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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*. Out-of-sample empirical features of KF* are impressive. For 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; and performs well against out-of-sample and in-sample filtering techniques. The gap between actual inflows and KF* also helps predict both 6-quarters ahead sudden stop episodes and medium-term equity returns. We close with how KF* and lessons from the global financial crisis help us think about capital flows during the Covid-19 shock.

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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. Likewise, in the case of volatile asset prices such as equities and exchange rates, market participants frequently turn to slower moving, fundamentally grounded reference points as a way to assess current market conditions and potentially predict future returns.[1]

Capital flows lack such a reference point *and* 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). The volatility makes it difficult to ascertain whether the current level of flows are likely to persist in the future. Relatedly, the empirical literature that attempts to model the quarter-to-quarter variation in capital flows has had strikingly little success (Cerutti, Claessens and Rose 2019). When there are material events such as index inclusion (Raddatz, Schmukler and Williams 2017) or an international cross-listing (Edison and Warnock 2004), the effect on flows is noticeable. But as Chari, Dilts Stedman and Lundblad (forthcoming) show, even for well-identified shocks an effect on flows can be difficult to discern.

[1] For example, the literatures on exchange rates and equity prices have made progress by distinguishing between transitory shocks that are associated with deviations from fundamentals and longer-term reversion; see, among many others, Mark (1995), Hong and Stein (1999), Froot and Ramadorai (2005, 2008), and Koijen and Yogo (2019).

A better understanding of the variation in flows matters for policymakers, firms and market participants. Cross-border financial flows impact the cost of borrowing for firms and governments, especially in emerging economies (Mendoza and Terrones 2012, Pandolfi and Williams 2019). And, with policymakers increasingly wary of the implications of volatile international capital flows on domestic conditions, uncertainties about the salient drivers of capital flows may contribute to countries' newfound propensity to institute capital controls. Firms' cost of capital decreases with the removal of capital controls (Bekaert and Harvey 2000, Edison and Warnock 2003) and increases with their reinstatement (Alfaro, Chari, and Kanczuk 2017). If segmentation has costs (Bekaert et al. 2011, Bekaert, Harvey, and Lundblad 2011) and capital controls might miss their intended mark (Forbes et al. 2015), a measure that improves our understanding of capital flows might help avoid policy mistakes.

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 a benchmark that helps gauge the amount of gross portfolio inflows countries can expect to receive. The precursors to our KF* measure include Tille and van Wincoop (2010) and Devereux and Sutherland (2011), both of which built out the underlying theory (but did not broadly apply it to portfolio flows). The nearest neighbor to this paper is Burger, Warnock and Warnock (2018), which applied the underlying theory to create a benchmark for portfolio flows for 47 countries and showed, using annual data, that there is a significant in-sample long-run relationship between actual flows and the benchmark and that the benchmark helps predict the direction of one-period-ahead changes in inflows. In this paper we broaden the analysis along a number of dimensions. We create a quarterly version (important because few have the luxury of waiting for annual data to be released) and do so for many more countries (184). Our empirical focus is on its out-of-sample medium-term (i.e., 4-8 quarters ahead) forecasting ability. We compare `KF*` to various out-of-sample and in-sample filtering methods, and also use it to predict extreme capital episodes (i.e., sudden stops and surges), and equity returns.[2]

`KF*` is an easy-to-construct, theory-based, slow-moving supply-side measure that helps gauge the amount of *gross portfolio inflows* countries can expect to receive by approximating the level one might expect flows to converge to over a medium-term horizon. `KF*` is a supply-side measure in that it is derived from the supply of rest-of-world savings. The underlying theory is from the Tille and van Wincoop (2010) and Devereux and Sutherland (2011) incorporation of portfolio choice in open economy DSGE models, and specifically their notion of zero-order weights and portfolio growth flows.

We show that `KF*`, available for a wide range of countries starting as early as 2000, helps distinguish between short-run transitory shocks and longer-run reversion. Just as interest rates, unemployment, inflation, GDP and exchange rates differ from `r*, u*, π*, y* and` PPP, actual flows deviate from `KF*`. 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, out-of-sample tests following Cogley (2002) indicate that deviations of actual flows from `KF*` are transitory, as portfolio inflows, especially for emerging market economies (EMEs) but also for most 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. `KF*` also outperforms various univariate filtering techniques. Finally, the out-of-sample `KF*` performs about as well as the in-sample (i.e., one that uses the full time series) Hamilton (2018) linear projection that was designed explicitly for analysis similar to Cogley (2002).

[2] We use the term out of sample because in every application in this paper KF* is predetermined and the time *t* deviation between it and actual flows is used to predict future values of variables of interest (usually flows, but also equity returns and sudden stops and surges).

The predictive power of the current deviation of flows from KF* extends to sudden stops and equity returns. In both cases, periods of strong global growth (so that global savings and thus KF* are increasing) and flows exceeding KF* predict a future downturn. KF* predicts future sudden stops (4 to 8 quarters ahead): When both the gap of actual flows from KF* and global growth are one standard deviation above their mean (that is, KF* gap of 3.4% of GDP and global growth of 4.2%) the probability of a sudden stop in six quarters is 31.8%.[3] On equities, mean annual excess returns in our sample are 11.2%, but if the gap of actual flows from KF* and global growth are both one standard deviation above their means, equity returns in the next year are predicted to be nearly 10 percentage points lower. For both sudden stops and future equity returns, KF* acts similarly to the BIS credit gap predictor of crises (Aldasoro, Borio and Drehmann, 2018). When the underlying is above the benchmark (for this paper, KF*, for BIS the HP-filtered trend) a downturn is likely. An added nuance in our analysis is that if the benchmark is also increasing strongly (specifically, if global growth is increasing) a sharp downturn in flows and equity prices is even more likely.

At the time of writing, the world is being buffeted by a global shock—the global Covid-19 pandemic—that is surely impacting global capital flows. Our sample ends on the eve of the global shock—in 2019Q4—so we cannot speak directly to flows during the pandemic. However, we can look back to the last large global shock, the GFC, when over 75% of the countries in the Forbes and Warnock (2012) study were experiencing a sudden stop. Viewing the GFC shock through the lens of KF*, we show a strong negative relation between the pre-shock gap of actual flows from KF* and the subsequent change in capital flows during the crisis (all scaled by GDP). That is, countries that were experiencing flows higher than KF* just prior to the GFC had the largest decreases in flows

[3] The relationship between KF* and future extreme capital flow episodes is asymmetric, as countries experiencing very low inflows relative to KF* are not more likely to experience a future sudden surge in inflows.

during the GFC. Moreover, the relationship is tight. Extrapolating to the eve of the global pandemic, we observe very few countries with inflows much greater than KF* suggesting less room to fall (relative to decreases during the GFC) and that for most countries any crisis-related fall in flows is likely to be transitory as flows can be expected to revert to KF* in the intermediate term.

Our work is related to the vast empirical literatures on international capital flows (see Koepcke (2018) for a survey) and international portfolio allocation. In those literatures, analysis is often couched in terms of recipient-country-specific 'pull' factors and origin-countries' 'push' factors (see Griffin, Nardari and Stulz 2003 among many others). In those terms, KF* can be thought of as a supply-side 'push' factor. Within that literature 'push' factors are most often indicators such as U.S. interest rates (starting with Calvo, Leiderman and Reinhart 1993, 1996) or the VIX (Rey 2013). Our focus on the supply of funds, much less prevalent in the literature, shares similarities with the limited set of papers that focus on funding shocks (see, for example, Jotikasthira, Lundblad and Ramadorai (2012) and Cerutti, Claessens and Puy (2019)).

The paper proceeds as follows. The next section briefly discusses various stars in macroeconomics before Section 3 presents our measure of KF*. Section 4 tests whether flows converge to KF* over the medium term. Section 5 compares our measure to various out-of-sample univariate filtering techniques as well as the in-sample Hamilton (2018) linear projection. Section 6 provides two applications: using the gap between actual flows and KF* to predict sudden stops and equity returns over the medium term. Section 7 applies lessons from the GFC to inform the likely path of flows during the Covid-19 pandemic. Section 8 concludes. We include graphs of some countries in the main text; graphs for all 56 countries for which we have quarterly flow data, as well as some additional design details and information on country coverage, are relegated to appendices.

2. From Macroeconomic Stars to KF*

An endeavor such as ours has much to learn from the long literatures on famous stars in macroeconomics such as r*, u*, y* and Π*. While no star is exactly like another, KF* is not precisely analogous to any particular star, and most readers already understand these literatures, we discuss them here because 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* and has taken many forms through the decades. In the English translation, Wicksell's 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^*.[4]

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. 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 2018.).

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.[5] 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

[4] See Crump, Eusepi, Giannoni and Sahin (2019) for an attempt to unify the u* literature.
[5] 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. (2018) 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) and Devereaux and Sutherland (2011)—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. KF*

*3.1 Construction of KF**

Our measure of the time *t* natural level of portfolio inflows for a destination country *d* is

$$KF^{*}_{d,t} = \frac{1}{5}\sum_{i=1}^{5} \omega_{ROW,d,t-i}\, S_{ROW,t} \tag{1}$$

where $\omega_{ROW,d,t}$ is the weight of destination country d in rest-of-the-world (ROW) portfolios, defined as ROW holdings of country *d* bonds and equities divided by ROW financial wealth, and $S_{ROW,t}$ is the flow of ROW private savings.

Portfolio weights in (1) are formed using Lane and Milesi-Ferretti (2018) data on ROW holdings of the destination country's equities and bonds (in BOP-speak, the country's portfolio equity and portfolio debt liabilities), available annually for over 100 countries starting in roughly 1995, and scaling these investment positions by ROW total financial assets (Davies, Lluberas, and Shorrocks (2018)).[6] Savings, from the IMF WEO dataset, is private savings (that is, national savings less fiscal savings or "General government net lending/borrowing" in IMF WEO terms). ROW savings is just world savings minus the recipient country's savings and ROW wealth is world wealth minus the recipient country's wealth. Throughout, our ROW savings and weights (and flows) are

[6] 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). Davies et al. (2018) provides a measure of household wealth, built wherever possible from household balance sheet data or household survey data (or, if those sources are not available, by estimation), for 212 countries at year end from 2000 to 2017 with mid-year estimates for 2018 and 2019; we average the last two mid-year estimates to form year-end 2018 estimate. For the period 1995-1999 we splice the Davies et al. (2018) data with total financial assets (TFA) data from McKinsey Global Institute (MGI); see McKinsey Global Institute (2018) for a description of the data. For years both measures are available (2000-2016), the correlation is 0.985.

“exChina” because over the past two decades there has a substantial disconnect between China’s savings (sizeable) and its outward portfolio investment (miniscule); see Appendix A for details.

KF* is theory-based: it is derived from the DSGE open economy models with portfolio choice of Tille and van Wincoop (2010) and Devereux and Sutherland (2011). The model, with finitely lived agents, is of two countries, although Meng and van Wincoop (2020) 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, 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. 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 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. Reallocation flows can be substantial (and volatile) but, arising primarily from time variation in second moments, ephemeral.

The 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.

As indicated in equation (1), we operationalize zero-order portfolio weights as a trailing 5-year moving average of past portfolio weights. That is an ad-hoc decision, but one that we are comfortable with for a number of reasons. An alternative of using a theory such as CAPM to construct zero-order portfolio weights is possible but runs into the practical limitation that there is a sizeable home bias in actual data. And modeling higher frequency fluctuations in portfolio weights as in Koijen and Yogo (2019, 2020) would run counter to our focus on the longer-run natural level of flows. We therefore employ a smoothed portfolio weight that abstracts from volatile transitory demand shocks. Finally, filtering a weight has precedence in another 'star', potential GDP: the CBO applies a filter to the capital share so the volatility in the capital-share series does not create volatile estimates of potential GDP (Shackleton 2018). Similarly, in our setting asset price movements produce period-to-period volatility in portfolio weights; a filter dampens that volatility.[7,8]

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., bilateral holdings data might improve so that a bilateral approach becomes a plausible alternative).[9] Others, such as what theory to use, are more philosophical and so of course other researchers might make different choices. That others will make different choices to construct a measure of the natural level of capital flows makes `KF*` much like stars such as `u*`, `y*`, `Π*`, and `r*`.

We construct `KF*` for the period 2000 to 2019. The number of countries for which we can do so is limited primarily by Lane and Milesi-Ferretti (2018) data on portfolio liabilities; if a country has portfolio liabilities data, we can create its `KF*` even if the country does not publish flow data.[10] 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).[11] For another 90 countries we can form `KF*` beginning later. In all, we create

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7 In practice, all of the empirical results in this paper hold whether we use a trailing 5-year moving average of weights or trailing moving averages of 1, 2, 3 or 4 years.

8 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.

9 A bilateral approach that attributes each origin country's savings according to its exposure to each destination country would be intuitively appealing but requires high quality bilateral portfolio holdings data. Such data, even if 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 (Warnock and Cleaver 2003). Our ROW approach, consistent with BOP capital flows data (which are also ROW) is less sensitive to these financial center biases. In addition, we consider the euro area as a whole to alleviate, to the extent possible, its substantial inter-area financial center bias (Felettigh and Monti 2008).

10 `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 global savings or wealth.

11 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.

KF* for 184 countries (see Table A1 in the Appendix). We form a quarterly version of KF* by linearly interpolating between year-end values.[12]

3.2 Descriptive Analysis

Annual KF*by region are plotted 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 1): increased ROW private savings, which is largely common to all regions, or foreigners' increased (lagged) weights on a region's stocks and bonds, which can vary substantially across regions. Indeed, global (excluding China) private savings increased 8.5% 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 34% per year between 2005 and 2011, as the 8.5% annual increase in ROW savings combined with a tripling of the weight of its equities and bonds in foreigners' portfolios. Other regions did not experience the same magnitude of change, but all had increased KF* over the 2005-2011 period, with annual increases of 13% in Latin America, 20% in EME Europe, 23% in Africa, 18% in the euro area, 11% in the US, and 14% in AE Other.

After 2011 things changed. Global (excluding China) private savings was essentially flat from 2011-2018, increasing only 0.2% per year—this is due to relatively stagnant global (excluding China)

[12] We are limited in ways to create quarterly values of our measure. For many countries positions and wealth data are only available annually, meaning that weights can only be annual. More importantly, quarterly savings data is available for surprisingly few countries. That said, we are not overly concerned by this linear interpolation as our measure is slow moving and it is the deviation between it and flows that matters.

GDP rather than changes in savings rates—so for that period any increase in KF* would have to come from increased foreign weights.[13] 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 slowed.

