The Global Financial Cycle and Capital Flows During the COVID-19 Pandemic

J. Scott Davis and Andrei Zlate

Globalization Institute Working Paper 416

May 2022 (Revised November 2022)

Research Department

https://doi.org/10.24149/gwp416r1

The Global Financial Cycle and Capital Flows During the COVID-19 Pandemic*

J. Scott Davis† and Andrei Zlate‡

April 29, 2022
Revised: November 2, 2022

Abstract

We estimate the heterogeneous effect of the global financial cycle on exchange rates and cross-border capital flows during the COVID-19 pandemic, using weekly exchange rate and portfolio flow data for a panel of 59 advanced and emerging market economies. We begin by estimating a global financial cycle (GFC) index at the weekly frequency with data through the end of 2021, and observe an outsized decline in the index over a period of just four weeks during February and March 2020. We then estimate the country-specific sensitivities of exchange rates and capital flows to fluctuations in the GFC. We show that the ability of the GFC to explain fluctuations in exchange rates and capital flows increased dramatically during the pandemic crisis. By using the law of the total variance we are able to decompose a panel of country-specific exchange rate or capital flow series into the time-series variance of the cross-sectional mean and the cross-sectional variance around that mean. We show that the GFC mainly explains the time-series variance of the cross-sectional mean. In addition, during the pandemic crisis like the COVID pandemic in 2020, relevant high-frequency indicators such as the weekly changes in cases and vaccination rates, which varied in timing and intensity across countries, improve the cross-sectional fit of our model by just as much as standard macroeconomic fundamentals such as the current account, reserves, and net foreign assets.

JEL Classification: F3; F4

Keywords: COVID-19; global financial cycle; capital flows; exchange rates

---

* We would like to thank participants at the conference "The COVID-shock and the new macroeconomic landscape: taking stock and looking ahead" and our discussant, Selien De Schryder, for many helpful comments and suggestions. We would also like to thank Mario Crucini for very helpful comments. The views presented here are those of the authors and do not necessarily represent the views of the Federal Reserve Bank of Dallas, the Board of Governors or the Federal Reserve System.

† Corresponding Author: J. Scott Davis, Federal Reserve Bank of Dallas, email: scott.davis@dal.frb.org.

‡ Andrei Zlate, Board of Governors of the Federal Reserve System.

1 Introduction

Over a brief four-week period from the end of February through the middle of March 2020, there was a fall in global risky asset prices comparable in scale to the dramatic fall seen during the Global Financial Crisis, when risky asset prices fell over a more protracted five-month period from October 2008 to March 2009. From hereon we will refer the common component of global risky asset prices as the global financial cycle (GFC), and to the fall in the GFC during late February/early March 2020 as the COVID shock. In this paper we ask what is the effect of fluctuations in the GFC on exchange rates and capital flows, and how did the effect of the GFC on exchange rates and capital flows during the COVID shock depended on macroeconomic and pandemic-related fundamentals?

We begin with a look at the data, which shows a dramatic fall in exchange rates and capital inflows over a short period of a few weeks in early 2020. Figure 1 plots the average paths of the nominal exchange rate, total portfolio inflows, and debt portfolio inflows in a sample of advanced and emerging market economies in 2020. All variables are observed at a weekly frequency and the capital flows data measures flows into country-specific bond and equity funds are recorded by EPFR.

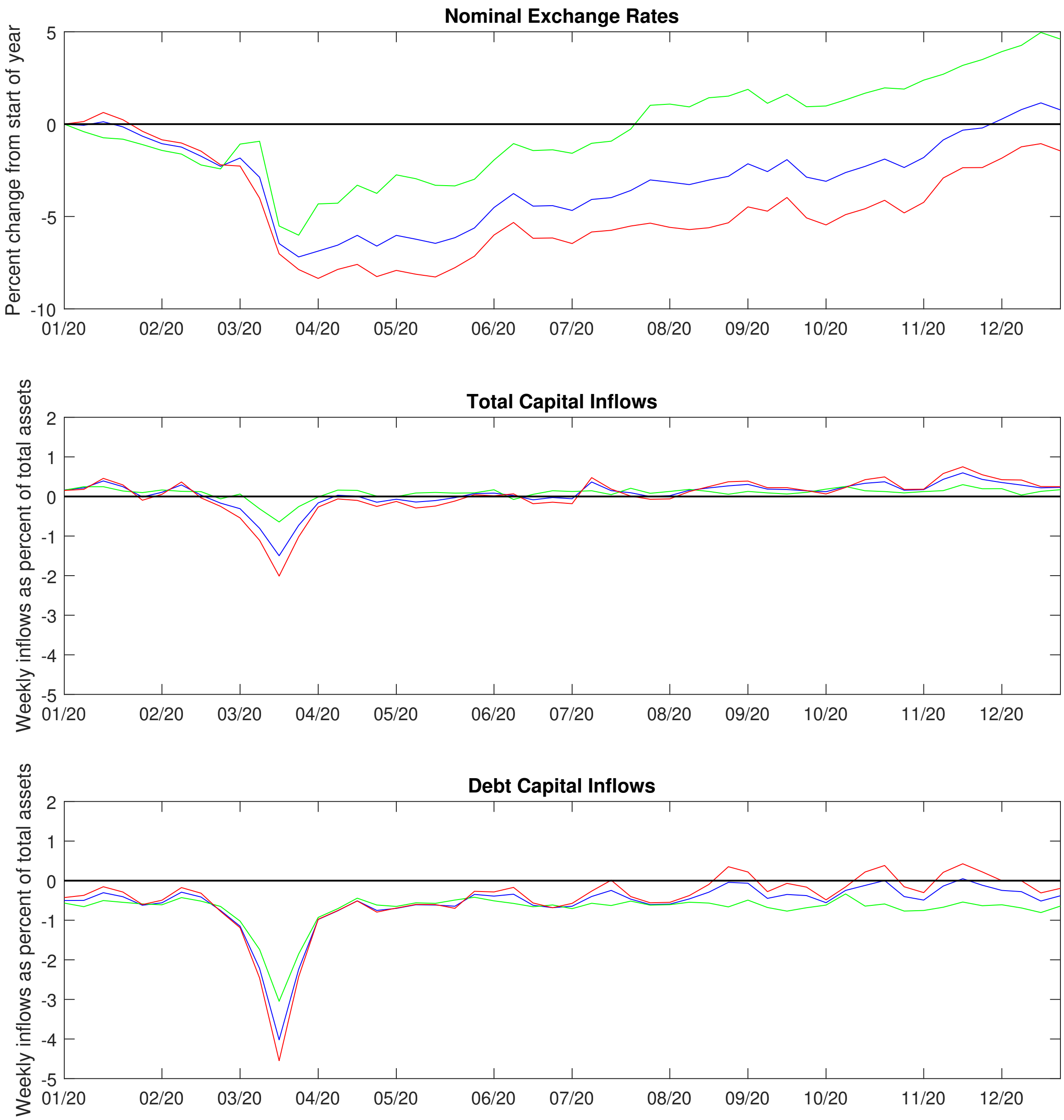
The figure shows that over the four-week period of the COVID shock, the U.S. dollar appreciated by nearly 6 percent against both advanced and emerging market foreign currencies, and by nearly 7 percent against the emerging market currencies. At the peak of the crisis in mid-March, the total portfolio inflows as a share of total fund assets were falling by about 1.5 percent per week, while inflows into debt funds as a share of total fund assets were falling by 4 percent per week. This weekly fall in debt flows was unprecedented, as the weekly fall in debt flows during the worst of the Global Financial Crisis in October 2008 was around 3 percent.

