	2000	2018
913	Belarus	2000	2018
915	Georgia	2004	2018
916	Kazakhstan	2000	2018
917	Kyrgyz Republic	2000	2018
921	Moldova	2000	2018
922	Russia	2000	2018
923	Tajikistan	2003	2018
925	Turkmenistan	2006	2018
926	Ukraine	2000	2018
927	Uzbekistan	2006	2018
	Emerging and Developing Europe		
914	Albania	2002	2018
963	Bosnia and Herzegovina	2003	2018
918	Bulgaria	2000	2018
960	Croatia	2000	2018
944	Hungary	2000	2018
967	Kosovo	2009	2018
962	Macedonia	2003	2018
964	Poland	2000	2018
968	Romania	2000	2018
942	Serbia	2004	2018
186	Turkey	2000	2018
	Sub-Saharan Africa		
614	Angola	2003	2018
638	Benin	2000	2018
616	Botswana	2000	2018
748	Burkina Faso	2005	2018
618	Burundi	2002	2018
662	Cote d'Ivoire	2000	2018
622	Cameroon	2002	2018
624	Cape Verde	2009	2018
626	Central African Rep.	2006	2018
632	Comoros	2006	2018
636	Congo, Dem. Rep. of	2000	2018
634	Congo, Republic of	2000	2018
642	Equatorial Guinea	2006	2018
643	Eritrea	2006	2018
644	Ethiopia	2010	2018
646	Gabon	2006	2018
648	Gambia, The	2003	2018
652	Ghana	2000	2018
656	Guinea	2000	2018
654	Guinea-Bissau	2006	2018
664	Kenya	2000	2018
666	Lesotho	2000	2018
668	Liberia	2006	2018
674	Madagascar	2006	2018
676	Malawi	2007	2018
678	Mali	2000	2018
684	Mauritius	2000	2018
688	Mozambique	2009	2018
728	Namibia	2005	2018
692	Niger	2000	2018
694	Nigeria	2009	2018
714	Rwanda	2003	2018
722	Senegal	2000	2018
718	Seychelles	2009	2018
724	Sierra Leone	2006	2017
199	South Africa	2000	2018
734	Swaziland	2009	2018
738	Tanzania	2000	2018
742	Togo	2004	2018
746	Uganda	2004	2018
754	Zambia	2011	2018
698	Zimbabwe	2000	2018
	Latin American and the Caribbean		
311	Antigua and Barbuda	2006	2018
213	Argentina	2000	2018
314	Aruba	2000	2018
313	Bahamas, The	2005	2018
316	Barbados	2000	2018
339	Belize	2000	2018
218	Bolivia	2000	2018

Table A1. Country Coverage for KF* (cont.)

code		Start	End
	Latin American and the Caribbean (cont.)		
223	Brazil	2000	2018
228	Chile	2000	2018
233	Colombia	2000	2018
238	Costa Rica	2000	2018
321	Dominica	2000	2018
243	Dominican Republic	2000	2018
248	Ecuador	2000	2018
253	El Salvador	2000	2018
328	Grenada	2000	2018
258	Guatemala	2000	2018
336	Guyana	2000	2018
263	Haiti	2003	2018
268	Honduras	2000	2018
343	Jamaica	2000	2018
273	Mexico	2000	2018
278	Nicaragua	2002	2018
283	Panama	2000	2018
288	Paraguay	2000	2018
293	Peru	2000	2018
361	St. Kitts and Nevis	2006	2018
362	St. Lucia	2007	2018
364	St. Vincent & Grens.	2006	2018
366	Suriname	2002	2018
369	Trinidad and Tobago	2000	2018
298	Uruguay	2000	2018
299	Venezuela, Rep. Bol.	2000	2018
	Middle East, North Africa Afghanistan and Paki		
512	Afghanistan, I.R. of	2012	2018
612	Algeria	2000	2018
419	Bahrain	2000	2018
611	Djibouti	2008	2018
469	Egypt	2000	2018
429	Iran, Islamic Republic of	2000	2018
433	Iraq	2010	2018
439	Jordan	2000	2018
443	Kuwait	2000	2018
446	Lebanon	2000	2018
672	Libya	2006	2018
682	Mauritania	2006	2018
686	Morocco	2000	2018
449	Oman	2007	2018
564	Pakistan	2000	2018
453	Qatar	2001	2018
456	Saudi Arabia	2013	2018
732	Sudan	2008	2018
463	Syrian Arab Republic	2002	2011
744	Tunisia	2000	2018
466	United Arab Emirates	2002	2018
474	Yemen, Republic of	2003	2018