Quarterly gross portfolio inflows and KF* are plotted in Figure 3 for the same six countries from Figure 1; see the Appendix Figure A1 for similar graphs for all 56 countries for which we have quarterly flow data. 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).[14] 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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[13] After being flat for almost a decade, global (excluding China) private savings increased by a modest 1.6% in 2019.

[14] 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 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. Issues with reported flow data are also evident for Iceland, specifically with respect to the late 2015 resolution of liabilities from its financial crisis (where some write downs, which should be valuation adjustments, appear to be recorded as flows) but also before that (there are large discrepancies across different data sources). KF* should be robust to many data issues, so in our main analysis we keep Switzerland and Iceland in our dataset as is and just note that disconnects between reported flows and positions will adversely impact the relationship between KF* and flows (and this affects our AE empirical results in subsequent sections).

4. KF* and Out-of-Sample Forecasts

The volatility of international capital flows makes it difficult to discern what level of flows will likely persist going forward. For our `KF*` to be successful, it should provide a time-series reference to pin down low-frequency "fundamental" movements. In practical terms, deviations from `KF*` should help forecast flows over the medium-term.

4.1 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 Cecchetti (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 (or market participant) looking at volatile quarterly flows series 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 country *i*'s portfolio inflows to converge in the future:

$$KF^{*}_{i,t} = E\left[flows_{i,t+h}\right] \tag{2}$$

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 (2) yields

$$E\left[flows_{i,t+h}\right] - flows_{i,t} = -(flows_{i,t} - KF^{*}_{i,t}) \tag{3}$$

Equation (3), the capital flow equivalent of the Cogley (2002) analysis of inflation, states that if (2) 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 (2) and (3) 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:

$$flows_{i,t+h} - flows_{i,t} = \alpha_{i,h} + \beta_{i,h}\left(flows_{i,t} - KF^{*}_{i,t}\right) + \varepsilon_{i,t} \qquad (4)$$

Cogley noted that $\alpha_{i,h}$ should equal zero, else `KF*` would be biased, but focused on β_h. If `KF*` satisfies equations (2) and (3), we expect to estimate $\beta_{i,h}$=-1 in equation (4) for medium-run horizons. An estimate of $\beta_{i,h}$=-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 (4) separately for each country.[15] Finally, note that this analysis is essentially out of sample, as it uses the period *t* gap between actual flows and the predetermined `KF*` to predict the *h*-period-ahead change in flows; the closeness of $\beta_{i,h}$ to -1 is in effect a summary measure of its performance.

Figure 4 (left column) presents box plots for the estimates of $\beta_{i,h}$ from equation (4) for the 18 AEs and 37 EMEs that have portfolio flows and `KF*` over the entire 2000Q4-2019Q4 sample. From left to right the box plots display $\beta_{i,h}$ estimates for horizons of 1 to 12 quarters. The top and bottom of each box indicate the 75th and 25th percentile estimates of $\beta_{i,h}$, the line inside a box

[15] 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.

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. For both the AE and EME subsamples we find $\beta_{i,h}$ estimates are generally less than one in absolute value for short time horizons but approach -1 at intermediate horizons. For example, at the 7-quarter horizon the median value for $\beta_{i,h}$ is -0.88 for AEs and -0.95 for EMEs. Wald tests indicate failure to reject the null hypothesis of $\beta_{i,h}$=-1 for 12 of the 18 AEs at a 6-quarter horizon, and more impressively, we fail to reject the null of $\beta_{i,h}$=-1 for 33 of the 37 EMEs at a 5-quarter horizon.[16]

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 $\beta_{i,h}$ is roughly -0.7 for AEs and -0.8 for EMEs, 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*`.

4.2 On the Explanatory Power of `KF*`

Cerutti, Claessens and Rose (2019) urges 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. The right

[16] Wald test results vary somewhat by horizon but we generally fail to reject $\beta_{i,h}$ =-1 for 9-12 of the 18 AEs and 22-33 of the EMEs over intermediate horizons. Wald tests also fail to reject the null hypothesis of $a_{i,h}$=0 for the vast majority of AEs and EMEs.

column of Figure 4 displays box plots for the adjusted R^2 from equation (6) for the 18 AEs and 37 EMEs with complete data on `KF*` and flows. The median R^2 peaks at 0.40 for AEs and 0.43 for EMEs at a 9-quarter horizon.

Of course, the literature Cerutti et al. (2019) 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 0.4 (for EMEs) and 0.33 (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 (measured as the average yield on long-term government bonds in the US, UK, Euro area and Japan), two variables that are commonly used in the empirical capital flows literature (Koepcke (2018)). As a pull factor we add local MSCI equity returns.[17] 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 (5):

$$flows_{i,t+h} - flows_{i,t} = \alpha_{i,h} + \beta^1_{i,h}(VIX_{t+h} - VIX_t\ ) + \beta^2_{i,h}(i_{t+h} - i_t\ ) + \beta^3_{i,h}\left(\left[\frac{msci_{i,t+h}}{msci_{i,t}}\right]^{1/h} - 1\right) + \varepsilon_{i,t}$$

(5)

Figure 5 (middle row) displays box plots for the adjusted R^2 from regression equation (5) estimated across 1 to 12 quarter horizons for the 17 AEs and 20 EMEs that in addition to having complete data on `KF*` and quarterly flows also have complete MSCI data. We find that push and

[17] MSCI equity returns, because they are based on U.S. dollar returns, are a useful 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).

pull factors explain much less of the variation in flows, with adjusted R^2 peaking at a median of 0.15 for the 6-quarter EME regressions and also at 0.15 for the 8-quarter AE regressions. For this sample, the R^2 in regressions containing just the gap between flows and `KF*` peaks around 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 0.51 for EMEs and 0.46 for 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.

5. Comparison to Other Plausible Natural Levels

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. (2018) 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 2018-19 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.[18]

[18] More generally, our construction of KF* 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.

5.2 Out-of-Sample Comparisons with Filter-based Measures

For a more concrete test of alternative statistical proxies for the natural rate of flows we re-estimate equation (4) replacing KF* with two univariate filters: a twelve-quarter moving average of portfolio flows and a one-sided HP filter of portfolio flows. Both are arguably out-of-sample measures and so relevant comparators to our out-of-sample KF*. For this comparison we include the 32 EMEs and 16 AEs that have complete flows data from 1998Q1 (which allows construction of the moving average and HP filter to match the KF* sample beginning in 2000Q4). Results are in Figure 7, with mean absolute deviation from $\beta_{i,h}$=-1 in the left column, mean R^2 in the right column, and samples varying from top to bottom (EMEs, AEs, and EMEs + non-UMP AEs, respectively). In each graph KF* is the thick blue line, moving average is the thin yellow line, and HP filter is the dashed line.

Recall that estimates of $\beta_{i,h}$ are expected to be -1 if deviations from the natural rate are transitory. For EMEs the mean absolute deviation bottoms out at 0.13 for KF* at the 9-quarter horizon and KF* outperforms the filters over 8-12 quarter horizons. For EMEs KF* also has the highest mean R^2 across all forecast horizons, peaking at 0.42 for the 7-quarter horizon.

For AEs, KF* performs less well, with larger deviations from $\beta_{i,h}$=-1 relative to univariate filters. 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 (or UMP, defined here as QE or negative policy rates). For example, for the 32 EMEs and 10 non-UMP AEs, mean absolute beta deviations from -1 bottom out at 0.14 for the 9-quarter horizon and KF* outperforms in terms of mean R^2 across all horizons (peaking at 0.42). In contrast, KF* performs less well for the 6 UMP AEs: the mean absolute deviation of $\beta_{i,h}$ from -1 over intermediate horizons is approximately 0.3 and R^2 averages 0.34. 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 their 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 out-of-sample alternatives. A useful characteristic of KF* is that being structural and not constructed as a filter, deviations from it are informative.

5.3 KF and Hamilton (2018)*

Hamilton (2018) argues forcefully against the use of an HP filter and proposes a simple alternative that seems tailor made for Cogley-like regressions. Hamilton, when forming his measure, asks (Hamilton p. 836): "How different is the value at date *t+h* from the value we would have expected to see based on its behavior through date t?" That is precisely, in a univariate setting, what the Cogley analysis is designed to ascertain. Hamilton's alternative uses an OLS regression of a variable at date *t* on a constant and 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, which we will use in Cogley regressions. Note that in our application of Hamilton's technique we use the entire time series (starting in 1998q1) and so the exercise should be considered in sample, not out of sample.[19]

Figure 8, similar in layout to Figure 7, shows the performance of KF* (which is by design out of sample) and the Hamilton (2018) linear projection (dashed line). For EMEs (top row), the

[19] Hamilton notes that the linear projection will converge to an out of sample estimate in the limit as the sample size gets large.

performance of KF* and Hamilton (2018) is nearly indistinguishable. For the mean absolute deviation from $\beta_{i,h}$=-1 the Hamilton linear projection performs slightly better at shorter horizons and KF* performs slightly better at longer horizons, but for every horizon the differences are very small. For EMEs the R^2 of KF* is for every horizon higher than that of the Hamilton projection, but again the differences are not large; the largest difference is 0.42 versus 0.39 for a horizon of 8 quarters. For AEs (middle row), Hamilton dominates KF*, as MA12 and the HP filter did. For EMEs plus non-UMP AEs (bottom row), the performance of KF* and the Hamilton method is similar, with Hamilton having slightly smaller mean absolute deviations from $\beta_{i,h}$=-1 and KF* having a slightly higher mean R^2. Overall, the Hamilton method (like MA12 and the HP filter) is better for AEs that have implemented UMPs, but for EMEs and non-UMP AEs the performance of the out-of-sample KF* and the in-sample Hamilton method is similar.

6. Applications: Predicting Extreme Capital Flow Episodes and Equity Returns Using KF*

In the previous sections we established that KF* helps identify the component in gross portfolio flows that is expected to persist over medium-run horizons. Given the boom-bust nature of international flows, the KF* benchmark might be 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 KF* helps forecast extreme capital flow episodes at a medium-run horizon. We then proceed to determine whether deviations from KF* help predict equity returns.

6.1 Predicting Sudden Stops

We test whether portfolio flows that are well above (below) KF* predict an upcoming sharp decline (increase) in flows, focusing on the Forbes and Warnock (2012, 2020) extreme capital flow episodes. That is, does the gap between actual flows and KF* help predict sudden stops and surges?

For sudden stops we estimate models of the form:

$$Prob(STOP_{i,t+h} = 1) = F(KF^{*}gap_{i,t}, Global\ Factors_{t}, Local\ Factors_{i,t}) \qquad (6)$$

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* and $KF^{*}gap_{i,t}$ is the gap (scaled by GDP) between current flows and KF*, averaged over the last 4 quarters. Everything is as in Forbes and Warnock (2020) with two exceptions: our forecast horizon is medium term, whereas Forbes and Warnock (2020) focus on one-quarter-ahead episodes, and we include $KF^{*}gap$. Global factors include global risk (measured using the year-over-year change in VXO), global liquidity (measured as the year-over-year percentage growth in the 'global' broad money supply, where global is the sum for the euro area, US, UK and Japan), global monetary policy (measured as the year-over-year change in the average shadow short rate for the US, UK, euro area and Japan), global growth (measured as year-over-year global GDP growth from the IMF's World Economic Outlook dataset), and the year-over-year percentage change in oil prices. Local factors are, as in Forbes and Warnock (2020), limited to local year-over-year real GDP growth and a regional contagion measure (an indicator equal to one if another country in the region has an episode). Because extreme capital flow episodes are rare, following Forbes and Warnock (2020) we estimate equation (6) using the complementary logarithmic framework, which assumes F(·) is the cumulative distribution function of the extreme value distribution. An analogous model is estimated for surges.

Results from panel estimation of equation (6) at a 6-quarter forecast horizon are presented in Table 1.[20] Merging our KF* dataset with the Forbes and Warnock (2020) capital flows episodes leaves us with a sample of 30 countries (14 AEs and 16 EMEs) and 2038 quarterly observations. The results in panel A of Table 1 indicate 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.[21]

To get a sense for economic magnitudes we calculate the model's estimated probability of a future stop when KF*gap is at its mean (zero) and one and two standard deviations above its mean (3.4% and 7.8% of GDP), holding all other variables at their means. When KF*gap is zero—that is, current flows are equal to KF*—there is an 8.8% 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 to 13.5% and 20.3%, respectively. We also find evidence that 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 means, the probability of a future stop climbs to 31.8%.

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-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.

[20] As a robustness check we also estimate equation (6) at 4- and 8-quarter forecast horizons. KF* gap is the only variable with statistically significant predictive power across all forecast horizons.

[21] In column (2) we present results for surge episodes and find that they are difficult to predict at a six-quarter horizon; only local GDP growth is strongly significant. 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.

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 likely in 6 quarters. One difference from the BIS indicators: Our 'trend' is not a mechanical trend but KF*.

6.2 Predicting Equity Returns

The gap between actual flows and KF* helps predict sudden stops (but not surges) over the medium term. A natural next question is whether the gap also helps predict equity returns. For this analysis, we operationalize 'medium term' by using an annual (year-end) dataset.

In Table 2 we present results from a panel fixed effects regression of annual MSCI returns (in U.S. dollars, in excess of the U.S. 3-month Treasury bill rate) for 39 countries (16 AEs and 23 EMEs) on a set of lagged explanatory variables.[22] Specifically, we evaluate the extent to which deviations from KF* during year *t-1* impact annual equity returns in year *t*. Deviations of actual flows from KF* are scaled by GDP and then averaged over the year. Control variables, guided by Bekaert, Harvey and Lundblad (2007) and data availability, include the lagged dependent variable, lagged global variables (world GDP growth and VXO), and lagged local variables (dividend yield, returns volatility measured as the standard deviation of 12 months of returns, and local GDP growth).

The results in Table 2 indicate that annual equity returns are negatively serially correlated (that is, the lagged dependent variable is negative and significant); periods of strong global growth

[22] There is a long literature on equity returns predictability. Within that literature, our analysis in this section is most similar to studies that focus on a set of countries rather than just one (see, among others, Bekaert, Harvey and Lundblad 2007) and, within that set, those that examine long-run predictability (see, for example, the output gap analysis in Cooper and Priestley (2009)).

and increased risk appetite (as measured by a low level of VXO) are followed by lower returns; and the gap between actual flows and KF* helps predict future equity returns.[23]

For KF*, the results are again statistically and economically significant. The coefficient on KF*Gap/GDP is negative and highly statistically significant, indicating that a year in which flows exceed KF* tends to be followed by lower equity returns in the following year. The impact is quantitatively significant; a one standard deviation gap in flows from KF* is associated with a 4.7 percentage point reduction in annual equity returns. And, consistent with the sudden stops analysis, the combination of strong global growth and flows above KF* predicts future trouble. In this case a country that is experiencing KF* gap/GDP that is one standard deviation above average during a year of strong global growth (also one standard deviation above average) is predicted to experience a subsequent annual decline in equity returns of nearly 10 percentage points.