We know from the global financial cycle literature that the sensitivity of a country's capital flows to a downturn in the global financial cycle largely depends on that country's external accounts (net foreign assets in debt and equity, stock of FX reserves, the current account balance, etc.).[1] We ask, did those same macroeconomic fundamentals explain capital flows and exchange rate fluctuations during the COVID-19 pandemic, and to what extent did "COVID fundamentals" such as the change in case numbers and vaccination rates add explanatory power to the model explaining these flows?

In this paper we first construct a GFC index at the weekly frequency as the common component of world risky asset prices, which shows a very large drop in early March 2020. Second, we estimate the sensitivities of exchange rates and capital flows to the GFC during

[1] See e.g. Frankel and Rose (1996), Bussiere and Fratzscher (2006), Rose and Spiegel (2011), Frankel and Saravelos (2012), Gourinchas and Obstfeld (2012), Catão and Milesi-Ferretti (2014), Eichengreen and Gupta (2015), Ahmed, Coulibaly, and Zlate (2017), Davis, Valente, and van Wincoop (2021)

Figure 1: The paths of nominal exchange rates and portfolio inflows in 2020.



Notes: Portfolio flows and exchange rate are observed at a weekly frequency. The exchange rate chart plots the percent change in the nominal exchange rate (USD/LCU) since the first week in 2020, with higher values showing foreign currency appreciation against the dollar. The portfolio flow charts plot the weekly capital flows into country-specific bond and equity funds as a percent of the total assets of those funds. The GDP-weighted average for all countries in our sample is plotted in blue, for the advanced economies in green, and for the emerging markets in red.

the pandemic and we estimate how country-specific macroeconomic and COVID fundamentals affected the elasticity of exchange rates or capital flows to the GFC. Third, we ask what share of the variance of fluctuations in the exchange rate or capital flows can be explained by the GFC and how this share changes when allowing for interactions with country-specific fundamentals.

In more detail, first, we estimate a GFC index using weekly data through the end of 2021. Like Miranda-Agrippino and Rey (2020), we estimate the GFC factor as a common component of risky asset price changes across a wide range of advanced and emerging market countries. But unlike Miranda-Agrippino and Rey (2020), we estimate the GFC from a smaller set of risky asset prices but at the weekly rather than the monthly frequency, which enables us to better keep track of the fast-paced developments during multiple waves of the pandemic. This way, we capture the unprecedented speed of the downturn and subsequent recovery in the late winter/early spring of 2020 in a way that lower-frequency data would miss. We find that in the four weeks from the middle of February to the middle of March 2020, there was a two-standard deviation fall in the GFC index, followed by a sizable recovery in the few weeks after the middle of March 2020. Using the same data and methodology, aggregating the data to a monthly frequency would only register a 1.5 standard deviation fall in the GFC over February and March 2020; aggregating the same data to a quarterly frequency would only record a 1.3 standard deviation fall in the GFC in the first quarter of 2020.

Second, after identifying the COVID shock to the GFC in early 2020, we ask what effect that shock had on nominal exchange rates and capital flows for our sample countries. Ideally, we would like to examine the effect on net capital inflows, the capital and financial account, or gross capital inflows *and* outflows, since those variables have direct macroeconomic connections. However, here there is a trade-off between the ideal variable and the ideal time frequency we would like to use in our analysis. The balance of payments data are generally only available at a quarterly frequency. Given the speed of the fall and partial recovery in the GFC during the COVID shock, we need to turn our attention to data available at a weekly frequency.

Therefore, we examine the effect of the GFC and the COVID shock on nominal exchange rates and on portfolio capital flows with data from EPFR. Using a panel of weekly log-changes in the nominal exchange rate, changes in total portfolio flows, and changes in debt portfolio flows across a range of advanced and emerging market economies, we estimate the elasticity of exchange rates and portfolio capital flows to fluctuations in the GFC. We find that on average across countries, a downturn in the GFC is associated with a foreign currency depreciation relative to the U.S. dollar and a fall in portfolio capital flows.

After estimating the average elasticities of weekly changes in exchange rates and capital flows to the GFC, we examine how country-specific macroeconomic and COVID fundamentals affect these elasticities. For the effect of country-specific macroeconomic fundamentals on the elasticity of a country's exchange rate and capital flows to fluctuations in the GFC, our results are similar to those in the literature. The exchange rate and capital flows tend to be less sensitive to fluctuations in the GFC in countries with positive net foreign assets positions or larger current account surpluses. Importantly, turning to the measures of pandemic intensity, we find that an increase in the weekly COVID cases raised the sensitivity of a country's exchange rate and capital flows to the GFC, while an increase in the vaccination rate lowered that sensitivity.

Third, we ask what share of the variance of exchange rate or capital flow fluctuations can be explained by the GFC. We can observe how this share changes across time, rising during crisis times and falling during more tranquil periods. We also ask how allowing for interactions of the GFC with country-specific fundamentals—i.e., with both macroeconomic fundamentals and high-frequency COVID fundamentals—increases the explanatory power of the model.

Using the law of total variance, the variance of a panel of changes in exchange rates or capital flows is simply the sum of the time series variance of the cross-sectional mean and the average cross-sectional variance around that mean. Using this approach, we find there was a sharp increase in the share of the panel variance explained by the common time-series trend during the COVID shock, indicating that in the immediate aftermath of the COVID shock, fluctuations in exchange rates and portfolio flows were more likely to be driven by a common cross-country trend than they were before the COVID shock.

We then calculate the share of the variance of a panel of changes in exchange rates or capital flows that can be explained by fluctuations in the GFC. We find that the GFC can explain a large portion of the variance of the panel during two distinct periods of our sample: one was the period between 2008 and 2012, encompassing the 2008 Global Financial Crisis and Euro Area crisis, and one was the 2020-2021 period, encompassing the COVID shock. We find that this increase in the explanatory power of the GFC results from the time-series variance of the panel, i.e. during both crises the GFC explained a larger share of fluctuations in the cross-sectional mean of exchange rates or capital flows over time. Furthermore, we find that allowing for interactions with country-specific macroeconomic and COVID fundamentals further increases the explanatory power of the GFC, by raising the share of the cross-sectional variance that can be explained by the GFC together with country-specific fundamentals. Importantly, the measures of pandemic intensity explain just as much of the cross-sectional variation in capital flows as the standard macro fundamentals such as the current account and net foreign assets.

To sum up, the results suggest that the COVID shock to the GFC in late February/early

March 2020 led to strong negative pressure on exchange rates and capital flows in many advanced and emerging market economies. During the pandemic, the share of the variance of exchange rate and capital flows changes that could be explained by fluctuations in the GFC increased and in some cases reached an all-time high. This is mostly due to the ability of the GFC to explain the time-series variance of the cross-sectional average of exchange rate or capital flow fluctuations. Allowing country-specific macroeconomic or COVID fundamentals to affect the elasticity of a country's exchange rate or capital flows with respect to the GFC raises the explanatory power of the model, particularly in the cross-sectional dimension, during a crisis.