code		Start	End
	Emerging and Developing Asia		
513	Bangladesh	2000	2018
514	Bhutan	2013	2018
516	Brunei Darussalam	2002	2018
522	Cambodia	2000	2018
924	China,P.R.: Mainland	2000	2018
819	Fiji	2010	2018
534	India	2000	2018
536	Indonesia	2000	2018
826	Kiribati	2012	2018
544	Lao People's Dem.Rep	2002	2018
548	Malaysia	2000	2018
556	Maldives	2000	2018
868	Micronesia	2000	2018
948	Mongolia	2008	2018
518	Myanmar	2006	2018
836	Nauru	2013	2018
558	Nepal	2006	2018
565	Palau	2006	2018
853	Papua New Guinea	2000	2018
566	Philippines	2000	2018
862	Samoa	2006	2018
813	Solomon Islands	2011	2018
524	Sri Lanka	2000	2018
578	Thailand	2000	2018
537	Timor-Leste	2015	2018
866	Tonga	2006	2018
869	Tuvalu	2006	2018
846	Vanuatu	2007	2018
582	Vietnam	2002	2018
	Financial centers nec		
319	Bermuda	2006	2018
379	British Virgin Islands	2005	2018
377	Cayman Islands	2006	2018
823	Gibraltar	2006	2018
113	Guernsey	2006	2018
118	Isle of Man	2006	2018
117	Jersey	2006	2018
839	New Caledonia	2006	2018
	Other countries nec		
312	Anguilla	2006	2018
354	Curacao	2015	2018
887	French Polynesia	2007	2018
147	Liechtenstein	2007	2017
352	Sint Maarten	2015	2018
381	Turks and Caicos	2006	2018
487	West Bank and Gaza	2003	2018

Table A2. Country Coverage for Quarterly Flow Data

Code		Start	End
	Advanced Economies		
193	Australia	2000q1	2018q4
156	Canada	2000q1	2018q4
935	Czech Republic	2000q1	2018q4
128	Denmark	2000q1	2018q4
163	Eurozone	2000q1	2018q4
532	Hong Kong	2000q1	2018q4
176	Iceland	2000q1	2018q4
436	Israel	2000q1	2018q4
158	Japan	2000q1	2018q4
196	New Zealand	2000q1	2018q4
142	Norway	2000q1	2018q4
576	Singapore	2000q1	2018q4
542	South Korea	2000q1	2018q4
144	Sweden	2000q1	2018q4
146	Switzerland	2000q1	2018q4
528	Taiwan	2000q1	2018q4
112	United Kingdom	2000q1	2018q4
111	United States	2000q1	2018q4
	Latin American and the Caribbean		
213	Argentina	2000q1	2018q4
218	Bolivia	2014q1	2018q4
223	Brazil	2000q1	2018q4
228	Chile	2000q1	2018q4
233	Colombia	2000q1	2018q4
238	Costa Rica	2000q1	2018q4
268	Honduras	2012q1	2018q4
273	Mexico	2000q1	2018q4
278	Nicaragua	2014q1	2018q4
293	Peru	2000q1	2018q4
298	Uruguay	2000q1	2018q4
299	Venezuela	2000q1	2016q4

Code		Start	End
	Emerging and Developing Asia		
513	Bangladesh	2000q1	2018q4
924	China	2005q1	2018q4
534	India	2000q1	2018q4
536	Indonesia	2000q1	2018q4
544	Lao PDR	2010q1	2018q4
548	Malaysia	2000q1	2018q4
564	Pakistan	2000q1	2018q4
566	Philippines	2000q1	2018q4
524	Sri Lanka	2000q1	2018q4
578	Thailand	2000q1	2018q4
582	Vietnam	2005q1	2018q1
	Other EMEs		
914	Albania	2008q1	2018q4
911	Armenia	2000q1	2018q4
913	Belarus	2000q1	2018q4
918	Bulgaria	2000q1	2018q4
960	Croatia	2000q1	2018q4
915	Georgia	2004q1	2018q4
944	Hungary	2000q1	2018q4
962	Macedonia	2000q1	2018q4
684	Mauritius	2000q1	2018q4
283	Panama	2000q1	2018q4
964	Poland	2000q1	2018q4
453	Qatar	2011q1	2018q4
968	Romania	2000q1	2018q4
922	Russia	2000q1	2018q4
199	South Africa	2000q1	2018q4
186	Turkey	2000q1	2018q4
926	Ukraine	2000q1	2018q4
487	West Bank & Gaza	2012q1	2018q4

Figure A1. KF* and Gross Portfolio Inflows (2000q1-2018q4, billions of USD)
All countries 59 countries for which we have at least ten years of KF* and some quarterly flow data are presented here alphabetically within each region.