7. Application: From the GFC to Covid

In previous sections we demonstrated that deviations from KF* have predictive power for medium-run portfolio flows, sudden stops, and equity returns. In the context of the current covid-19 health crisis one might be curious whether KF* provides useful information about future portfolio flows in the face of a sudden large global shock. With the covid-19 crisis ongoing we lack data for formal analysis of the current episode, so instead we turn back to the last sudden large global shock—the GFC—to see what lessons might be applicable.

If KF* represents the natural level of portfolio flows, we predict countries receiving flows well above KF* are most likely to experience a sharp reduction in flows in response to an external global shock. We use data from the GFC to test this hypothesis. First, for each country, we calculate

[23] As a robustness check, we also measure returns in local currency, and the results (not reported) are very similar.

the average KF* gap/GDP over the four quarters of 2007 as a measure of pre-GFC vulnerability. Then we calculate the GFC-impact of the crisis on flows as average flows/GDP during the GFC period (2008Q4-2009Q3) minus flows/GDP during 2007.

Figure 9 provides visual evidence in support of the hypothesis that countries with large deviations from KF* during 2007 subsequently suffered the largest (scaled by GDP) reductions in flows during the crisis. The top left panel includes the full sample of 51 countries, of which Hong Kong is an outlier that happens to fit the hypothesis perfectly. During 2007 Hong Kong received massive financial inflows that then evaporated during the GFC. In the top right panel we drop Hong Kong from the sample and still see a clear relationship for the remaining countries. Countries with flows well above KF* in 2007 subsequently experienced a sharp drop in flows while countries that entered the crisis with flows closer to the natural level tended to experience more moderate changes in flows. The bottom left panel demonstrates that the relationship becomes even stronger after dropping countries that conducted unconventional monetary policy (consistent with our earlier stronger results when this group is excluded) and in the bottom right panel we see that the relationship also holds for a sample of 33 EMEs. Finally, Table 3 provides the linear regression results corresponding to scatter plots provided in Figure 9. For each sample the relationship between the KF* gap in 2007 and subsequent change in flows during the GFC is highly statistically significant.

The pre-GFC gap between actual flows and KF* was a very strong predictor of the magnitude of the decrease in flows during the GFC. To apply that insight to the current pandemic we plot, in Figure 10, the pre-pandemic (i.e., 2019) deviation of portfolio flows from KF* (scaled by GDP). Notably, most countries in our sample were experiencing flows *below* KF* during 2019, suggesting they are less vulnerable to a dramatic decline in flows during the current covid-19 crisis. The few countries that experienced flows significantly above KF* during 2019—Ecuador, Chile, and

Ukraine each had positive gaps on the order of 2% of GDP—seem more susceptible to a large correction in portfolio flows during 2020.

Overall, applying what we learned from the GFC to the current crisis suggests (i) flows have less room to fall as many countries were below KF* at the eve of the current global shock, (ii) for most countries any drop in flows experienced during the crisis is likely to be temporary as a rebound toward KF* should be expected in the intermediate term, and (iii) a few countries (Ecuador, Chile, and Ukraine) seem more vulnerable than others.

8. 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.

Empirically, KF* performs well. Quarterly flows, which are quite volatile, oscillate around KF*; deviations of actual flows from their natural level (approximated by KF*) are transitory; with portfolio flows (especially for EMEs and non-UMP AEs) reverting to KF* over a 1-to-2-year horizon. This 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. Moreover, a positive gap between actual flows and KF* is a strong predictor of sudden stops and negative equity returns, especially when coupled with above-average global growth. Specifically, when strong global growth (and, hence, global savings) drives an acceleration of KF*, if actual flows are growing even faster than KF*, then a subsequent sudden stop and negative equity returns are likely.

While empirical tests suggest KF* is a useful construct which helps 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 constructed from underlying fundamentals, 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.

Finally, we note that KF* is a potentially useful tool for understanding the outlook for capital flows in the aftermath of the covid-19 crisis. As of end-2019 most countries in our sample experienced flows that were below KF* which suggests any decline in flows during the crisis is likely to be temporary and a rebound toward KF* should be expected in the intermediate term. And the long-run outlook for flows depends crucially on a post-crisis rebound in global growth (and hence global savings) which, along with steady-state portfolio weights, are the underlying fundamentals of KF*.

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Figure 1. Gross Portfolio Inflows (2000q4-2019q4, 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

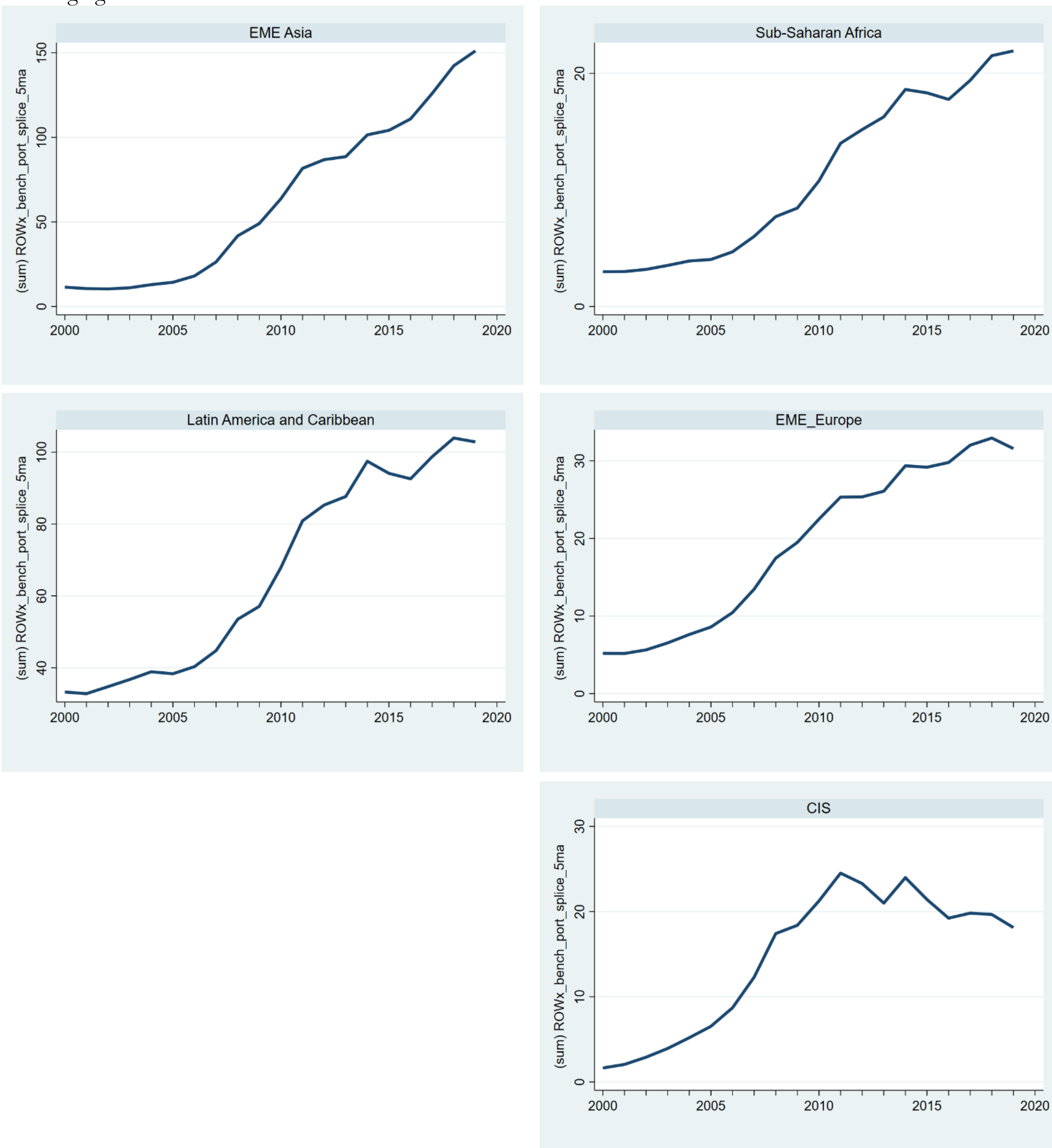
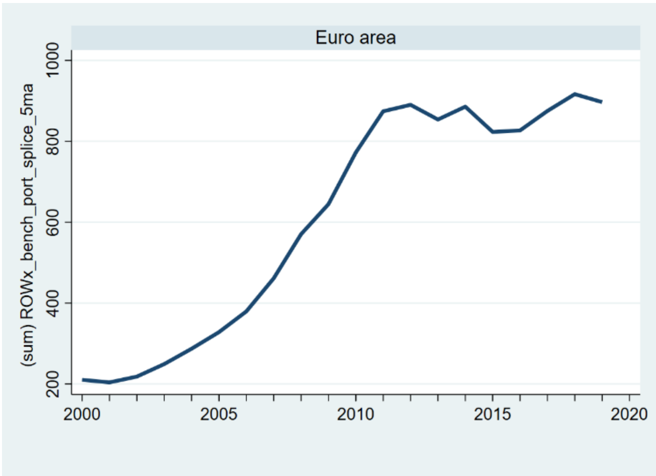
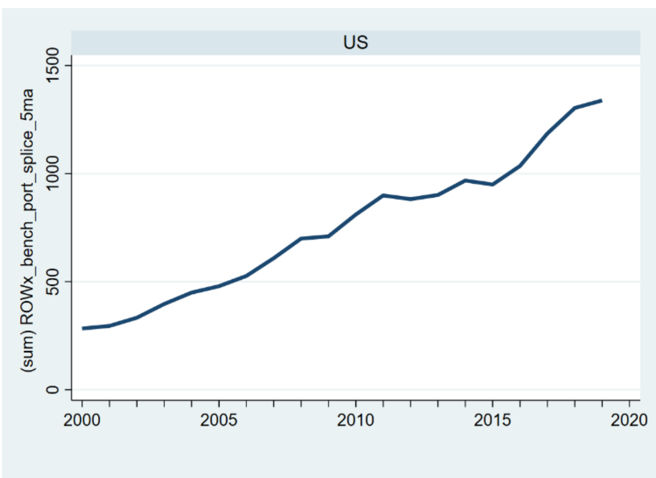


Figure 2. `KF*` by Region (cont.)

B. Advanced Economies





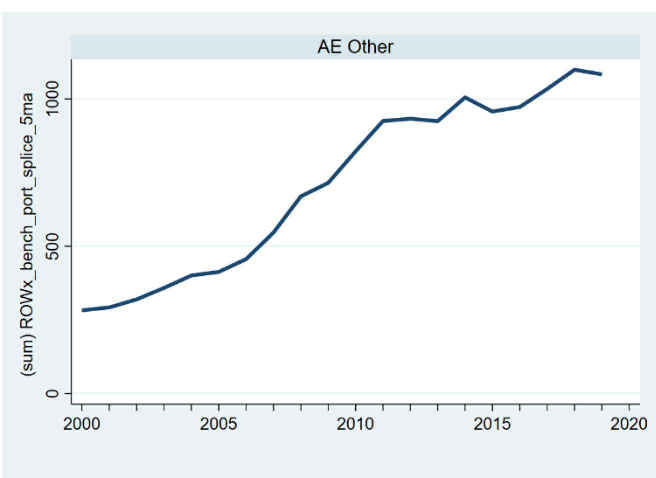


Figure 3. `KF*` and Gross Portfolio Inflows (2000q4-2019q4, billions of USD)

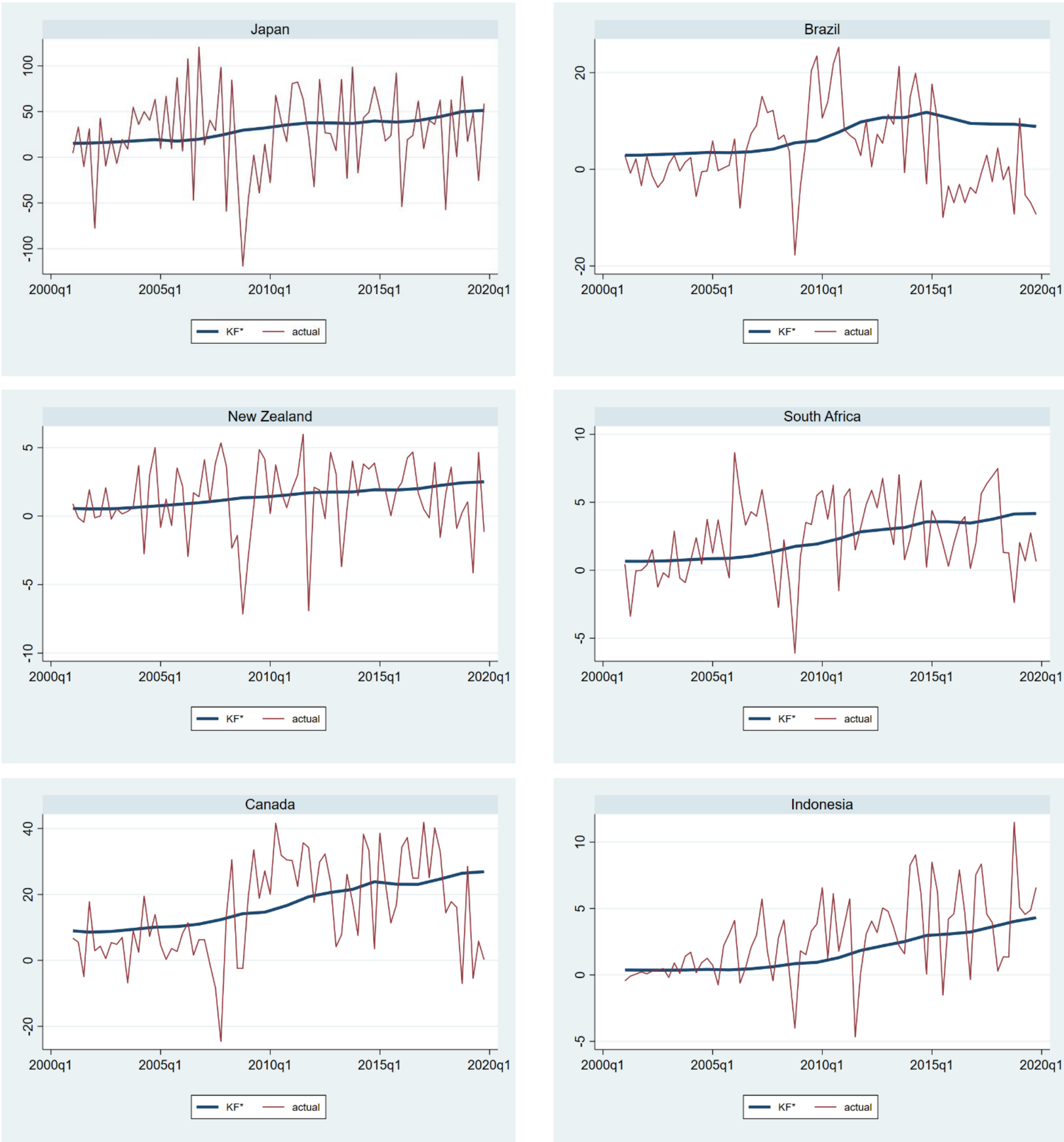


Figure 4. Cogley Results

The graphs summarize estimates of $\beta_{i,h}$ (left column) and the adjusted R^2 (right column) from country-level regressions of eq. (4) for the 18 AEs and 37 EMEs that have KF* and flows data for the entire sample starting 2000q4. In each graph, 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 $\beta_{i,h}$ or the adjusted R^2), 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.