This paper is organized as follows. In the remainder of this section we provide a short literature review to place this paper within the wider GFC literature. In section 2 we estimate the GFC factor at a weekly frequency from a cross-country panel of risky asset prices. Section 3 discusses the data and methodology that we use to examine the effect of the GFC on changes in exchange rates and capital flows. The results are presented in section 4. The economic interpretation of those results, including a discussion of the recent theoretical literature that seeks to model the effect of the GFC on exchange rates and capital flows is presented in section 5. Finally section 6 concludes.

1.1 Literature

This paper is related to the literature on the global financial cycle (GFC). Rey (2015 and 2016) present the idea that there is a common global cycle to asset prices and capital flows, and Miranda-Agrippino and Rey (2020) estimate a common global factor from over 800 asset price series at a monthly frequency, which reflects the global financial cycle. Using a different data, we are able to compute a similar GFC at the weekly frequency. (see Miranda-Agrippino and Rey (2021) for a review of the extensive GFC literature).

This paper is also related to the literature that seeks to find the latent factors to explain international capital flows. This literature includes Davis et al. (2021), Cerutti, Claessens, and Rose (2019b), Barrot and Serven (2018), Sarno, Tsiakas, and Ulloa (2016), and Cerutti, Claessens, and Puy (2019a). These papers however all consider capital flows at a much lower frequency than us, either annual or quarterly (or monthly in the case of Sarno et al.). As we will discuss in the next section, the speed to the COVID shock from mid-February to mid-March 2020 with a partial recovery in late-March highlights the need to use higher frequency weekly data to examine rapidly-evolving crisis-like events.

In addition, this paper is related to the literature documenting the capital flow push and pull factors. There is of course an extensive literature on the fluctuations in net capital flows (see e.g. Calvo, Leiderman, and Reinhart (1996)). A more recent literature looking at the factors driving gross flows includes Forbes and Warnock (2012, 2014, and 2021), Milesi-

Ferretti and Tille (2011), Fratzscher (2012), Broner, Didier, Erce, and Schmukler (2013), Ahmed and Zlate (2014), Chari, Dilts-Stedman, and Forbes (2022) among others. Our contribution to this literature is to add certain certain country-specific COVID fundamentals as potential pull factors for global capital flows.

And finally this paper is related to the papers describing fluctuations in capital flows, currency values, and asset prices during the COVID shock. Writing early in the crisis, Kalemli-Ozcan (2020), Akinci, Benigno, and Queraltó (2020), Corsetti and Marin (2020) all described the potential for capital flight, sudden stops, and currency depreciation in emerging market economies as a result of the pandemic. Hördahl and Shim (2020) discuss how the COVID-19 shock led to an unprecedented fall in portfolio bond flows to emerging market economies, and Hofmann, Shim, and Shin (2021) discuss the related spike in local currency bond yield and spreads in emerging markets. Beirne, Renzhi, Sugandi, and Volz (2021) regress a number of financial indicators and capital flow variables on the number of COVID cases using data from early in the pandemic. They show that the number of cases had a negative effect on exchange rates and capital flows. Similarly, Ahmed, Hoek, Kamin, Smith, and Yoldas (2020) show that the COVID-related deaths and the intensity of pandemic restrictions had adverse effects on emerging market exchange rates, the CDS spreads on dollar-denominated debt, and equity prices; the paper focuses on the initial months of the pandemic and does not cover high-frequency portfolio flows throughout the pandemic duration, which we do.

2 Estimating the GFC factor

We begin by identifying a common factor to global risky asset prices that we can call a global financial cycle at a weekly frequency, in a sample that covers the COVID shock and recovery. We estimate the common component to the weekly equity prices across 52 countries over the period from 2001 to 2021.

We follow Bai and Ng (2004) in their method of estimating a common component in a set of series with different trend growth rates. First we estimate f_t using a static factor model, where f_t is the first principal component of the weekly log change in the stock price index, $x_{i,t}$:

$$x_{i,t} - \bar{x}_i = \lambda_i^{'} f_t + \epsilon_{i,t} \tag{1}$$

where $\bar{x}_i$ is the cross-time average of the the weekly log change in the stock price index $x_{i,t}$, and thus is equivalent to country i's trend growth of the log-stock price index over the sample period). The GFC factor in levels is $F_t = \sum_{s=1}^{t} f_s$. To ease the interpretation of the results, we then normalize F_t to have a mean 0 and a standard deviation 1 over our 2001 to 2021 period.

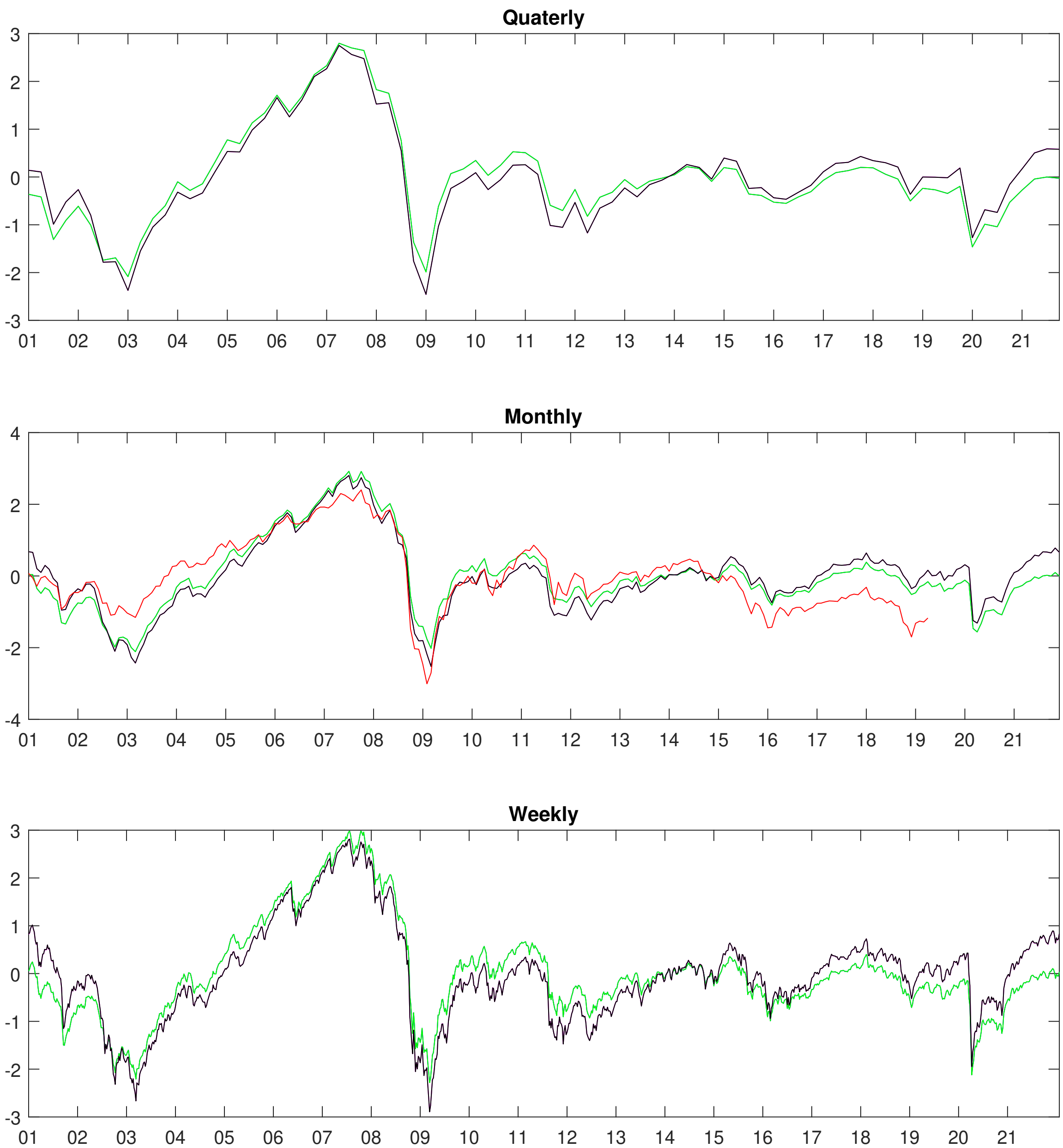
This method of estimating f_t in a static factor model assumes that f_t is distributed i.i.d. Alternatively we can estimate f_t with a dynamic factor model and assume that f_t follows an AR(p) structure with i.i.d. innovations. In Figure 2, we plot the GFC factor in levels F_t estimated with both a static factor model and dynamic factor model, where the results from the static factor model are plotted in green and those from the dynamic factor model are plotted in black. As we can see in the figure, there is very little difference between the GFC estimated with the two factor models, and when an AR(p) model is estimated as part of computing the dynamic factor model, there is very little autocorrelation in f_t, making the two models very similar. The main results in the paper use the GFC results from the static factor model. The results using the dynamic factor model are nearly identical and are presented in the appendix.