A. Advanced Economies

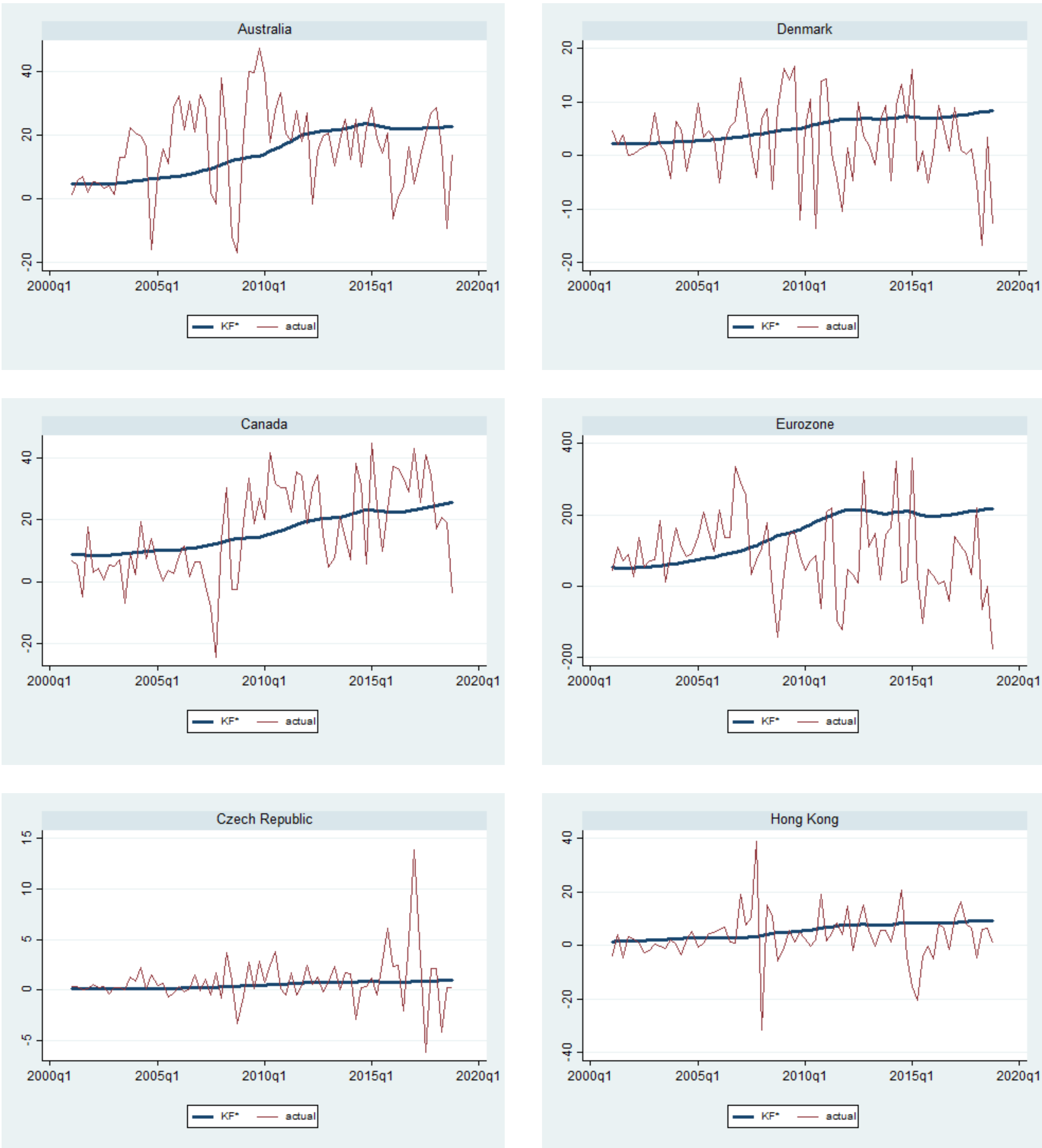


Figure A1 (cont.)