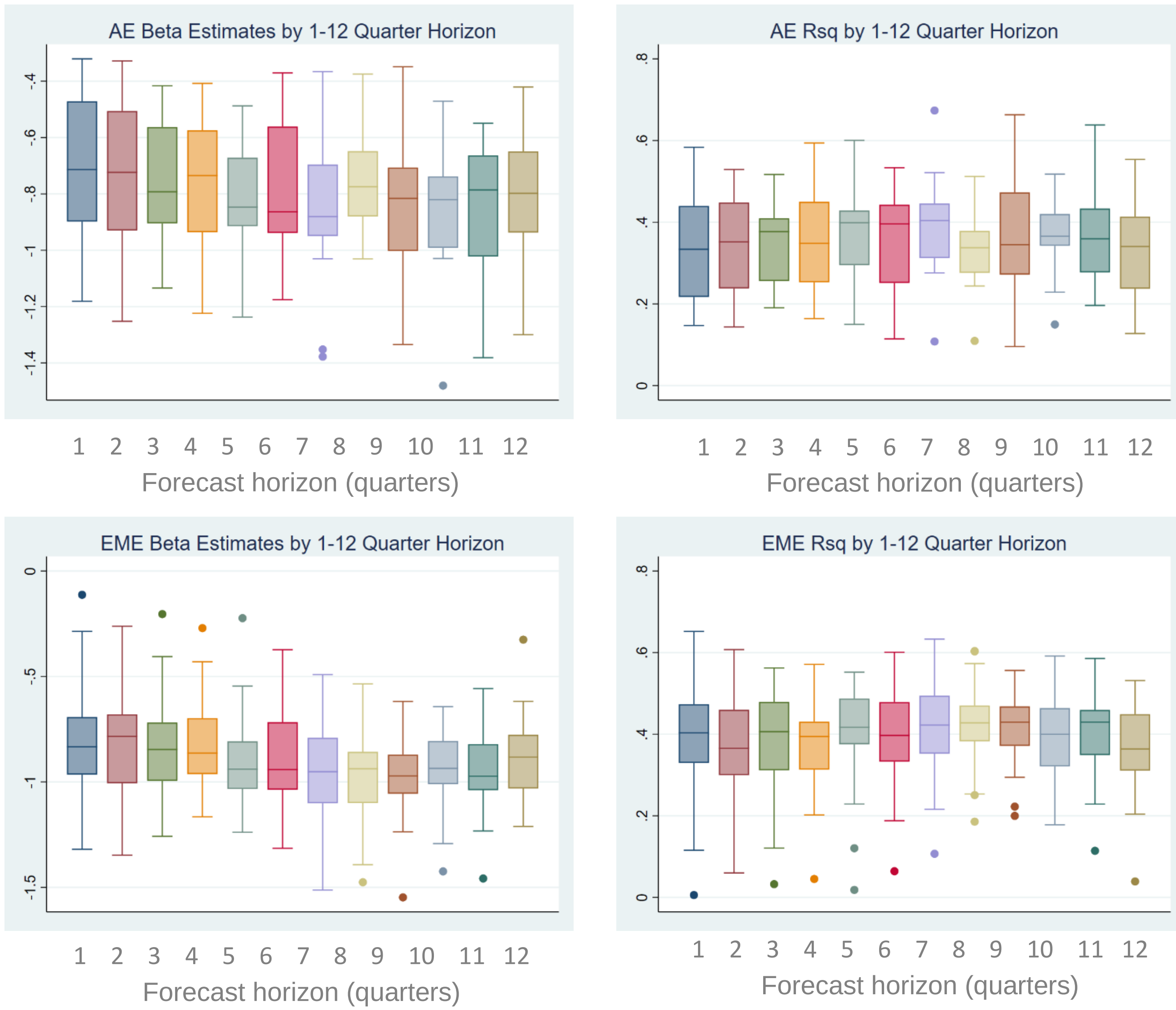


Figure 5. Cogley R^2 Comparison

The graphs summarize the adjusted R^2 from individual country regressions for the 17 AEs and 20 EMEs that have KF*, flows, and MSCI equity returns for the entire sample. The top row of graphs include only KF*, as in eq. (4); the middle row includes only push and pull factors, as in eq. (5); and the bottom row includes both. See note to Figure 4 for details on how to interpret the box and whisker 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 2019q4; 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.

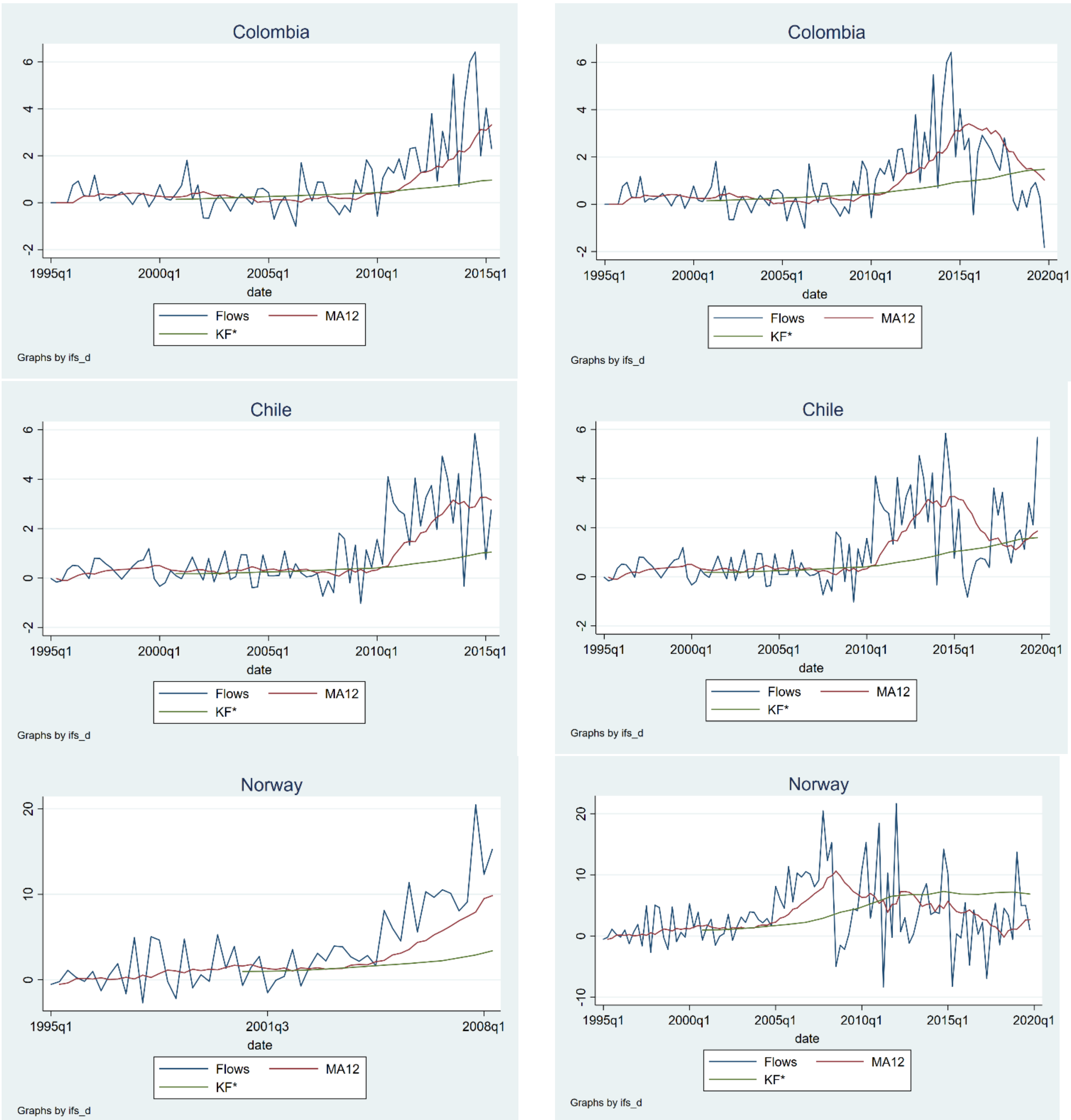
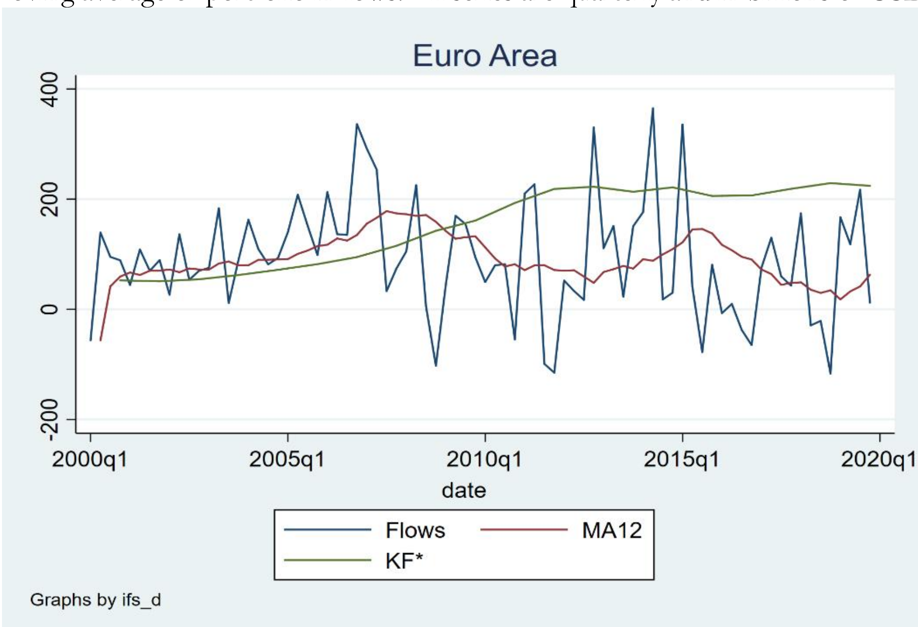


Figure 6b. `KF*` and a Moving Average Measure

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.



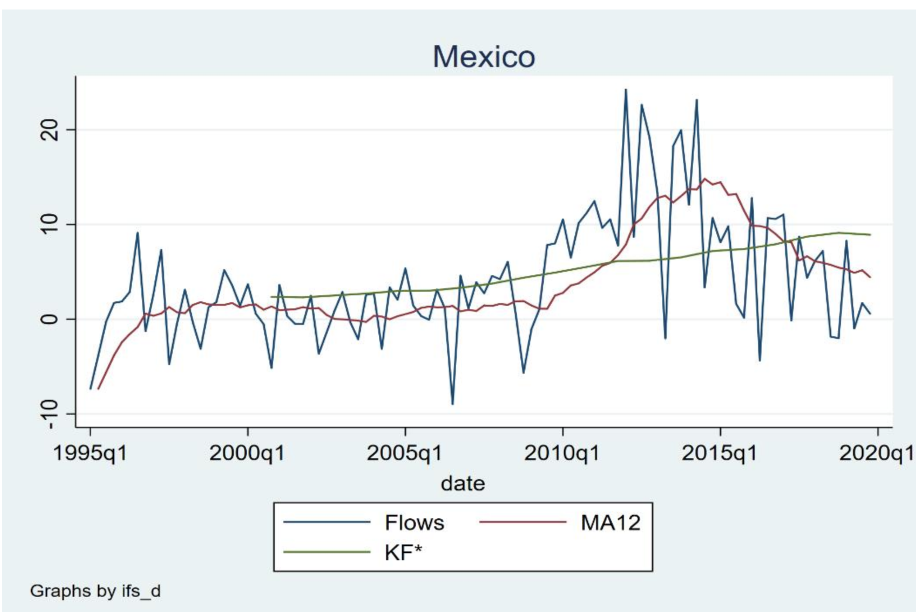


Figure 7. Out-of-Sample Predictive Power of KF*, HP Filter and MA12

The figure presents the absolute value of mean average deviation (left column) of beta from negative 1 and the mean R^2 (right column) for a sample of 32 EMEs and 16 AEs for forecast horizons (plotted on the horizontal axes) of 1 to 12 quarters. The forecast periods are 2000Q4-2018Q1 (so that the last forecast period is 2019Q4). MA (thin yellow line) is a 12-quarter moving average and HP (dashed line) is a one-sided HP filter. UMP is defined here as quantitative easing and/or negative policy rates.