As shown in the figure, we estimate the GFC factor using stock index data at the quarterly, monthly, and weekly frequency. We use the weekly frequency for most of the paper, but the estimation at a monthly frequency allows us to compare our GFC factor to that in Miranda-Agrippino and Rey (2020), which is plotted in red in the monthly frequency chart. Their factor is estimated at a monthly frequency, is estimated from a dynamic factor model, and the common component is derived from a much wider set of 858 asset prices, including not only stock indices but also corporate and government bonds. Through April 2019, when the Miranda-Agrippino and Rey sample ends, the correlation between our GFC factor and that in Miranda-Agrippino and Rey (2020) is 0.87. However the the Miranda-Agrippino and Rey sample ends before the COVID shock, and our estimation continues through the end of 2021 and thus contains the COVID shock in February/March 2020 and the subsequent recovery.

Considering the GFC factor at the weekly frequency, we estimate that from the local maximum in the week of February 21 to the local minimum in the week of March 20, 2020, our GFC factor fell from -0.15 to -2.11. Quantitatively, this 2 standard deviation fall in the global financial cycle factor is similar to the fall from February 2001 to March 2003 or the fall from October 2008 to March 2009. Although it should be noted that the 2 standard deviation fall in the GFC factor from September 2008 to March 2009 was part of a larger 5 standard deviation fall from July 2007 to March 2009.

One notable feature about the COVID shock is the speed of the downturn and the subsequent recovery. The 2 standard deviation fall in the GFC factor early in the sample in the wake of the dot-com bubble took 109 weeks, from the local maximum in the week of February 16, 2001 to the local minimum in the week of March 14, 2003. The 2 standard deviation fall from the week of October 3, 2008 to March 6, 2009 took 23 weeks (and the larger 5 standard deviation fall starting the week of July 20, 2007 took 86 weeks). Remarkably, the 2 standard deviation fall in the GFC during the COVID-19 pandemic from the pre-pandemic

Figure 2: Estimated GFC factor from panel of stock market returns across 52 countries.



Notes: Our GFC factor estimated from either quarterly, monthly or weekly data is in black or green. The green is the first factor estimated from a static factor model and the black is from a dynamic factor model allowing for 12 lags in the factor VAR. For comparison the global financial cycle factor from Miranda-Agrippino and Rey (2020) is plotted in red in the monthly frequency plot.

local maximum to the local minimum during March 2020 took only 4 weeks. During the subsequent sharp recovery, the GFC factor regained about half a standard deviation in the 3 weeks after reaching the local minimum.

The speed of the decline and subsequent recovery in global asset prices is a reason why for the rest of this paper we rely on data at the weekly frequency, which allows us the capture the magnitude of the COVID shock and its effects most precisely. Otherwise, the data at a monthly frequency would understate the decline, as the factor fell only 1.5 standard deviations during February and March 2020. Similarly, using data at the quarterly frequency, the GFC fell 1.3 standard deviations during the first quarter of 2020. This shallower fall is due to the fact that the GFC factor was already beginning to recover from the COVID shock in late March, so the data at a monthly or quarterly frequencies will conflate some of the fall in early March with some of the recovery in late March.

3 The COVID shock, exchange rates, and capital flows

After identifying the GFC factor at the weekly frequency in the previous section, we now turn to a panel data regression analysis to identify the effect of the GFC on the exchange rate and capital flows, while taking into account country-specific macro and COVID fundamentals.

3.1 Data

For a total of 59 advanced and emerging market countries, we collect weekly data for the nominal exchange rate (USD/LCU) from 2001 to 2021 from the BIS, and weekly debt and equity portfolio capital inflow data data from EPFR. The EPFR capital flow data records flows into or out of country-specific debt or equity mutual funds and ETFs. The weekly flows are normalized by the total net assets of a country-specific debt or equity mutual funds or ETFs as recorded by EPFR.

In addition, we use annual data on external asset and liability positions and the current account from IFS. Importantly, we also use a weekly count of the total COVID-19 cases and vaccination rates from the Our World in Data COVID-19 database (Ritchie et al. 2020), which will enter our regressions in first-differences.

The 59 countries include 26 advanced countries and 33 emerging markets. The advanced countries in the sample are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, the Netherlands, New Zealand, Portugal, Singapore, South Korea, Spain, Sweden, Switzerland, Taiwan, and the United Kingdom. The emerging market countries in the sample are: Albania, Argentina, Brazil, Bulgaria, Chile, China, Colombia, Croatia, Cyprus, Czech

Republic, Estonia, Hungary, India, Indonesia, Kuwait, Latvia, Lithuania, Malaysia, Malta, Mexico, North Macedonia, Peru, Philippines, Poland, Romania, Russia, Slovakia, Slovenia, South Africa, Thailand, Turkey, Ukraine, and Uruguay. When the dependent variable is the exchange rate, the data from the 12 advanced and 7 emerging euro area countries in the sample are aggregated into one single Euro Area aggregate. Thus there are 41 countries in the full sample, 15 in the advanced country sample, and 26 in the emerging market sample. When the dependent variable is one of the capital flow variables, we do not aggregate the euro area countries, but we lose three advanced countries (Iceland, Luxembourg, and Germany), leaving 23 countries in the advanced country sample, and we lose 9 emerging markets (Cyprus, Malta, Latvia, Slovakia, Bulgaria, Albania, Kuwait, North Macedonia, Uruguay), leaving 24 countries in the emerging markets in the sample.