A. Advanced Economies (cont.)

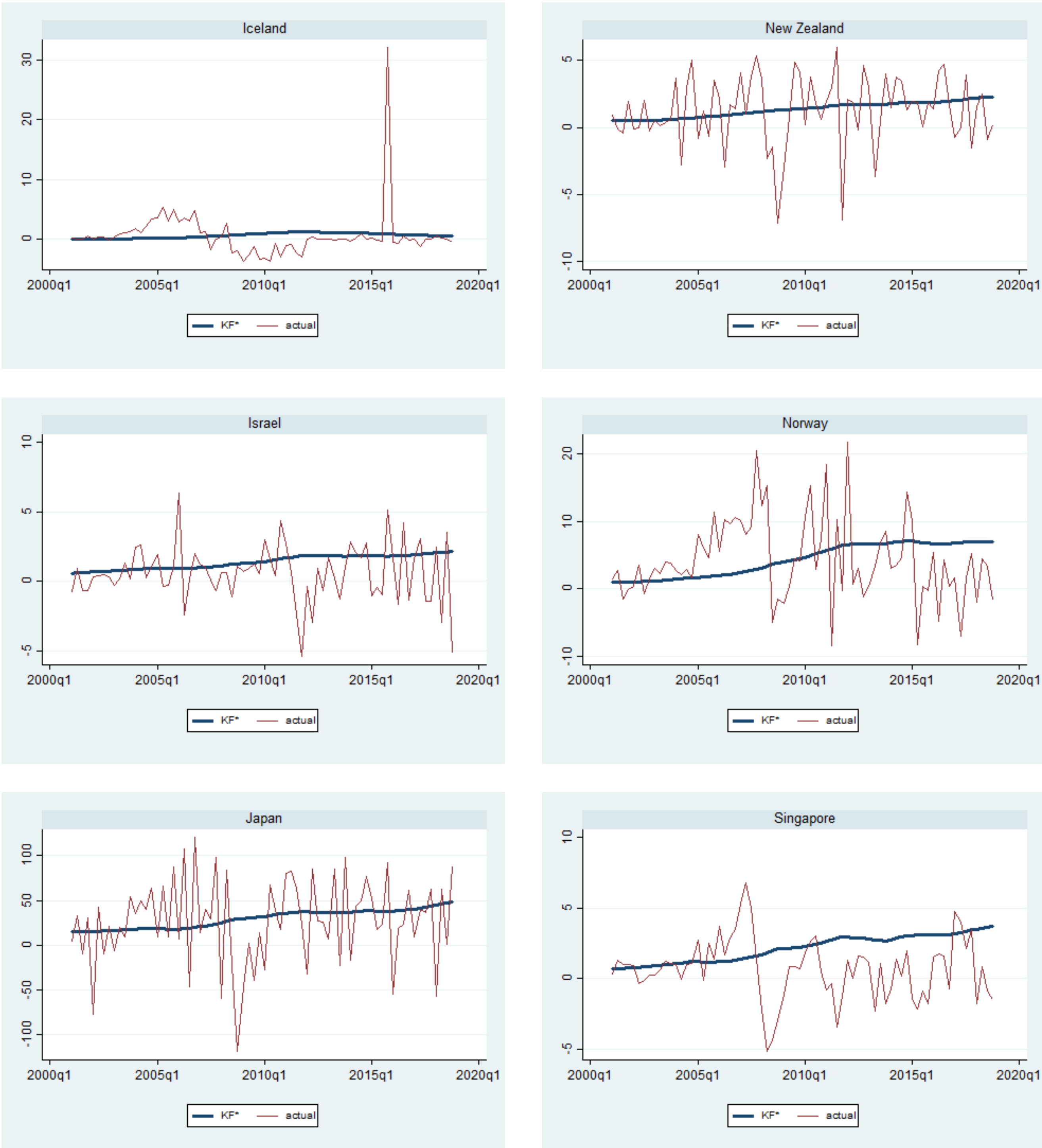


Figure A1 (cont.)