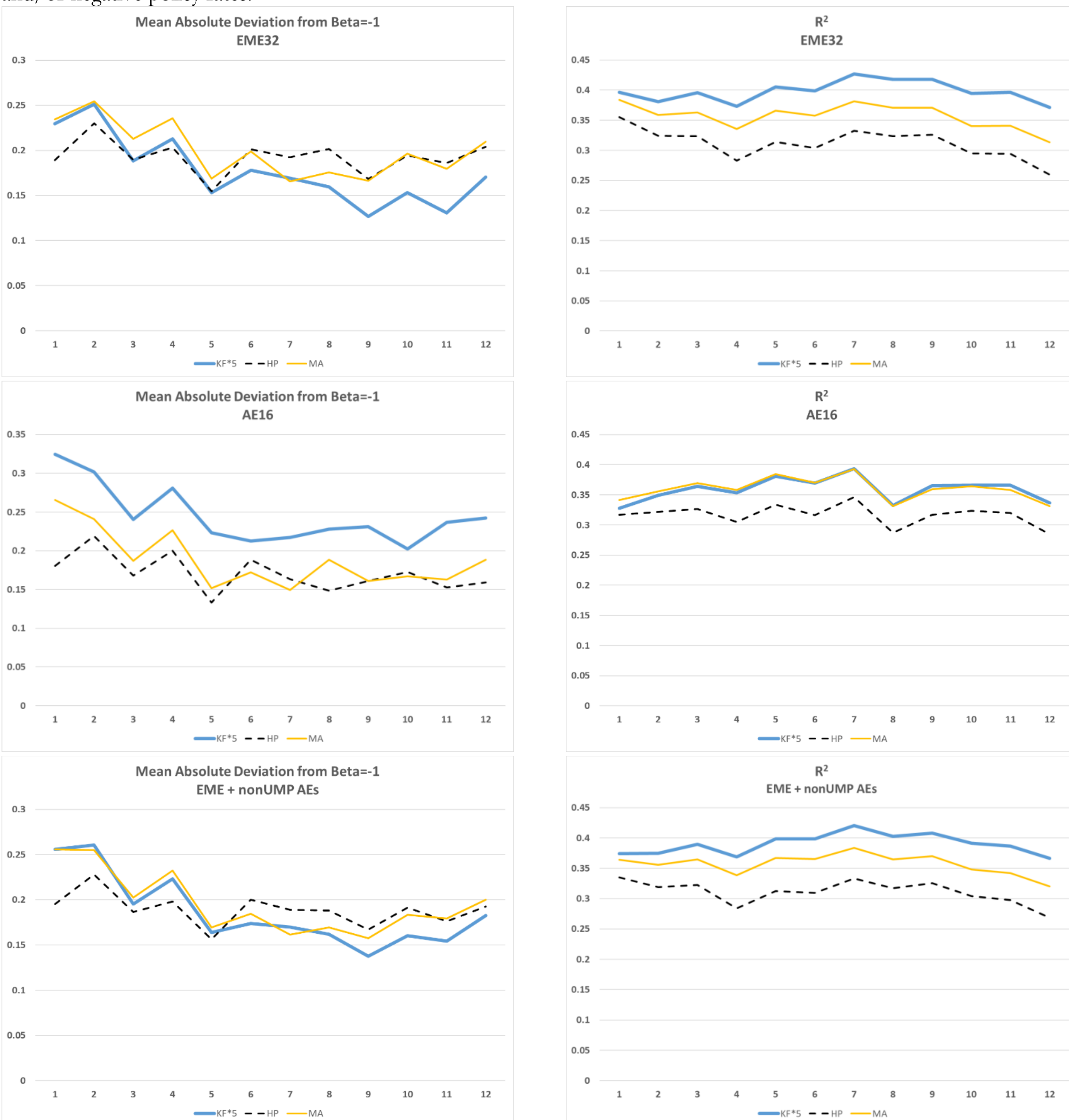


Figure 8. Predictive Power of KF* and Linear Projections

The figure presents the absolute value of mean average deviation (left column) of beta from negative 1 and the mean R^2 (right column) for a sample of 32 EMEs and 16 AEs for forecast horizons (plotted on the horizontal axes) of 1 to 12 quarters. The forecast periods are 2000Q4-2018Q1 (so that the last forecast period is 2019Q4). The Hamilton (2018) linear projection (dashed line) is described in the text. UMP is defined as quantitative easing and/or negative policy rates.

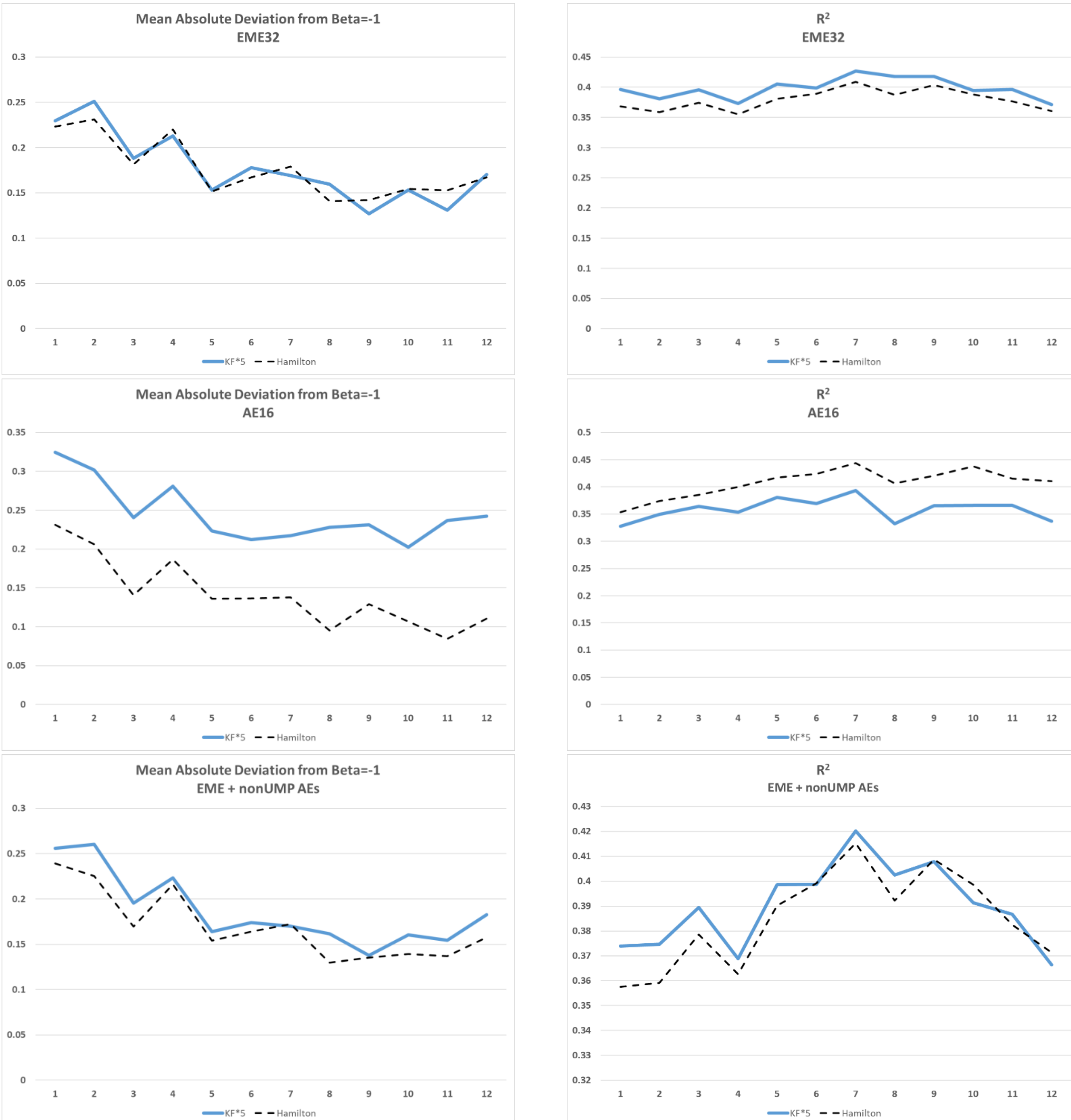


Figure 9. KF* and Portfolio flows during the Global Financial Crisis

The figure presents scatterplots for the relationship between the average 2007 KF*gap/GDP (the deviation of actual flows from KF*, expressed as a share of GDP) and the subsequent change in portfolio flows during the GFC. The change in flows is calculated as average flows/GDP during the GFC period (2008Q4-2009Q3) minus flows/GDP during 2007. UMP is defined here as quantitative easing and/or negative policy rates.

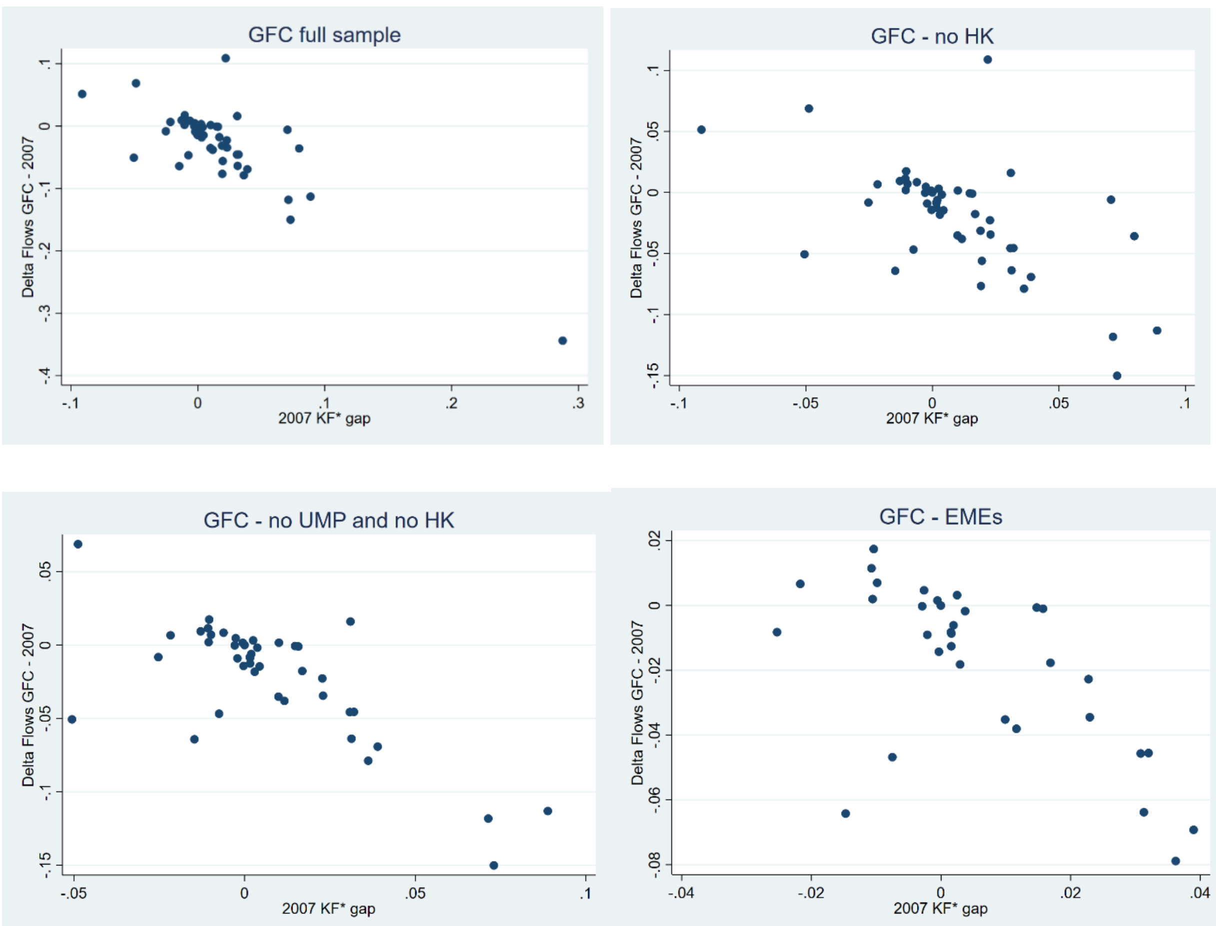


Figure 10. KF* Gap on the Eve of the Global Pandemic

The figure presents the average 2019 KF*gap/GDP (that is, the deviation of actual flows from KF*, expressed as a share of GDP).

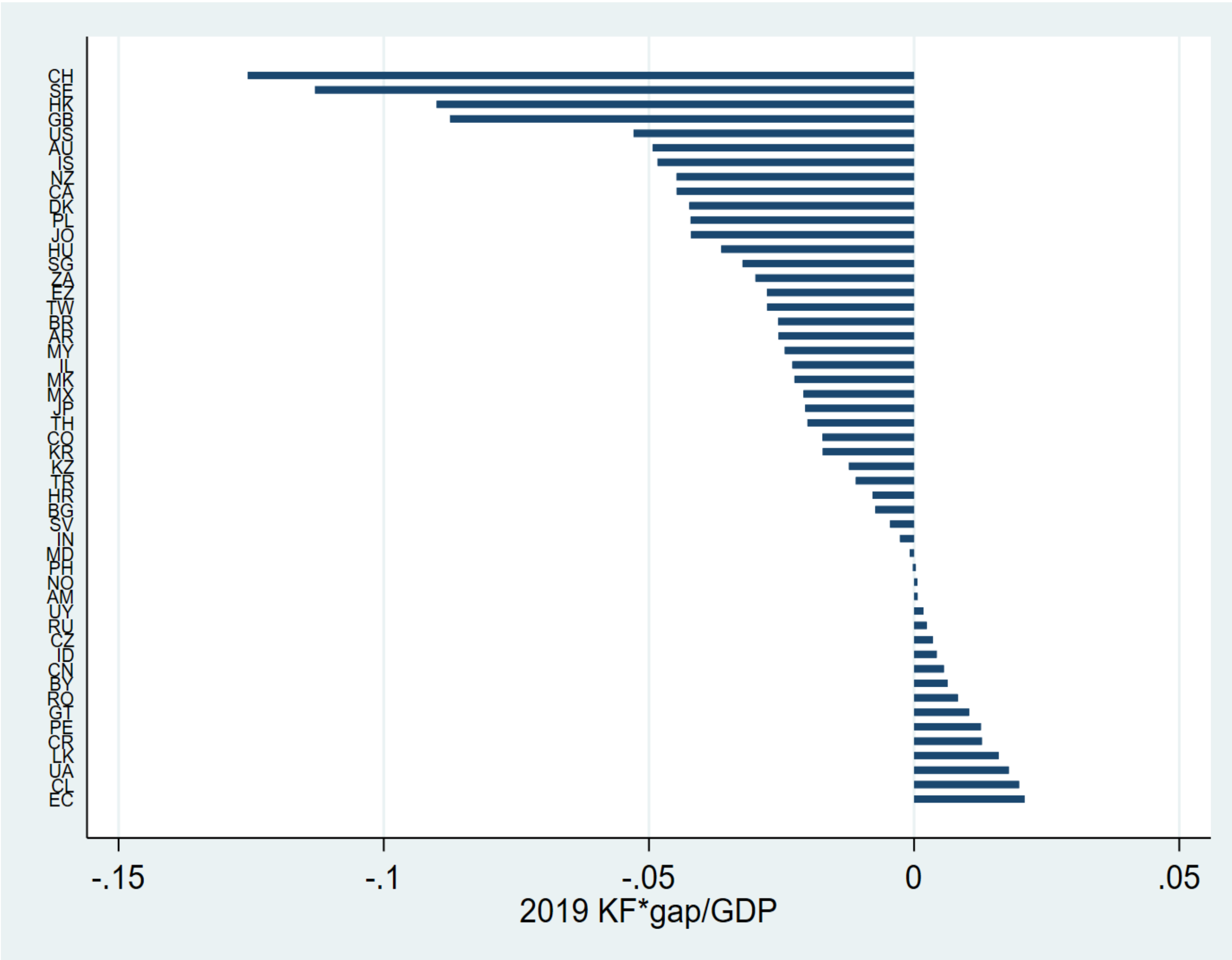


Table 1. KF* and Extreme Capital Flow Episodes

Panel A presents regressions of period *t+6* sudden stops and surges on period *t* KF*gap/GDP (the deviation of actual flows from KF*, expressed as a share of GDP) and global and local variables. Global variables include global GDP growth (year-over-year), risk (measured as the change in the VIX), liquidity (measured as the year-over-year percentage growth in the 'global' broad money supply, where global is the sum for the US, UK, euro area and Japan), monetary policy (measured as the year-over-year change in the average shadow short rate for the US, UK, euro area and Japan), and the year-over-year percentage change in oil prices. Local factors are local year-over-year real GDP growth and a regional contagion measure (an indicator equal to one if another country in the region has an episode). Panel B shows, using marginal effects from those regressions, 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 (3.4% and 6.8%), holding all other variables at their means, and (ii) both KF*gap/GDP and global GDP growth are 1 standard deviations above their means.