As mentioned in the introduction, there is a trade-off between the data we would like to use for the analysis and the data frequency necessary to study the COVID shock. While we would want to use the current account, capital and financial account, or gross inflows *and* gross outflows as dependent variables to get the most complete picture of pressures on the balance of payments, these data are not available at a weekly frequency.[2]

Among the dependent variables we use, the nominal exchange rate is available at the desired frequency and does give a picture of the exogenous pressure on a country's capital and financial account, where a fall in net capital inflows (an increase in the capital and financial account, by BPM6 accounting) tends to lead to a depreciation in the exchange rate. However, that picture may be clouded by the use of tools like foreign exchange intervention to manage and smooth fluctuations in the currency, especially in the short run (see e.g. Ilzetzki, Reinhart, and Rogoff (2019)).

The EPFR capital flows data gives us a weekly picture of net purchases or redemptions in country-specific bond or equity exchange-traded funds (ETFs), and thus is a proxy for portfolio capital inflows. Several caveats apply to using the EPFR data in the analysis.

First, the EPFR data measures only portfolio flows and not flows like FDI and banking flows, which are also included in the balance of payments. However, one could argue that this is less of an issue since these FDI and banking flows are less likely to shift in the short time span and high frequency around the COVID shock.

Second, the EPFR flows do not measure capital inflows in a balance of payments sense, where a capital inflow is the purchase of a domestic asset by a foreign resident. With this data we observe what type of asset was purchased, but not who purchased it. So if a U.S. investor rebalances their portfolio by selling shares in a European fund and buying shares in a U.S. fund, in balance of payments terms this creates smaller gross inflows into Europe and smaller gross outflows from the United States (but no change in U.S. inflows). In the

[2]See Koepke and Paetzold (2020) for a review of the available high frequency capital flow data.

EPFR data this is a negative inflow into Europe and a positive inflow into the U.S.

Third, the most important caveat about the EPFR capital flow data we use is that it only provides data on inflows, not outflows. The positive correlation between gross inflows and gross outflows is well documented (see e.g. Broner et al. (2013), Davis and van Wincoop (2018), Avdjiev, Hardy, Kalemli-Özcan, and Servén (2017)). A sudden stop in gross inflows may not result in a sudden stop in net inflows if it is offset by a retrenchment in gross outflows (see e.g. Forbes and Warnock, 2012). This retrenchment in gross outflows could either be the result of private agents rebalancing or reallocating portfolios away from foreign assets and towards home assets, or it could be the result of the central bank selling foreign exchange reserves to support the economy given the exogenous fall in capital inflows.

3.2 Methodology

Mindful of these data caveats, we run the following panel data regression:

$$y_{i,t} = \alpha_i + \sum_{s=1}^{L} \nu_s y_{i,t-s} + \beta f_t + \boldsymbol{\gamma Z_{i,t-52}} f_t + \boldsymbol{\theta Z_{i,t-52}} + \boldsymbol{\delta C_{i,t-1}} f_t + \boldsymbol{\eta C_{i,t-1}} + \mu_{i,t} \qquad (2)$$

where our dependent variable $y_{i,t}$ is either the week-over-week log change in the exchange rate (USD/LCU), $\Delta fx_{i,t}$, the week-over-week change in total portfolio inflows, ΔIF, or the week-over-week change in portfolio debt inflows, ΔIF^{Debt}. The weekly change in flows into and out of country-specific bond and equity funds are then normalized by the total assets of those funds at the beginning of the week. The log-change in the exchange rate or the change in capital inflows are then multiplied by 100 to put them in percent terms.

The regression includes a country fixed effect and L lags of the dependent variable. f_t is the first principal component of the log-change in the stock market index that we estimated in the last section (the first difference of the weekly GFC factor plotted in 2), and $\boldsymbol{Z_{i,t-52}}$ is a vector of variables related to the external asset position of country i: the ratio of net foreign assets in equity securities to GDP, nfa^{eq}, the ratio of net foreign assets in debt securities (excluding central bank reserves) to GDP, nfa^{de}, the ratio of central bank foreign exchange reserves to GDP, R, and the ratio of the current account to GDP, CA. This data is annual and in the regression is lagged one year (52 weeks). Finally $\boldsymbol{C_{i,t-1}}$ is a vector of country-specific variables related to the Covid situation in country i in week $t-1$: the week-over-week log change in the number of Covid cases in country i, $\Delta C_{i,t-1}$, and the week-over-week log change in the the share of the population vaccinated against COVID-19, $\Delta Vacc^{f}_{i,t-1}$. Note that these variables are lagged by one week.

When presenting the regression results we will move in steps, and in each step add new variables to the existing regression specification. First, we regress the dependent variable on just the country fixed effect and lags, $\alpha_i + \sum_{s=1}^{L} \nu_s y_{i,t-s}$. Second, we add the GFC factor as a stand-alone variable, βf_t. Third, we add the country-specific macroeconomic variables and the GFC factor interacted with those macroeconomic variables, $\boldsymbol{\gamma Z_{i,t-52}} f_t + \boldsymbol{\theta Z_{i,t-52}}$. Fourth, we add country-specific Covid variables and the GFC factor interacted with those Covid variables, $\boldsymbol{\delta C_{i,t-1}} f_t + \boldsymbol{\eta C_{i,t-1}}$.

The number of lags of the dependent variable is chosen as the number of lags that minimizes the Bayesian Info Criterion (BIC). We select an optimal number of lags for each dependent variable, but then keep that optimal lag length through all regression specifications using that dependent variable. We regress the dependent variable on the country fixed effect and various numbers of lags of the dependent variable over our full 2001-2021 sample period. We then select the number of lags that minimizes the Bayesian Info Criterion. When the dependent variable is the weekly log change in the nominal exchange rate, we find the optimal number of lags is 3. When the dependent variable is the weekly change in total capital inflows or debt capital inflows, we find that the optimal number of lags is 18.

In this regression model, the elasticity of the dependent variable, either the log change in the exchange rate or the change in capital inflows, with respect to changes in the GFC factor is given by $\beta + \boldsymbol{\gamma Z_{i,t-52}} + \boldsymbol{\delta C_{i,t-1}}$, and thus macroeconomic fundamentals like net external assets or the current account and Covid fundamentals like the weekly increase in cases or vaccination rates affect how a country's exchange rate or capital flows respond to exogenous fluctuations in the global financial cycle.

Table 1 presents descriptive statistics for the dependent and independent variables in the model. Since the data is a panel, we report both the time series and cross-sectional dispersion of the data. The mean column simply reports the mean value of the variable across all country-period observations. The standard deviation column reports the cross-country average of the time series standard deviation of the variable. The median, 25th, and 75th percentile columns report the average across periods of the cross-sectional percentiles of the variable. The minimum and maximum are simply the minimum and maximum values of all country-period observations.