A. Advanced Economies (cont.)

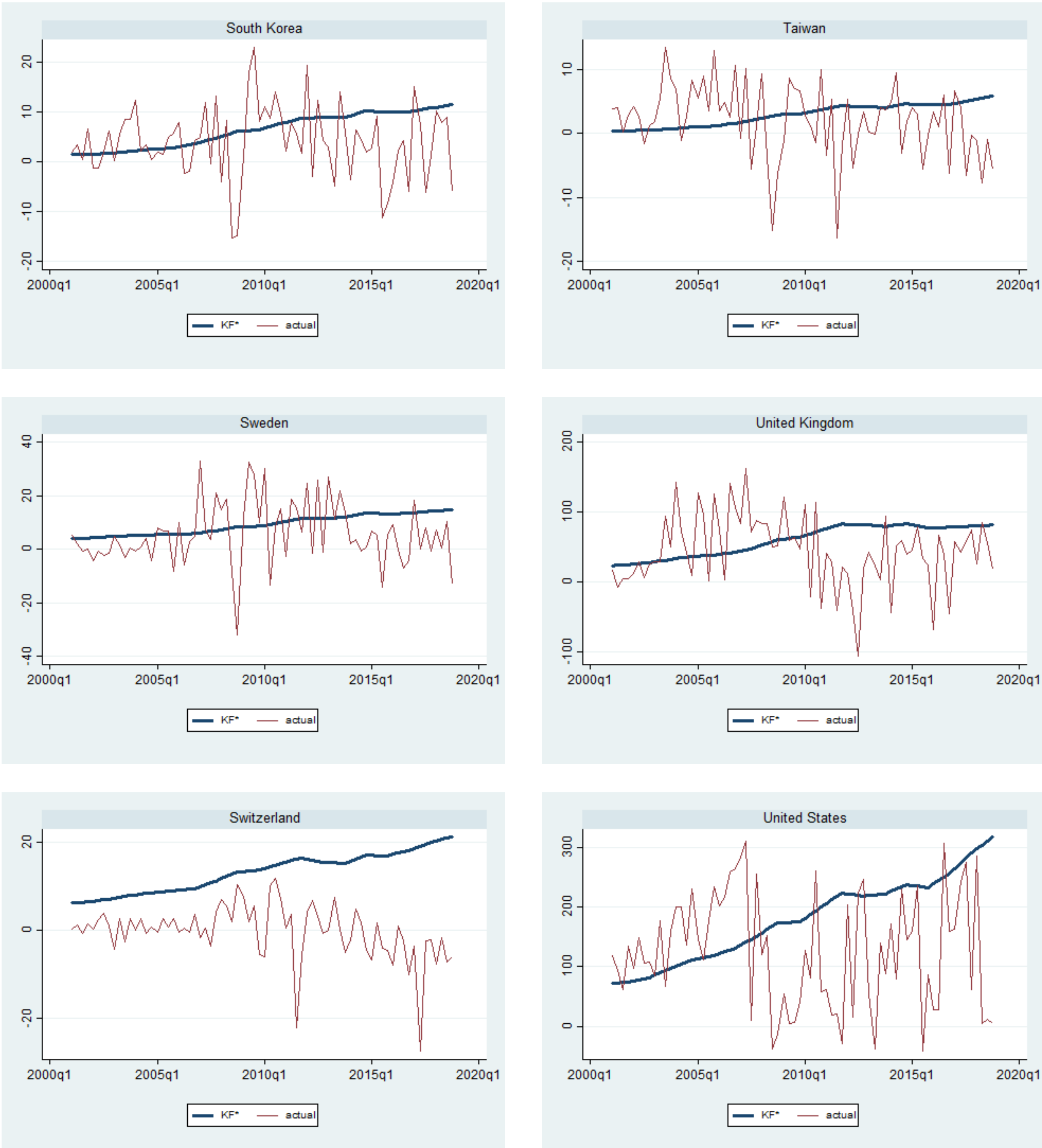


Figure A1 (cont.)