Panel A	**Prob(Stop) t+ 6 quarters**	**Prob(Surge) t+ 6 quarters**
KF* gap/GDP	13.328**	0.887
	(5.763)	(2.357)
Global Variables		
Global GDP Growth	0.605***	-0.173*
	(0.200)	(0.101)
Risk	0.072***	-0.002
	(0.020)	(0.076)
Liquidity	0.091	-0.000
	(0.069)	(0.039)
Oil Prices	-0.003	0.005
	(0.003)	(0.004)
Monetary Policy	0.225	0.241*
	(0.173)	(0.133)
Local and Contagion Variables		
Local GDP Growth	0.012	0.062***
	(0.027)	(0.024)
Regional Contagion	-0.132	0.200
	(0.154)	(0.155)
Observations	2038	2038
Countries	30	30

Panel B	**Prob (Stop) t+6 quarters**
KF* gap/GDP = 0%	8.8%
KF* gap/GDP = 3.4%	13.5%
KF* gap/GDP = 6.8%	20.3%
KF* gap/GDP = 3.8% & Global growth = 4.2%	31.8%

Table 2. KF* and Equity Returns

Panel fixed effects regressions of annual period *t* MSCI equity returns on period *t-1* explanatory variables. Explanatory variables include the lagged dependent variable, lagged KF*gap/GDP (the deviation of actual flows from KF*, expressed as a share of GDP), lagged global variables (global GDP growth, VXO) and lagged local variables (dividend yield, 12-month returns volatility, local GDP growth). Sample period is 2002-2019. Robust standard errors are reported in parentheses.

Lagged Dependent Variable	-0.105*
	(0.052)
KF* Gap / GDP	-1.150***
	(0.273)
Global Variables	
Global GDP Growth	-3.729***
	(1.350)
VXO	-0.794***
	(0.260)
Local Variables	
Dividend Yield	1.338
	(1.371)
Returns Volatility	0.786
	(0.260)
Local GDP Growth	0.505
	(0.781)
Country Fixed Effect	YES
Within R^2	0.141
Observations	712
Countries	39

Table 3. KF* and Portfolio Flows during the Global Financial Crisis

The table presents simple bivariate regression results for the relationship between the average 2007 KF*gap/GDP (the deviation of actual flows from KF*, expressed as a share of GDP) and the subsequent change in portfolio flows during the GFC. The change in flows is calculated as average flows/GDP during the GFC period (2008Q4-2009Q3) minus flows/GDP during 2007. UMP is defined here as quantitative easing and/or negative policy rates.

	Full Sample	Drop HK	Drop HK + UMP	EMEs
KF* Gap/GDP	-1.023***	-0.810***	-1.094***	-1.000***
(2007)	(0.103)	(0.159)	(0.083)	(0.214)
R^2	0.661	0.336	0.540	0.395
Countries	51	50	43	33

Appendix A: The exChina Adjustment

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 suggests a three-step adjustment.

First, we exclude China from ROW savings.

Second, we make flows consistent with excluding China. For the seven reserve currency countries identified in IMF COFER data (US, UK, Eurozone, Japan, Switzerland, Australia, and Canada), we remove China's bond flows. There is no direct measure of China's official bilateral flows (or its positions)—that is, the People's Bank of China does not publish the details of its international portfolio—so we must estimate these. 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.

Third, ROW portfolio weights must be consistent with excluding China's holdings. This follows from our bond flows adjustment: implied China bond holdings are simply the stock of China's reserves multiplied by the COFER currency weights.

We can construct this exChina 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, to the IMF).

Table A1. Country Coverage for KF*

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

	Start	End
United States	2000	2019
Euro Area	2000	2019
Other Advanced Economies		
Australia	2000	2019
Canada	2000	2019
China,P.R.:Macao	2000	2019
Czech Republic	2000	2019
Denmark	2000	2019
Hong Kong	2000	2019
Iceland	2000	2019
Israel	2000	2019
Japan	2000	2019
Korea	2000	2019
New Zealand	2000	2019
Norway	2000	2019
San Marino	2006	2019
Singapore	2000	2019
Sweden	2000	2019
Switzerland	2000	2019
Taiwan	2000	2019
United Kingdom	2000	2019
Commonwealth of Independent States		
Armenia	2000	2019
Azerbaijan	2000	2019
Belarus	2000	2019
Georgia	2004	2019
Kazakhstan	2000	2019
Kyrgyz Republic	2000	2019
Moldova	2000	2019
Russia	2000	2019
Tajikistan	2003	2019
Turkmenistan	2006	2019
Ukraine	2000	2019
Uzbekistan	2006	2019
Emerging and Developing Europe		
Albania	2002	2019
Bosnia and Herzegovina	2003	2019
Bulgaria	2000	2019
Croatia	2000	2019
Hungary	2000	2019
Kosovo	2009	2019
Macedonia	2003	2019
Poland	2000	2019
Romania	2000	2019
Serbia	2004	2019
Turkey	2000	2019

code		Start	End
	Sub-Saharan Africa		
614	Angola	2003	2019
638	Benin	2000	2019
616	Botswana	2000	2019
748	Burkina Faso	2005	2019
618	Burundi	2002	2019
662	Cote d'Ivoire	2000	2019
622	Cameroon	2002	2019
624	Cape Verde	2009	2019
626	Central African Rep.	2006	2019
632	Comoros	2006	2019
636	Congo, Dem. Rep. of	2000	2019
634	Congo, Republic of	2000	2019
642	Equatorial Guinea	2006	2018
643	Eritrea	2006	2019
644	Ethiopia	2010	2019
646	Gabon	2006	2019
648	Gambia, The	2003	2019
652	Ghana	2000	2019
656	Guinea	2000	2019
654	Guinea-Bissau	2006	2019
664	Kenya	2000	2019
666	Lesotho	2000	2019
668	Liberia	2006	2019
674	Madagascar	2006	2019
676	Malawi	2007	2019
678	Mali	2000	2019
684	Mauritius	2000	2019
688	Mozambique	2009	2019
728	Namibia	2005	2019
692	Niger	2000	2019
694	Nigeria	2009	2019
714	Rwanda	2003	2019
722	Senegal	2000	2019
718	Seychelles	2009	2019
724	Sierra Leone	2006	2019
199	South Africa	2000	2019
734	Swaziland	2009	2019
738	Tanzania	2000	2019
742	Togo	2004	2019
746	Uganda	2004	2019
754	Zambia	2011	2019
698	Zimbabwe	2000	2019
	Latin American and the Caribbean		
311	Antigua and Barbuda	2006	2019
213	Argentina	2000	2019
314	Aruba	2000	2018
313	Bahamas, The	2005	2019
316	Barbados	2000	2019
339	Belize	2000	2019
218	Bolivia	2000	2019

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

code		Start	End
	Latin American and the Caribbean (cont.)		
223	Brazil	2000	2019
228	Chile	2000	2019
233	Colombia	2000	2019
238	Costa Rica	2000	2019
321	Dominica	2000	2019
243	Dominican Republic	2000	2019
248	Ecuador	2000	2019
253	El Salvador	2000	2019
328	Grenada	2000	2019
258	Guatemala	2000	2019
336	Guyana	2000	2019
263	Haiti	2003	2019
268	Honduras	2000	2019
343	Jamaica	2000	2019
273	Mexico	2000	2019
278	Nicaragua	2002	2019
283	Panama	2000	2019
288	Paraguay	2000	2019
293	Peru	2000	2019
361	St. Kitts and Nevis	2006	2019
362	St. Lucia	2007	2019
364	St. Vincent & Grens.	2006	2019
366	Suriname	2002	2019
369	Trinidad and Tobago	2000	2019
298	Uruguay	2000	2019
299	Venezuela, Rep. Bol.	2000	2019
	Middle East, North Africa Afghanistan and Paki		
512	Afghanistan, I.R. of	2012	2019
612	Algeria	2000	2019
419	Bahrain	2000	2019
611	Djibouti	2008	2019
469	Egypt	2000	2019
429	Iran, Islamic Republic of	2000	2019
433	Iraq	2010	2019
439	Jordan	2000	2019
443	Kuwait	2000	2019
446	Lebanon	2000	2019
672	Libya	2006	2019
682	Mauritania	2006	2019
686	Morocco	2000	2019
449	Oman	2007	2019
564	Pakistan	2000	2019
453	Qatar	2001	2019
456	Saudi Arabia	2013	2019
732	Sudan	2008	2019
463	Syrian Arab Republic	2002	2011
744	Tunisia	2000	2019
466	United Arab Emirates	2002	2019
474	Yemen, Republic of	2003	2019

code		Start	End
	Emerging and Developing Asia		
513	Bangladesh	2000	2019
514	Bhutan	2013	2019
516	Brunei Darussalam	2002	2019
522	Cambodia	2000	2019
924	China,P.R.: Mainland	2000	2019
819	Fiji	2010	2019
534	India	2000	2019
536	Indonesia	2000	2019
826	Kiribati	2012	2019
544	Lao People's Dem.Rep	2002	2019
548	Malaysia	2000	2019
556	Maldives	2000	2019
868	Micronesia	2000	2019
948	Mongolia	2008	2019
518	Myanmar	2006	2019
836	Nauru	2013	2019
558	Nepal	2006	2019
565	Palau	2006	2019
853	Papua New Guinea	2000	2019
566	Philippines	2000	2019
862	Samoa	2006	2019
813	Solomon Islands	2011	2019
524	Sri Lanka	2000	2019
578	Thailand	2000	2019
537	Timor-Leste	2015	2019
866	Tonga	2006	2019
869	Tuvalu	2006	2019
846	Vanuatu	2007	2019
582	Vietnam	2002	2019
	Financial centers nec		
319	Bermuda	2006	2019
379	British Virgin Islands	2005	2019
377	Cayman Islands	2006	2019
823	Gibraltar	2006	2019
113	Guernsey	2006	2019
118	Isle of Man	2006	2019
117	Jersey	2006	2019
839	New Caledonia	2006	2019
	Other countries nec		
312	Anguilla	2006	2019
354	Curacao	2015	2019
887	French Polynesia	2007	2018
147	Liechtenstein	2007	2019
352	Sint Maarten	2015	2019
381	Turks and Caicos	2006	2019
487	West Bank and Gaza	2003	2019

Table A2. Country Coverage for Quarterly Flow Data

Countries are listed in alphabetical order within regions, which are primarily from the IMF's Classification of Countries. All 56 countries that had 20 years of quarterly portfolio inflow data in the IMF's IFS dataset as of September 27 2020 are included.

	Advanced Economies		
193	Australia	1998q1	2019q4
156	Canada	1998q1	2019q4
935	Czech Republic	1998q1	2019q4
128	Denmark	1998q1	2019q4
163	Eurozone	1998q1	2019q4
532	Hong Kong	1999q1	2019q4
176	Iceland	1998q1	2019q4
436	Israel	1998q1	2019q4
158	Japan	1998q1	2019q4
196	New Zealand	1998q1	2019q4
142	Norway	1998q1	2019q4
576	Singapore	1998q1	2019q4
542	South Korea	1998q1	2019q4
144	Sweden	1998q1	2019q4
146	Switzerland	1999q1	2019q4
528	Taiwan	1998q1	2019q4
112	United Kingdom	1998q1	2019q4
111	United States	1998q1	2019q4

	Latin American and the Caribbean		
213	Argentina	1998q1	2019q4
314	Aruba	1998q1	2019q4
223	Brazil	1998q1	2019q4
228	Chile	1998q1	2019q4
233	Colombia	1998q1	2019q4
238	Costa Rica	1999q1	2019q4
248	Ecuador	1998q1	2019q4
253	El Salvador	1998q1	2019q4
258	Guatamala	1998q1	2019q4
273	Mexico	1998q1	2019q4
293	Peru	1998q1	2019q4
298	Uruguay	2000q1	2019q4
299	Venezuela	1998q1	2019q1

	Emerging and Developing Asia		
513	Bangladesh	1998q1	2019q4
924	China	1998q1	2019q4
534	India	1998q1	2019q4
536	Indonesia	1998q1	2019q4
548	Malaysia	1999q1	2019q4
564	Pakistan	1998q1	2019q4
566	Philippines	1998q1	2019q4
524	Sri Lanka	1998q1	2019q4
578	Thailand	1998q1	2019q4

	Other EMEs		
911	Armenia	1998q1	2019q4
913	Belarus	1998q1	2019q4
918	Bulgaria	1998q1	2019q4
960	Croatia	1998q1	2019q4
944	Hungary	1998q1	2019q4
439	Jordan	1999q1	2019q4
916	Kazakhstan	1998q1	2019q4
962	Macedonia	1998q1	2019q4
684	Mauritius	2000q1	2019q4
921	Moldova	1998q1	2019q4
964	Poland	2000q1	2019q4
968	Romania	1998q1	2019q4
922	Russia	1998q1	2019q4
199	South Africa	1998q1	2019q4
186	Turkey	1998q1	2019q4
926	Ukraine	1998q1	2019q4

Figure A1. KF* and Gross Portfolio Inflows (2000q4-2019q4, billions of USD)
All countries 56 countries for which we have KF* and quarterly flow data for the entire period are presented here alphabetically within each region.