3.3 Cross-sectional and time-series goodness of fit

The R^2 of the regressions in equations 2 tell us how well the GFC factor and the additional macroeconomic or COVID-related explanatory variables can explain the variance of weekly exchange rate fluctuations in our panel. While the R^2 statistics show the share of the total variance that can be explained by the model, we are also interested in the extent to which the model can explain the time-series variance of the cross-sectional mean exchange rate or capital flow fluctuations, or the cross-sectional variance around that mean.

Table 1: Descriptive statistics for the variables in the model over the 2020-2021 period.

	Mean	St. Dev.	Median	25th	75th	Min	Max
	All						
Δfx	-0.01	1.08	-0.04	-0.52	0.42	-12.68	13.43
ΔIF	0.00	0.33	0.00	-0.10	0.10	-5.35	8.42
ΔIF^{Debt}	0.00	0.46	0.00	-0.12	0.12	-6.13	9.70
nfa^e	0.00	0.08	-0.16	-0.39	0.04	-0.61	3.06
nfa^d	-0.06	0.05	-0.22	-0.34	0.03	-0.61	1.99
R	0.25	0.04	0.22	0.15	0.36	0.03	1.44
CA	0.01	0.02	0.01	-0.02	0.04	-0.05	0.18
$\Delta Cases$	0.12	0.33	0.09	0.04	0.17	0.00	4.25
$\Delta Vacc$	0.10	0.21	0.04	0.02	0.09	0.00	3.99
	Advanced						
Δfx	0.01	0.83	0.01	-0.34	0.39	-8.48	3.96
ΔIF	0.00	0.22	0.00	-0.08	0.09	-1.38	1.74
ΔIF^{Debt}	0.00	0.40	-0.01	-0.14	0.13	-2.95	2.75
nfa^e	0.27	0.15	0.05	-0.10	0.55	-0.61	3.06
nfa^d	-0.04	0.07	0.01	-0.49	0.51	-0.61	1.99
R	0.29	0.06	0.26	0.07	0.81	0.03	1.44
CA	0.03	0.01	0.04	0.01	0.07	-0.03	0.18
$\Delta Cases$	0.14	0.32	0.09	0.03	0.18	0.00	3.55
$\Delta Vacc$	0.10	0.23	0.04	0.02	0.10	0.00	3.99
	Emerging						
Δfx	-0.03	1.23	-0.09	-0.66	0.46	-12.68	13.43
ΔIF	0.00	0.40	0.00	-0.08	0.08	-5.35	8.42
ΔIF^{Debt}	0.00	0.50	0.00	-0.08	0.08	-6.13	9.70
nfa^e	-0.16	0.03	-0.33	-0.41	-0.13	-0.55	0.43
nfa^d	-0.08	0.03	-0.26	-0.30	-0.11	-0.42	0.32
R	0.23	0.03	0.21	0.16	0.31	0.10	0.68
CA	0.01	0.02	0.00	-0.02	0.02	-0.05	0.07
$\Delta Cases$	0.12	0.34	0.11	0.07	0.18	0.00	4.25
$\Delta Vacc$	0.10	0.20	0.04	0.02	0.08	0.00	3.29

Notes: Δfx is the weekly log-change in the exchange rate (USD/LCU), ΔIF is the weekly change in total capital inflows, ΔIF^{Debt} is the weekly change in debt capital inflows, and all 3 changes are multiplied by 100 to put them in percent terms. nfa^e is the ratio of net foreign assets in equity securities to GDP, nfa^d, is the ratio of net foreign assets in debt securities (excluding central bank reserves) to GDP, Res is the ratio of central bank foreign exchange reserves to GDP, and CA the ratio of the current account to GDP. $\Delta Cases$ is weekly log change in the number of COVID cases, $\Delta Vacc$ is the weekly log change in the share of the population that has received at least one dose of a COVID vaccine. The table reports the descriptive statistics over the 2020-2021 sample period. The mean column simply reports the mean value of the variable across all country-period observations. The standard deviation column reports the cross-country average of the time series standard deviation of the variable. The median, 25th, and 75th percentile columns report the average across periods of the cross-sectional percentiles of the variable. The minimum and maximum are simply the minimum and maximum values of all country-period observations.

Following Crucini and Telmer (2020), we use the law of total variance, where the unconditional variance of the panel, $y_{i,t}$, can be expressed as the sum of the average cross-sectional variance of $y_{i,t}$, and the cross-time variance of the cross-sectional average value of $y_{i,t}$:

$$var\left(y_{i,t}\right) = \overbrace{var_t\left(E_j\left(y_{i,t}|t\right)\right)}^{Time-series} + \overbrace{E_t\left(var_j\left(y_{i,t}|t\right)\right)}^{Cross-section} \tag{3}$$

.

In other words, the variance of the panel is equal to the time series variance of the cross-sectional mean, $var_t\left(E_j\left(y_{i,t}|t\right)\right)$, plus the average cross-sectional variance around this mean, $E_t\left(var_j\left(y_{i,t}|t\right)\right)$. Using this law of total variance, we can then express the goodness of fit, R^2, in the panel data regression as the weighted average of the cross sectional goodness of fit and the time series goodness of fit:

$$R^2 = \frac{var\left(\hat{y}_{i,t}\right)}{var\left(y_{i,t}\right)} = \omega_y R^2_{CS} + \left(1 - \omega_y\right) R^2_{TS} \tag{4}$$