B. Latin American and the Caribbean

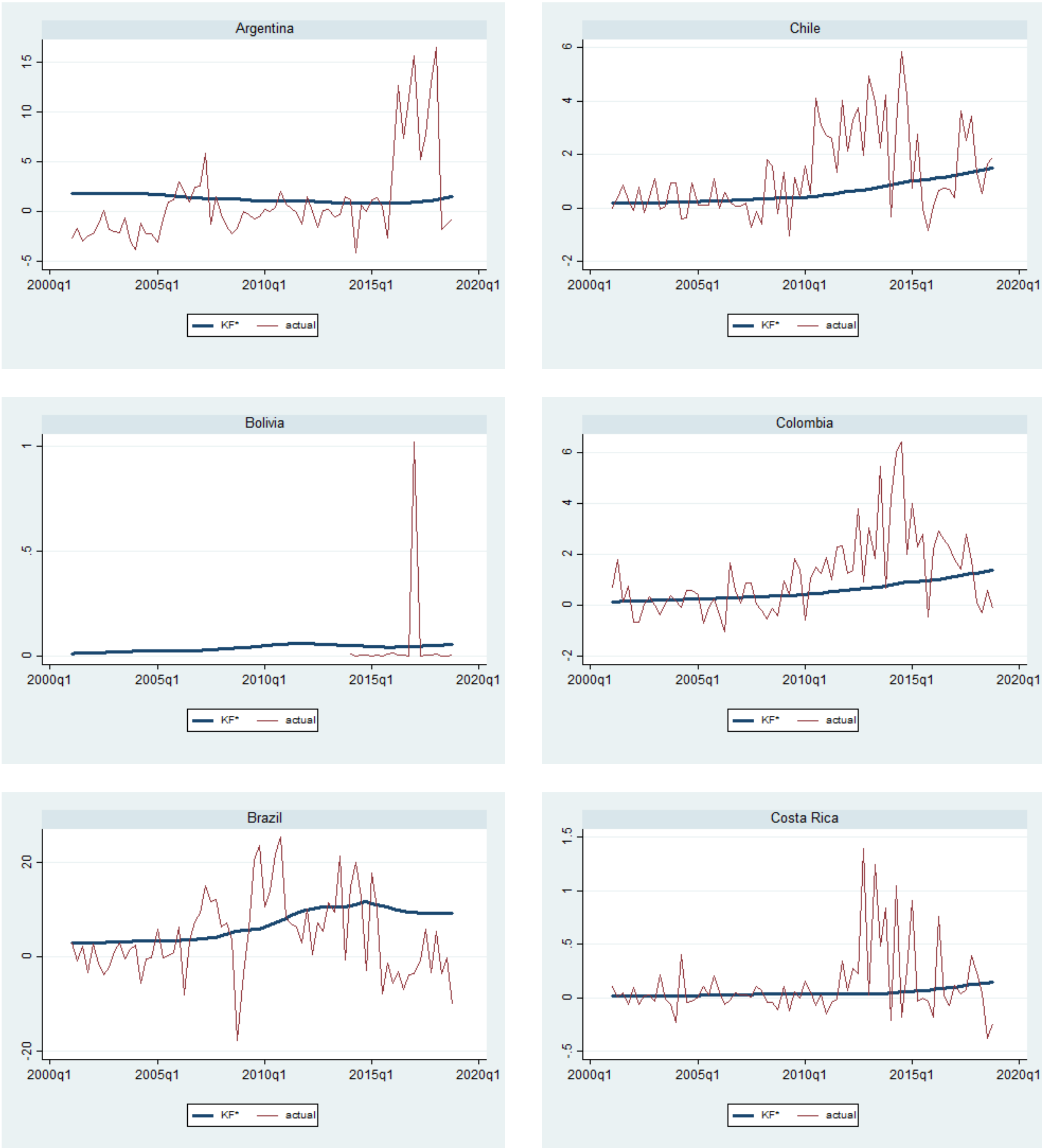


Figure A1 (cont.)