A. Advanced Economies

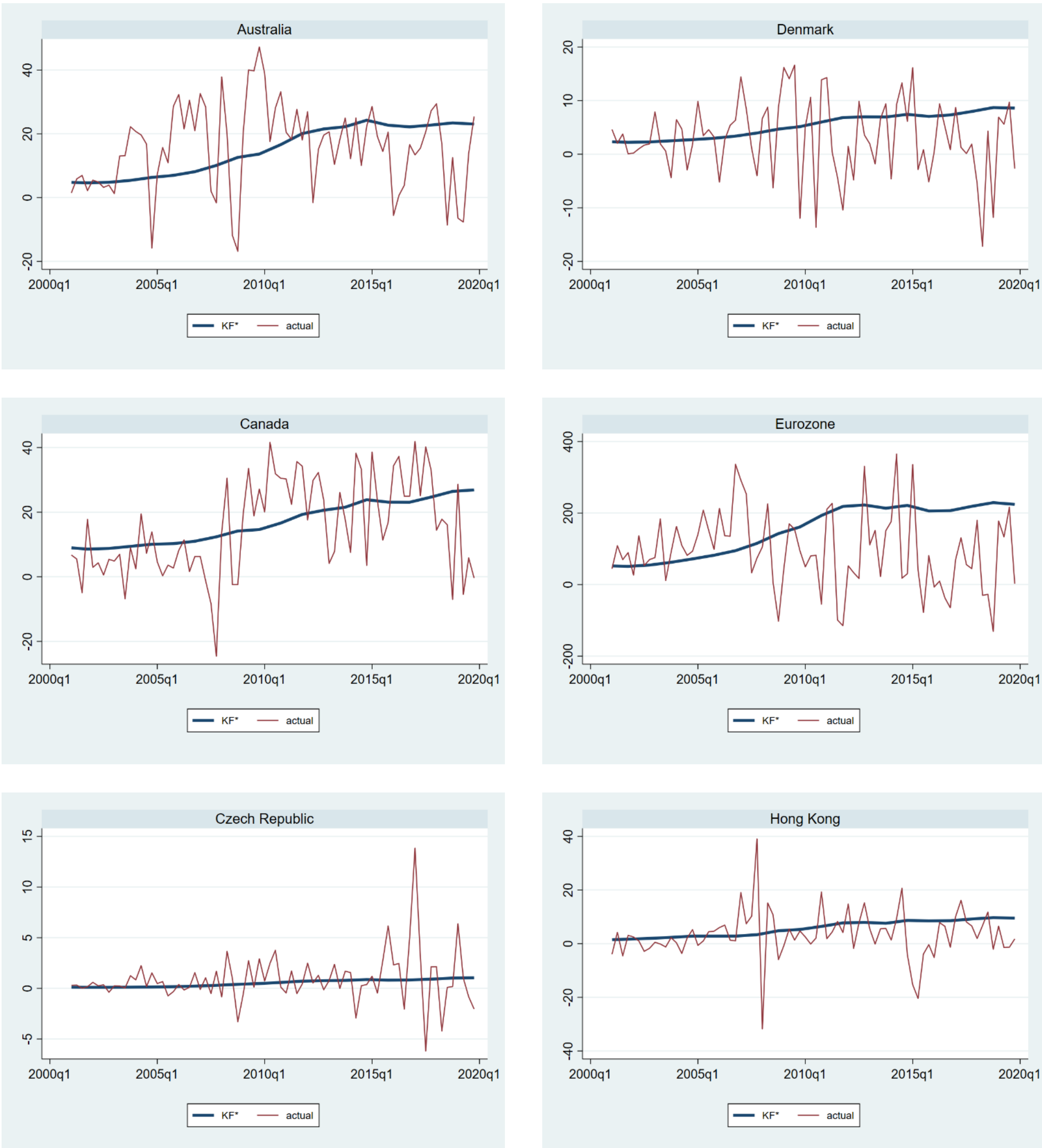


Figure A1 (cont.)

A. Advanced Economies (cont.)

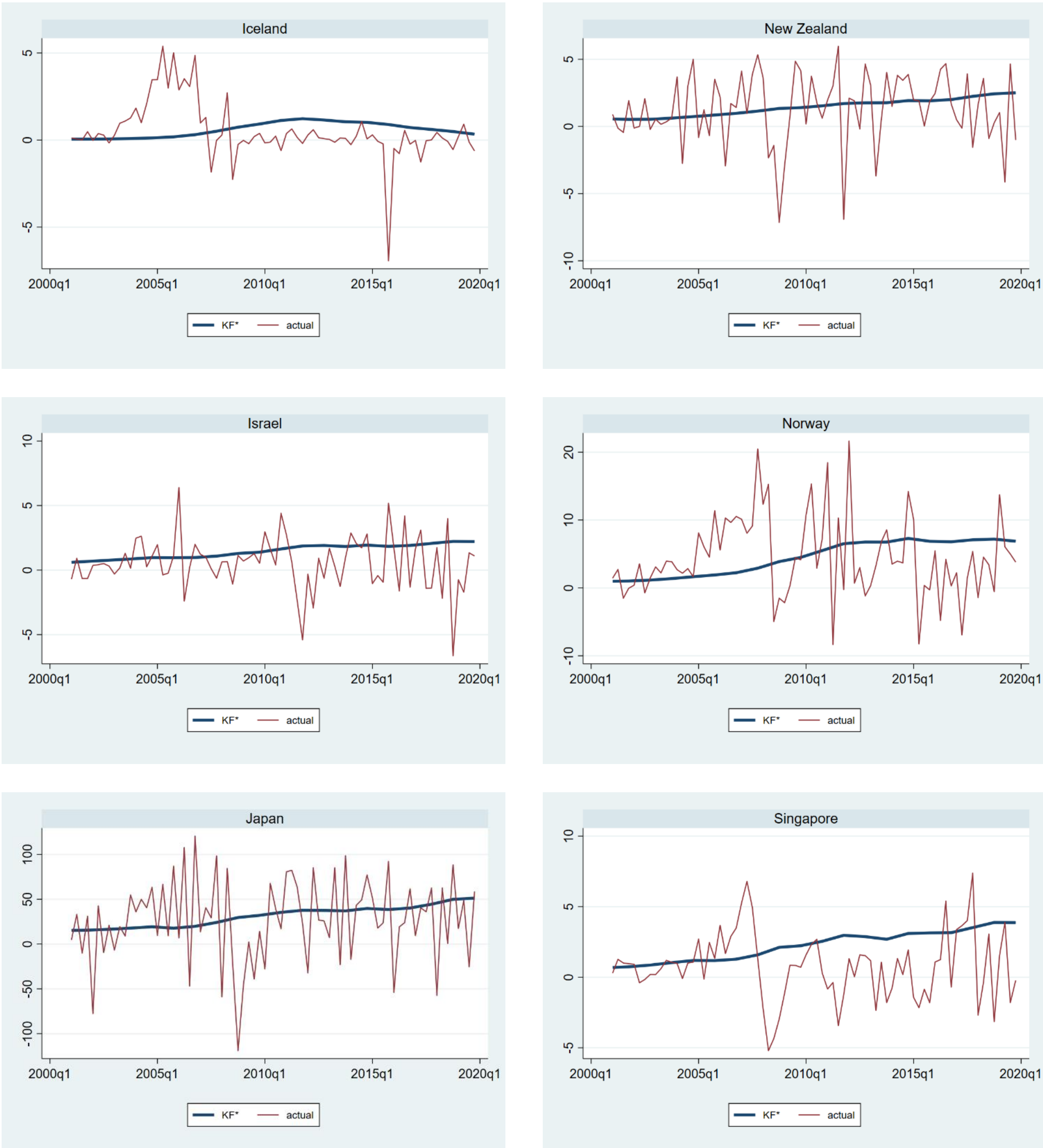


Figure A1 (cont.)

A. Advanced Economies (cont.)

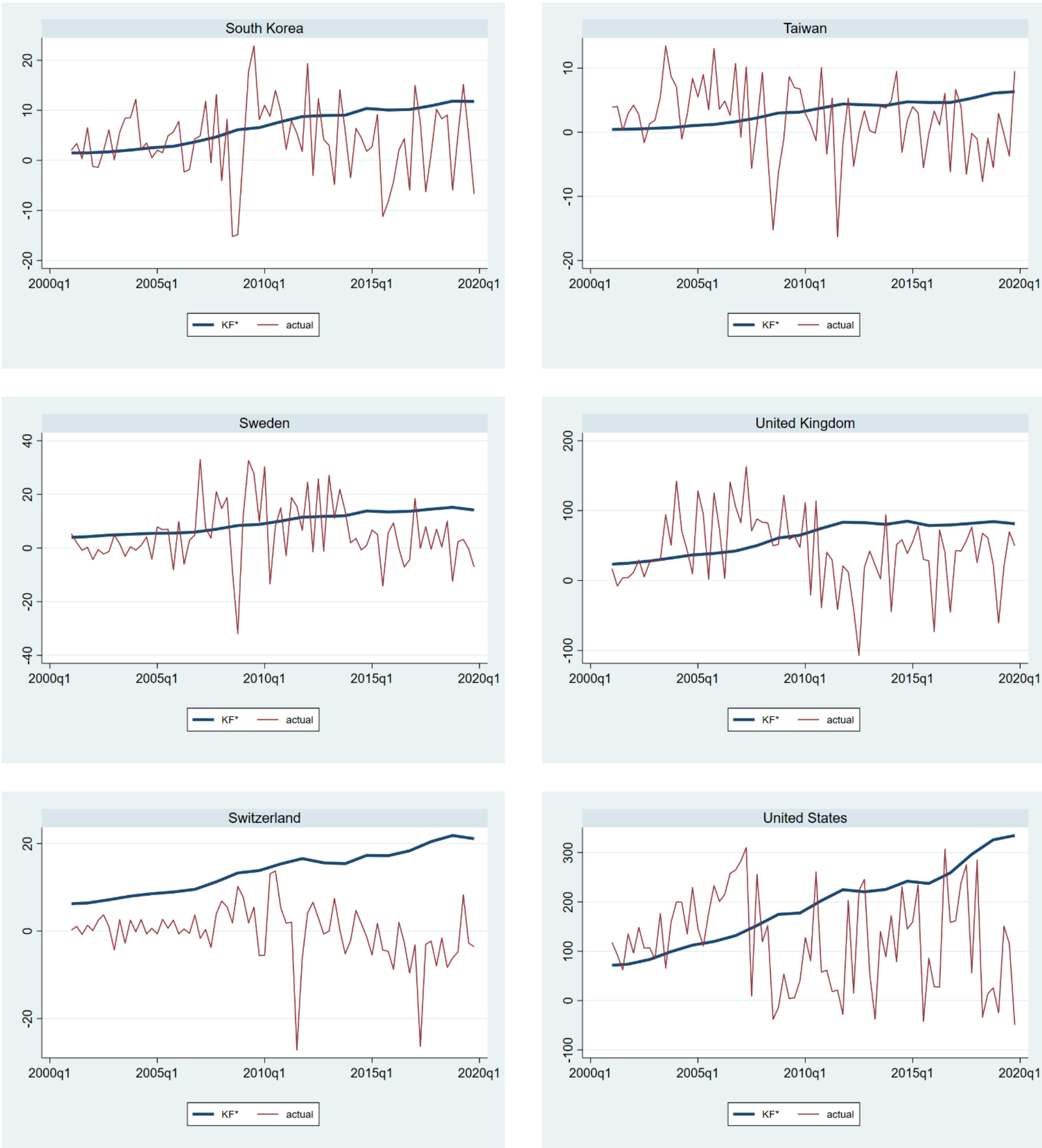


Figure A1 (cont.)