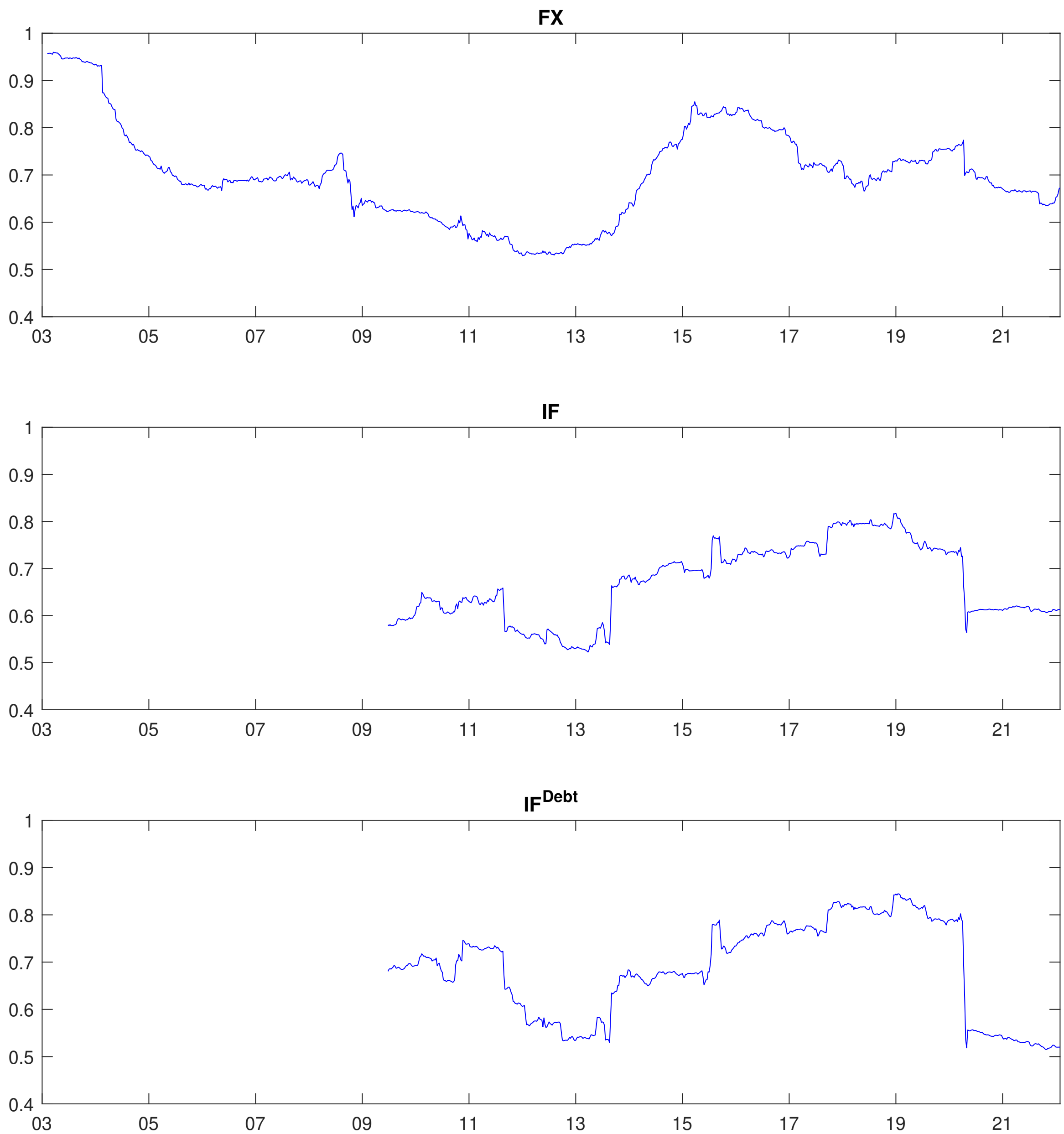
where $\hat{y}_{i,t}$ is the fitted value from the estimated regression, $\omega_y = \frac{E_t(var_j(y_{i,t}|t))}{E_t(var_j(y_{i,t}|t))+var_t(E_j(y_{i,t}|t))}$, $R^2_{CS} = \frac{E_t(var_j(\hat{y}_{i,t}|t))}{E_t(var_j(y_{i,t}|t))}$, and $R^2_{TS} = \frac{var_t(E_j(\hat{y}_{i,t}|t))}{var_t(E_j(y_{i,t}|t))}$.

Figure 3 plots the ω_y statistic, which reflects the share of the panel variance that is due to the cross-sectional variance, for our 3 dependent variables in 104 week-wide moving windows across our sample period. The figure shows that the share of the total variance that is due to the time-series variance of a common trend and the share due to idiosyncratic country-specific variance changes across time; the share of cross-sectional variance ω_y tends to fall during turbulent times when global factors dominate exchange rate or capital flow fluctuations and rise during calmer times. The results for the exchange rate in the top panel show that there was an abrupt fall in the ω_y statistic in late 2008 and it remained low until late 2012/early 2013. The figure also shows there was an abrupt fall in the ω_y statistic, from 78 percent to 69 percent during the COVID shock in early 2020.

The ω_y statistic for total inflows in the middle panel of the figure shows that like the statistic for the exchange rate, the value of ω_y fell throughout the 2008 crisis and the Euro Area crisis before reaching a local minimum in late 2012. The value then rose steadily as idiosyncratic factors played a relatively larger role up to early 2020. Then there was an abrupt fall in ω_y, from 70 percent to close to 60 percent, during the COVID shock.

The ω_y statistic for portfolio debt inflows is similar to the statistic for total portfolio flows, but the fluctuations during the COVID-crisis are amplified. During the COVID shock there was an abrupt fall in the share of the cross-sectional share of the variance of debt inflows from 80 percent to close to 50 percent. The share of the panel variance of portfolio debt inflows that is explained by a common trend is currently the highest on record (admittedly

Figure 3: The ω_y statistic, the share of the total panel variance that is due to cross-sectional variance around a common mean for the three dependent variables.



Notes: This figure plots the share of the panel variance that is due to cross-sectional variation around a the cross-sectional average, as opposed to time series variance of the cross-sectional average. The results panel of the weekly log change in the exchange rate are plotted in the top panel, the weekly change in total portfolio inflows in the middle panel, and the weekly change in portfolio debt flows in the bottom panel.

the sample is short and only begins in 2007).

4 Results

We first discuss the regression of the weekly change in the exchange rate or capital inflows on the GFC factor over the whole 2001-2021 sample. Then we repeat the regression analysis over the last two years of this sample, 2020-2021, to examine specifically how the GFC factor affected these dependent variables over the duration of the COVID-19 pandemic.

4.1 Results over full 2001-2021 sample

The results from the panel data regression in (2) are presented in Table 2. The table presents the results for the full set of advanced and emerging market countries in the sample for each of our three dependent variables: the week-over-week log change in the nominal exchange rate (columns 1a to 3a), the week-over-week change in total inflows (columns 1b to 3b), the week-over-week change in debt inflows (columns 1c to 3c). Note that while the weekly exchange rate data is available for the full 21 year sample, the capital flow data is only available starting in May 2007.

Here we only present the results from the first three regression specifications mentioned earlier, (1) regressing on a country fixed effect and lags, (2) adding the GFC factor as a stand-alone variable, and (3) adding the interaction between the GFC factor and country-specific macroeconomic variables. Since the country-specific Covid variables are only relevant in the last two years of the sample, we save that final regression specification for the regression looking at results over just the 2020-2021 period.

Coefficient Estimates: Columns 1a, 1b, and 1c in the table simply regress the dependent variable on its own lags and a country fixed effect. Columns 2a, 2b, and 2c add the change in the GFC factor. A one standard deviation fall in the GFC factor leads to about a 3.5 percent currency depreciation, total portfolio flows decline by about 1.5 percentage points, and inflows in debt securities decline by about 1.7 percentage points.

Columns 3a, 3b, and 3c then add the interaction terms, and thus ask how macroeconomic fundamentals like external assets and liabilities or the current account affect the elasticity of the dependent variable with respect to changes in the GFC.

First we look at the regression where the weekly log change in the nominal exchange rate is the dependent variable. The coefficient on the interaction between the change in the GFC factor and the net foreign asset position in equity securities is not significant. Meanwhile the coefficients on the interaction between the change in the GFC factor and the net foreign asset position in debt securities (excluding reserves) or the interaction between the change in

Table 2: Regression of weekly log changes in the exchange rate, weekly changes in portfolio inflows, or weekly changes in portfolio debt inflows on the weekly change in the GFC factor over full 2001-2021 sample.