B. Latin American and the Caribbean (cont.)

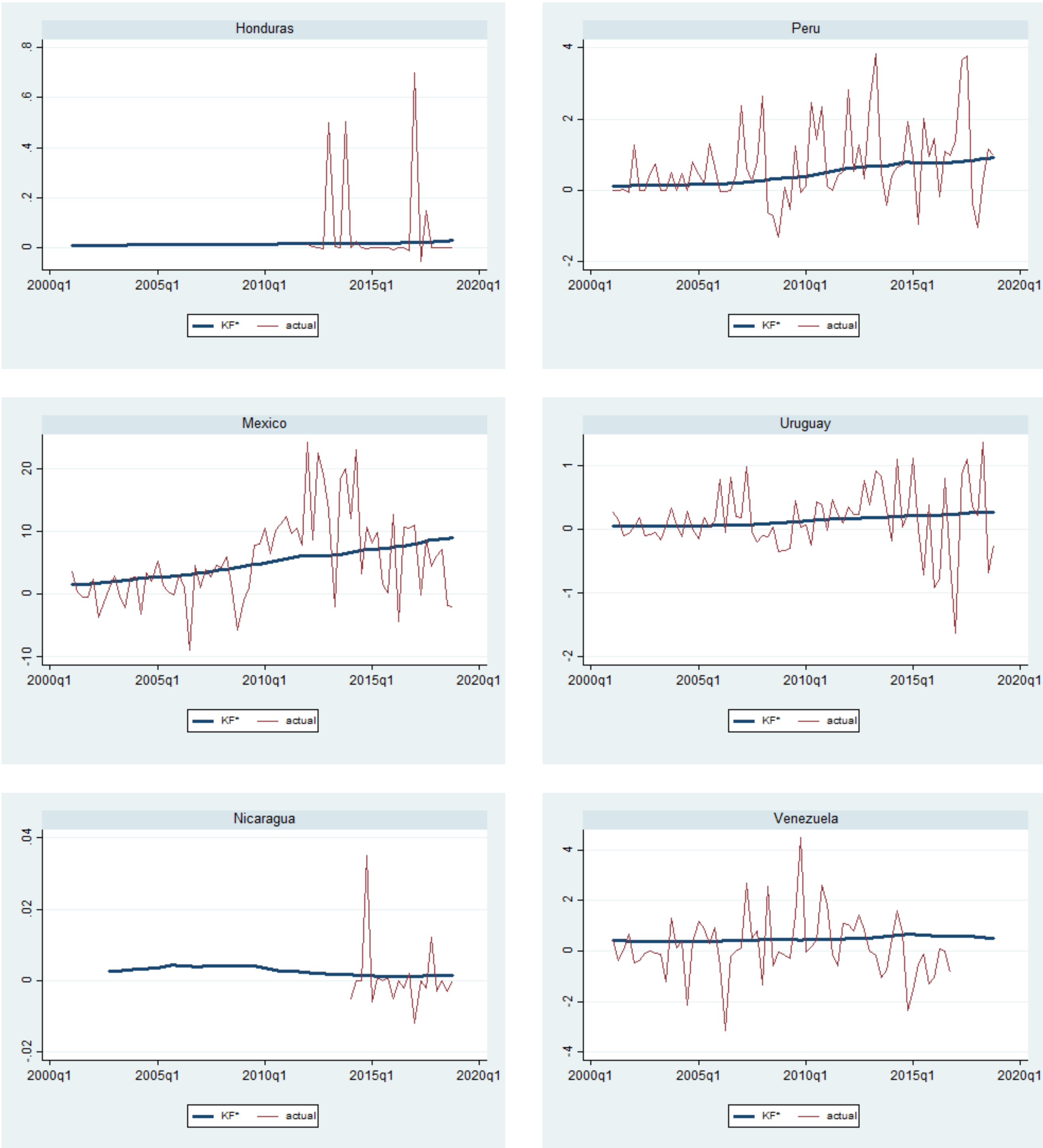


Figure A1 (cont.)

C. Emerging and Developing Asia

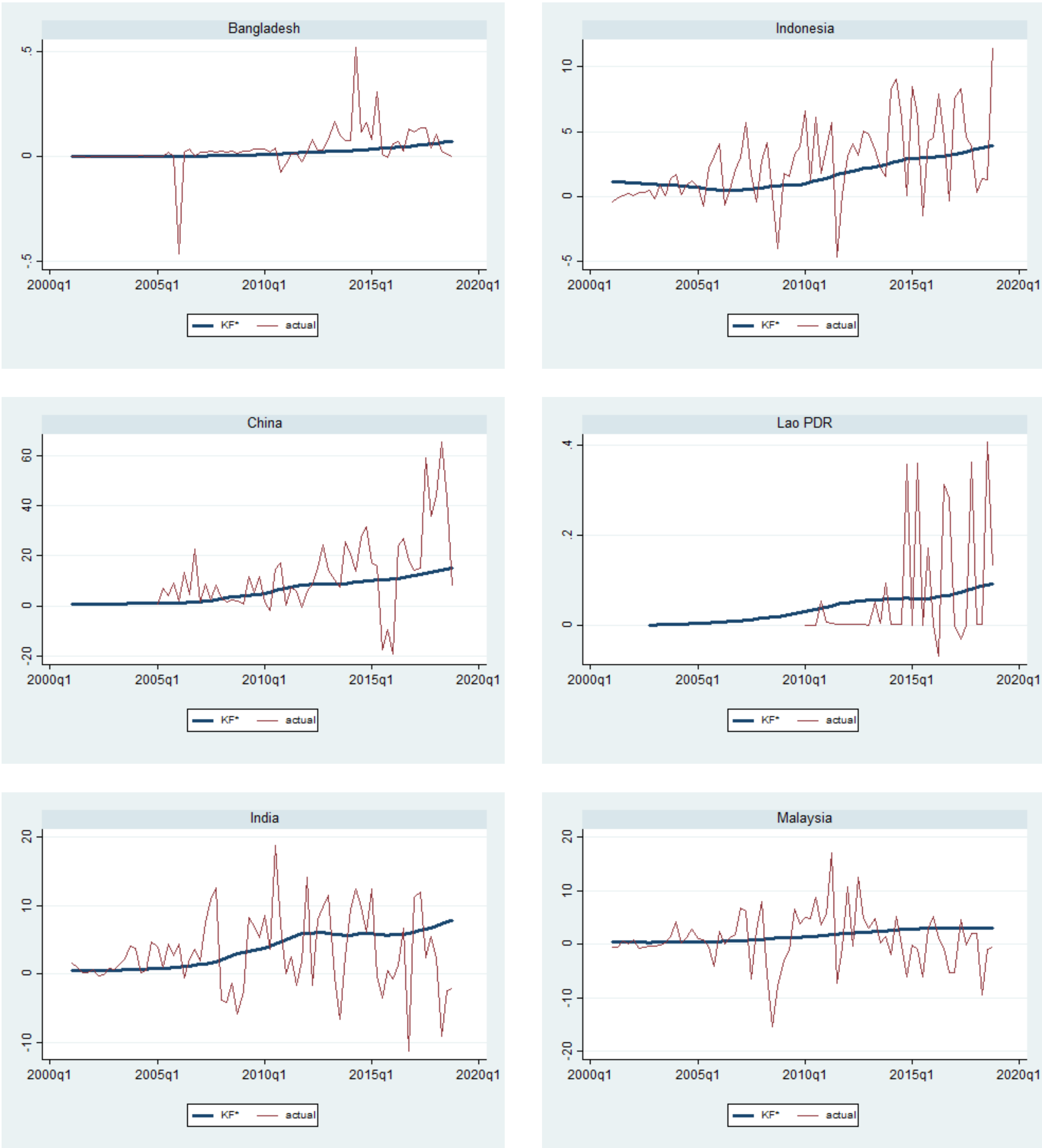


Figure A1 (cont.)