B. Latin American and the Caribbean

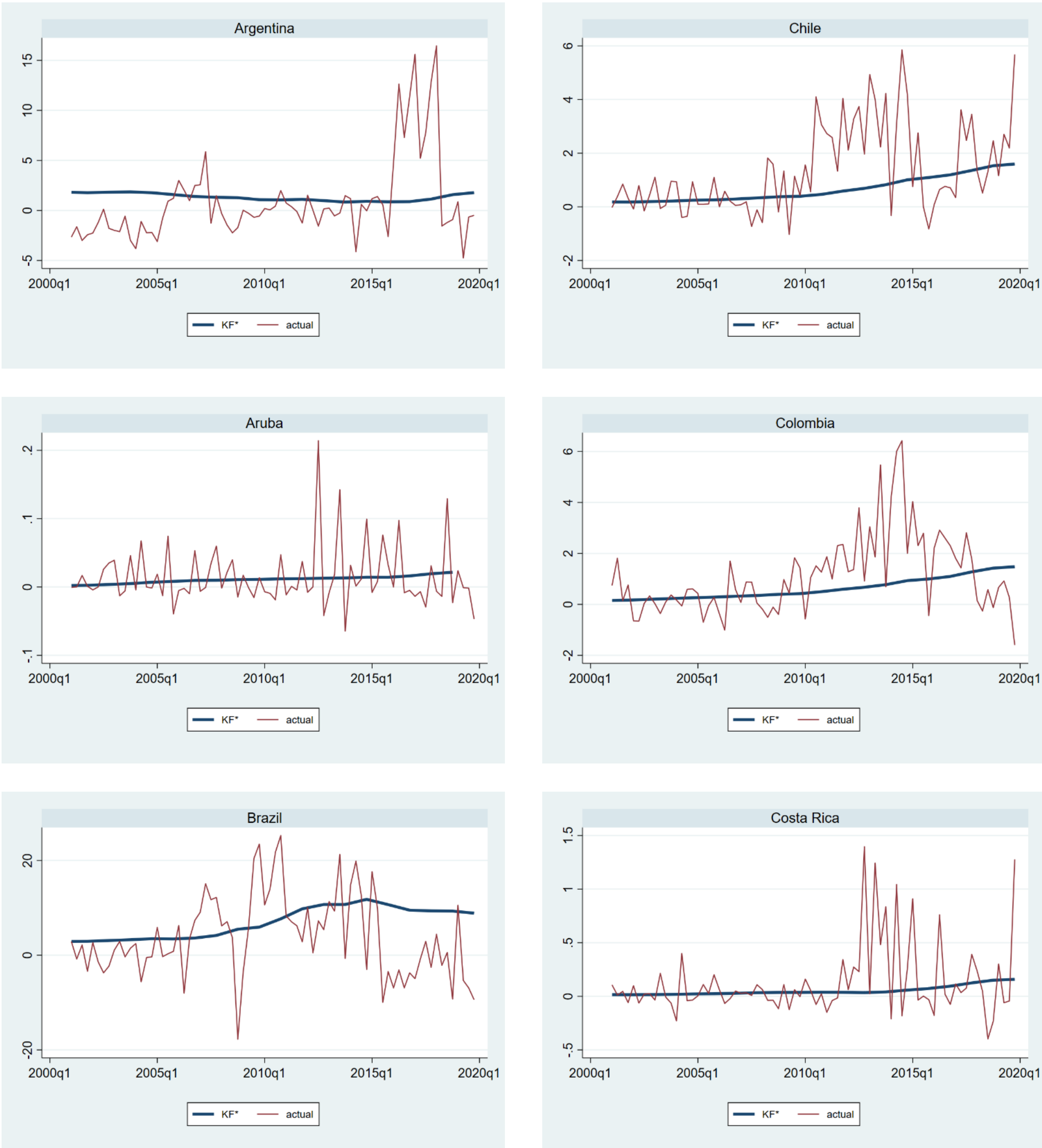
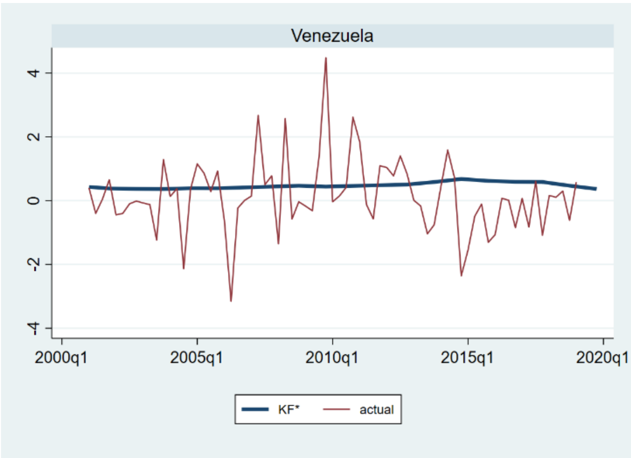


Figure A1 (cont.)

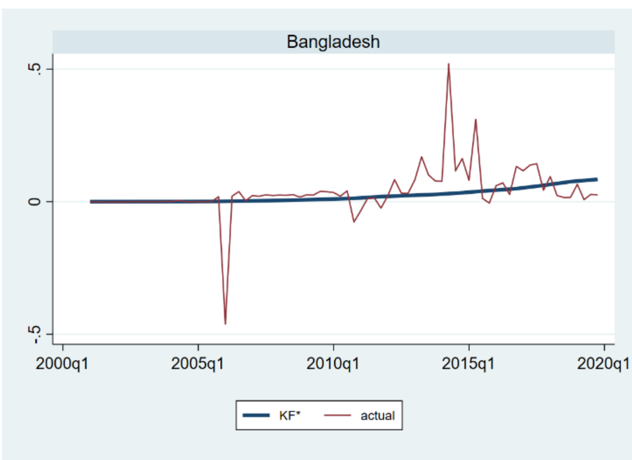
B. Latin American and the Caribbean (cont.)

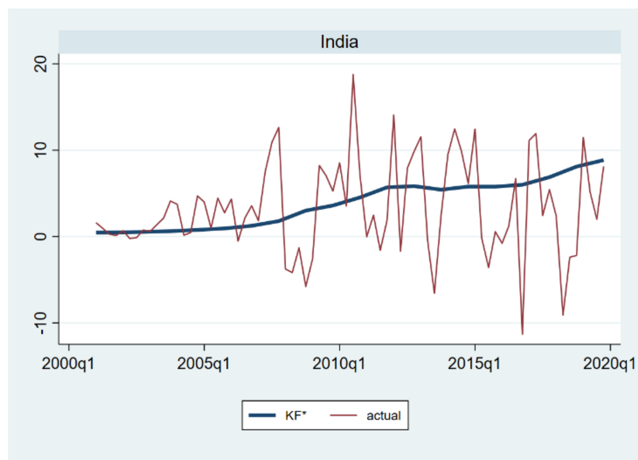
Figure A1 (cont.)

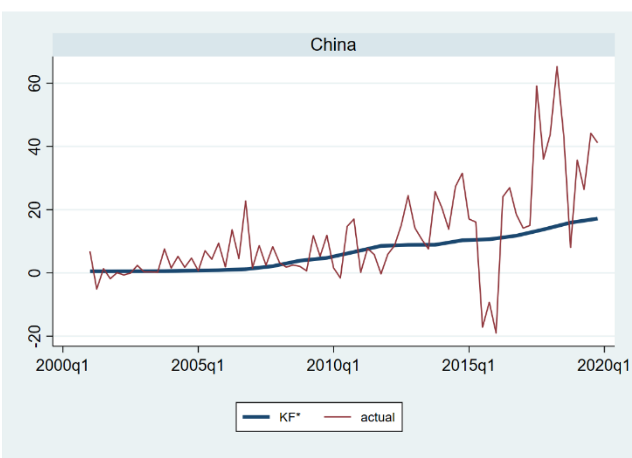
B. Latin American and the Caribbean (cont.)



C. Emerging and Developing Asia







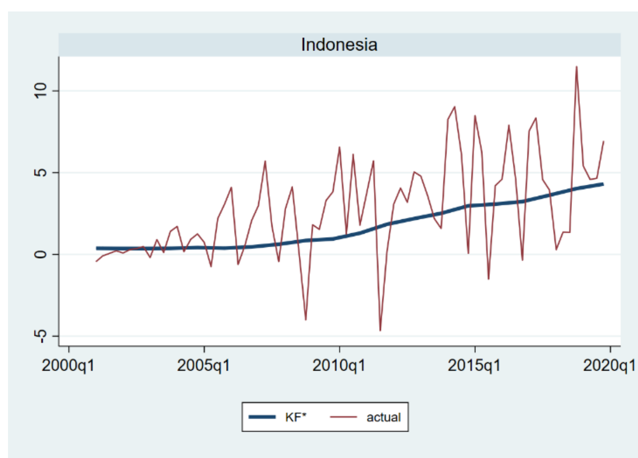


Figure A1 (cont.)

C. Emerging and Developing Asia (cont.)

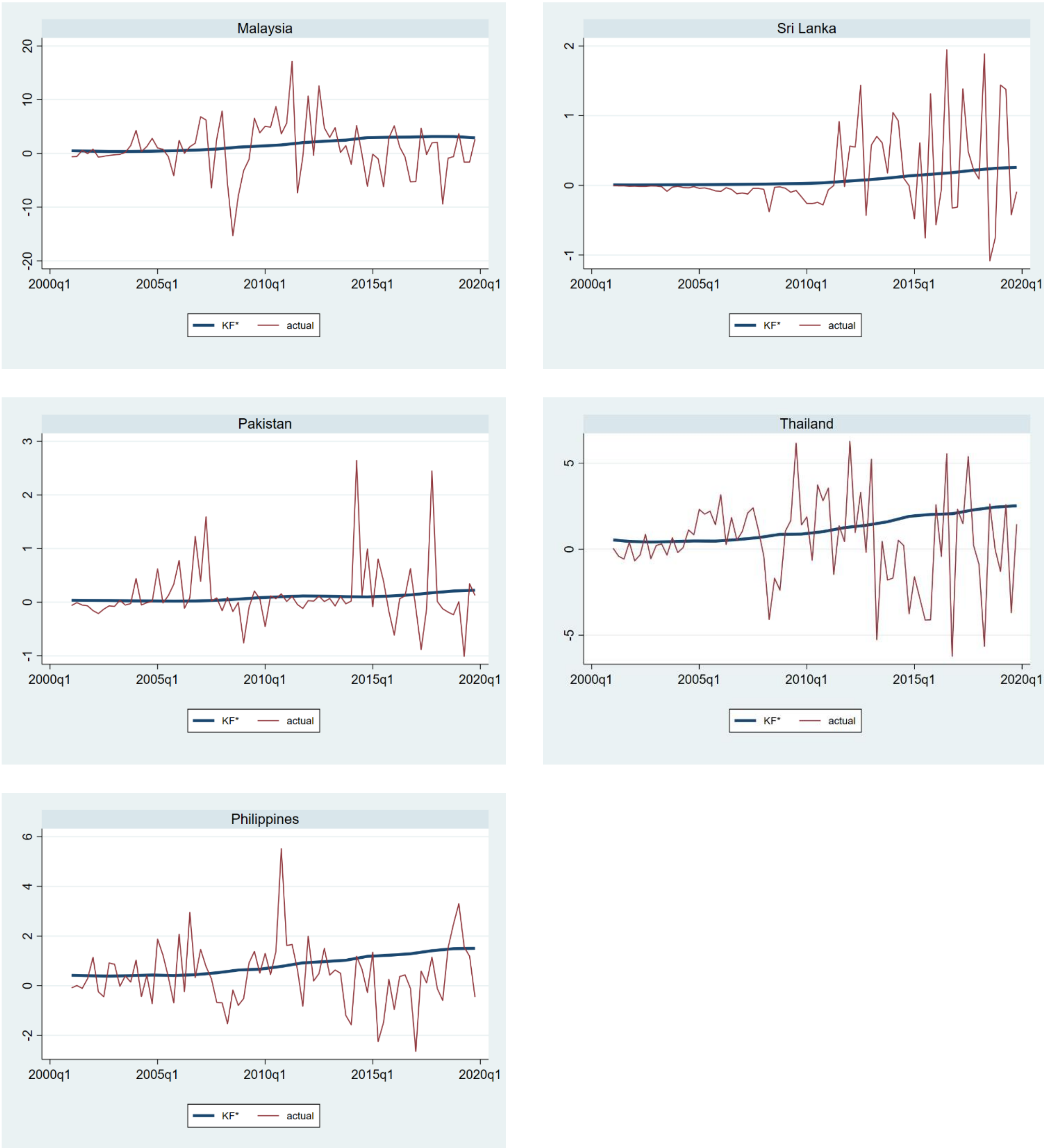


Figure A1 (cont.)

D. Other EMEs

Figure A1 (cont.)

D. Other EMEs (cont.)

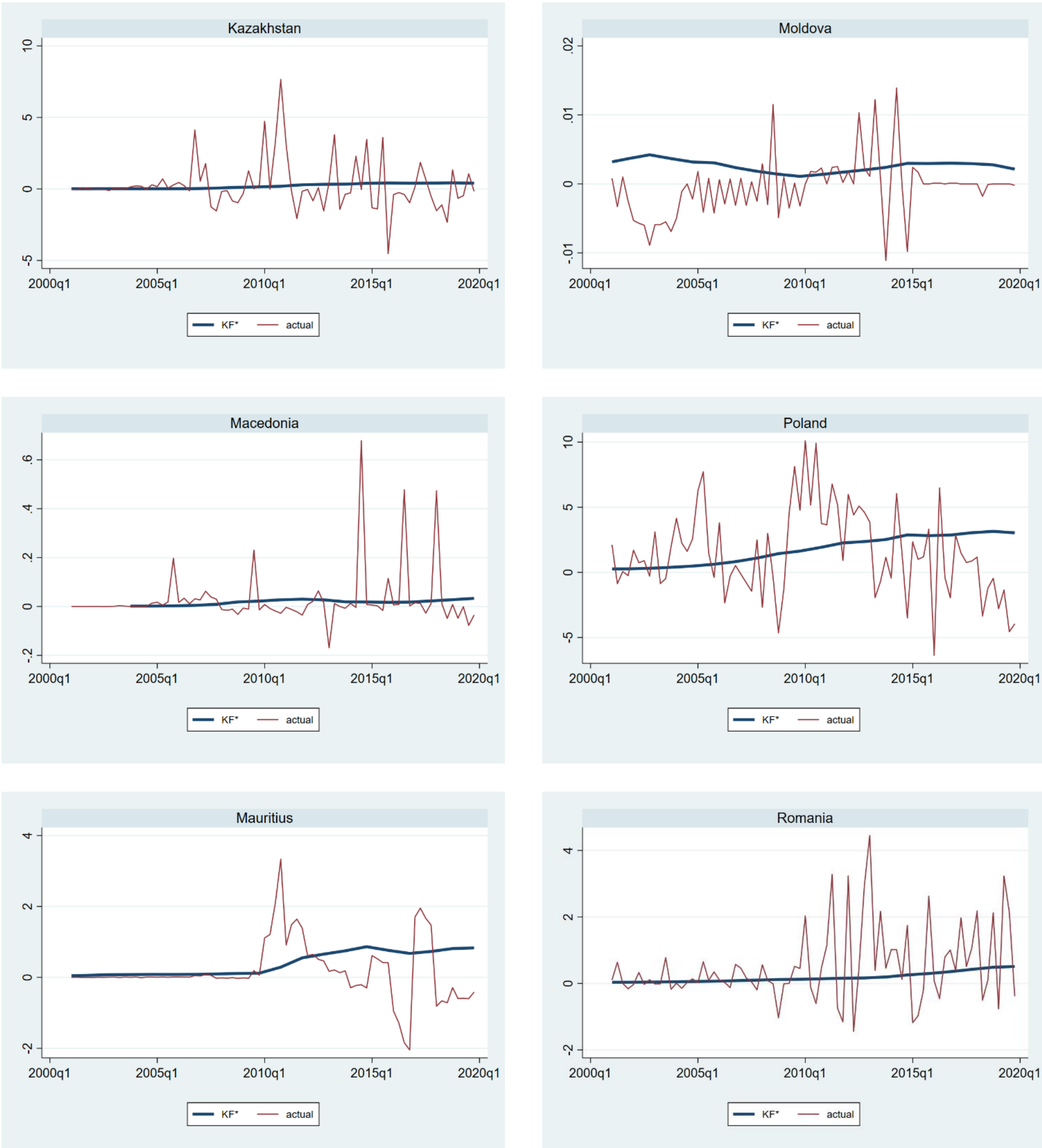


Figure A1 (cont.)

D. Other EMEs (cont.)