C. Emerging and Developing Asia (cont.)

Figure A1 (cont.)

D. Other EMEs

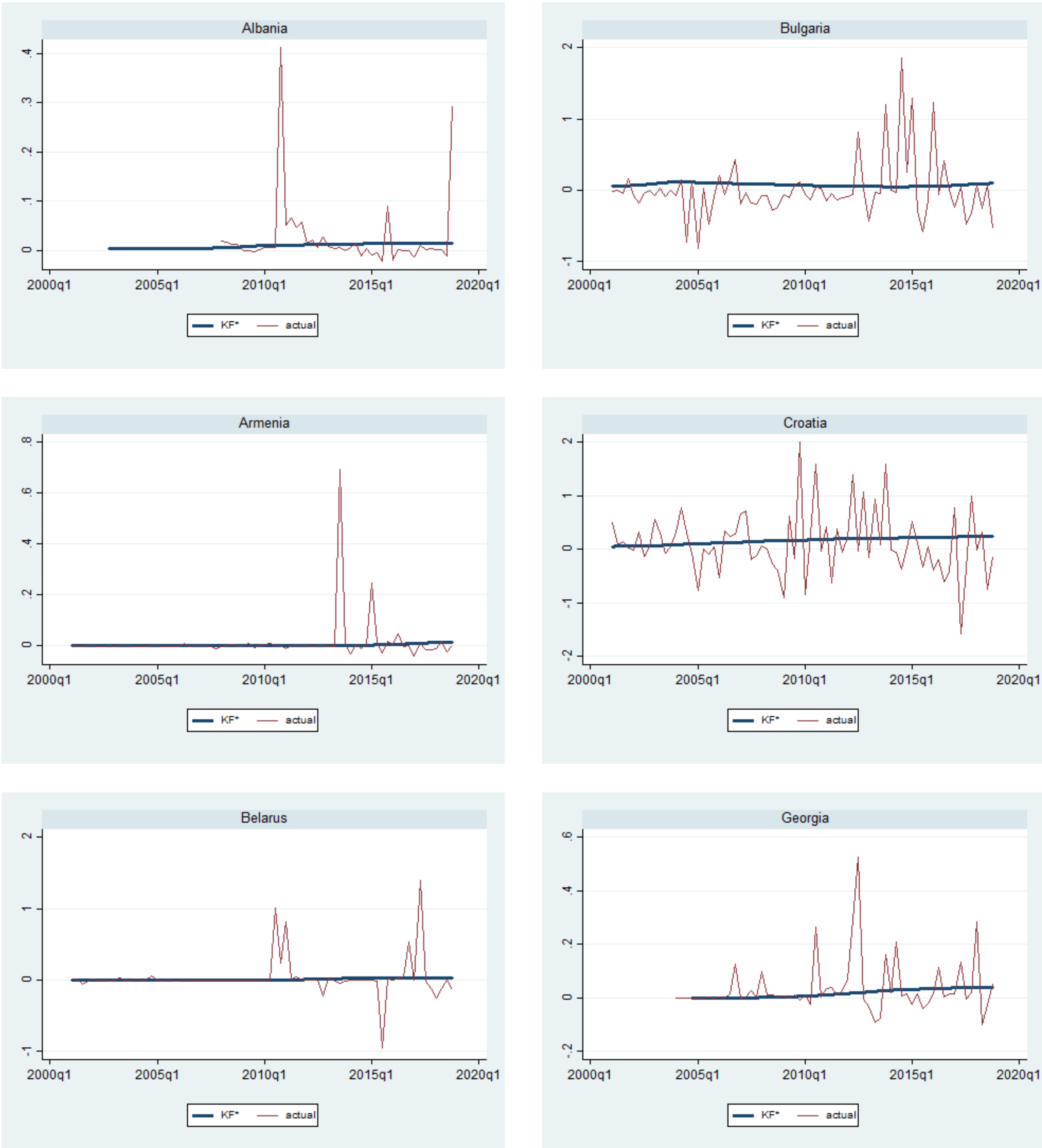


Figure A1 (cont.)

D. Other EMEs (cont.)

Figure A1 (cont.)

D. Other EMEs (cont.)