	Δfx_t			ΔIF_t			ΔIF_t^{Debt}		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)
f_t		3.50***	4.17***		1.56***	1.17***		1.69***	1.41***
		(0.06)	(0.10)		(0.01)	(0.03)		(0.02)	(0.04)
$nfa^e_{t-52} \times f_t$			-0.13			-0.45***			-0.25***
			(0.19)			(0.03)			(0.05)
$nfa^d_{t-52} \times f_t$			-0.38***			-0.52***			-0.27***
			(0.10)			(0.03)			(0.05)
$R_{t-52} \times f_t$			-2.71***			1.34***			1.11***
			(0.30)			(0.08)			(0.12)
$CA_{t-52} \times f_t$			-8.52***			-2.12***			-3.32***
			(0.86)			(0.30)			(0.44)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.13	0.14	0.22	0.41	0.42	0.22	0.34	0.35
R^2_{CS}	0.05	0.05	0.06	0.19	0.22	0.24	0.18	0.20	0.21
R^2_{TS}	0.05	0.31	0.31	0.26	0.72	0.72	0.31	0.62	0.62
Weeks	1071	1071	1071	765	765	765	765	765	765
Countries	41	41	41	47	47	47	47	47	47

Notes: Columns 1a, 1b, and 1c regress the dependent variable on its own lags and a country fixed effect. Columns 2a, 2b, and 2c add the change in the GFC factor. Columns 3a, 3b, 3c add interactions between the change in the GFC factor and the net foreign asset and current account variables defined in the notes to Table 1. The coefficients on the non-interacted net foreign asset and current account variables are insignificant and are omitted.

the GFC factor and central bank foreign exchange reserves are negative and significant–more FX reserves lower the elasticity of exchange rates to the GFC shock. These results mirror those in Davis and Zlate (2016). The coefficient on the interaction term between the current account and the change in the GFC factor is negative and significant. These indicate that a the exchange rate of a country with a positive current account balance or a positive net foreign asset position in debt securities tends to be less sensitive to fluctuations in the global financial cycle. The coefficients on the non-interacted external asset variables, the terms given by the $\boldsymbol{\theta Z_{i,t-52}}$ term in equation (2) are generally not significant and are omitted from the table for brevity.

The results from the regressions of total or debt capital inflows in columns 3b and 3c are broadly similar. The coefficients on the interaction term between the change in the GFC factor and the net foreign asset position in equity or debt securities (excluding reserves) are negative and significant. Interestingly, the coefficient of the interaction between foreign reserves and the change in the GFC factor is positive, indicating that countries with a greater stock of reserves tend to have capital inflows that are more sensitive to fluctuations in the GFC factor. This reflects the fact that countries where capital inflows are more sensitive to exogenous fluctuations have a greater incentive to hold a large stock of central bank foreign exchange reserves, which enables the central bank to respond by adjusting reserve accumulation (a component of capital outflows) in line with exogenous fluctuations in gross capital inflows to lessen volatility in net capital flows (see e.g. Obstfeld, Shambaugh, and Taylor, 2010). The coefficient of the interaction between the change in the GFC factor and the current account balance is negative and significant, indicating that capital inflows for a country with a current account surplus are less sensitive to fluctuations in the GFC factor.

Table 2 presents the results for our full set of advanced and emerging market countries. In Table 3 we divide the sample into advanced economies (top panel) and emerging market economies (bottom panel). First and foremost, the results are robust when dividing the country sample, in both samples the GFC factor is significant and a fall in the GFC factor leads to currency depreciation and a fall in capital inflows. Furthermore the coefficients on the interactions between macroeconomic variables and the GFC do not change qualitatively when dividing the sample of countries.

However, quantitatively there are some interesting differences between the two groups of countries. In the regression of the exchange rate, column 2a, the coefficient is higher in the emerging market subgroup. This indicates that while both advanced and emerging market currencies depreciate relative to the U.S. dollar during a downturn in the GFC, emerging market currencies depreciate by more. Another way to put this is that the non-U.S. advanced economy currencies appreciate relative to emerging marekt currencies when there is a downturn in the GFC. Furthermore, in columns 2b and 2c, the coefficient on the

GFC factor is much higher (around twice as high) in the emerging markets. So while both groups of countries see a fall in capital inflows, the fall in capital inflows in emerging markets is about double that in advanced economies.

Goodness of fit: The R^2 statistics show that the regression model with lags of the dependent variable and a country fixed effect can explain about 5 percent of the variance of weekly log differences in the nominal exchange rate, about 21 percent of the weekly change in total inflows, and 22 percent of the variance of weekly changes in debt inflows. Adding the change in the GFC factor in the next column more that doubles the R^2 in the regression of the exchange rate or total inflows, and nearly doubles the R^2 in the regression of debt inflows. Furthermore nearly all of this increase in the explanatory power of the model comes from the ability to explain the time series variance of the panel, not the cross-sectional variance of the panel. Before adding the change in the GFC factor, the model based on lags of the dependent variable explained about 5 percent of the time series variance of the panel of weekly changes in exchange rates and around 25 to 30 percent of weekly change in capital inflows. After adding the change in the GFC factor to the regression, the time series goodness of fit for the exchange rate rises above 30 percent, for total inflows it rises above 60 percent, and for debt inflows it rises above 50 percent.

The model with the change in the GFC factor explains a relatively small portion of the cross-sectional variance of weekly exchange rate fluctuations. The R^2_{CS} statistics in the column 3a, where we add the change in the GFC factor as a stand-alone variable and interacted with macroeconomic variables is just a little higher than the R^2_{CS} in column 1a, when the change in the exchange rate was regressed on its own lags and a country fixed effect. However, the improvement in the cross-sectional goodness-of-fit in the regressions of total inflows and debt inflows is larger. In the regression of total inflows in columns 1b and 3b, using the change in the GFC factor as a stand-alone variable and interacted with macroeconomic variables raises the cross-section goodness-of-fit by about 4 percentage points, while the gain is slightly smaller when we focus on debt inflows in columns 1c and 3c.

In Table 3, where we divide the sample into advanced economies and emerging market economies, the results are similar, with a few informative differences. When looking at the coefficient results earlier we saw that emerging market capital flows were more sensitive to fluctuations in the GFC. In the goodness of fit statistics, we see that the improvement in goodness of fit from adding the GFC factor to the regression (moving from column 1 to column 2) is much higher for emerging markets than for advanced economies. This is mainly due to a higher time-series goodness-of-fit.

Table 3: Regression of weekly log changes in the exchange rate, weekly changes in portfolio inflows, or weekly changes in portfolio debt inflows on the weekly change in the GFC factor over full 2001-2021 sample. Results from dividing the sample of countries into advanced and emerging subgroups.

Advanced:									
		Δfx_t			ΔIF_t			ΔIF_t^{Debt}	
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)
f_t		3.10***	3.86***		1.04***	0.91***		1.23***	1.17***
		(0.08)	(0.12)		(0.02)	(0.02)		(0.03)	(0.04)
$nfa_{t-52}^e \times f_t$			-0.69***			-0.21***			-0.01
			(0.25)			(0.03)			(0.06)
$nfa_{t-52}^d \times f_t$			-0.32***			-0.23***			0.02
			(0.10)			(0.04)			(0.07)
$R_{t-52} \times f_t$			-0.82**			0.52***			0.32**
			(0.33)			(0.08)			(0.15)
$CA_{t-52} \times f_t$			-15.26***			1.10***			-0.72
			(1.72)			(0.35)			(0.61)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.13	0.15	0.26	0.40	0.40	0.26	0.33	0.33
R^2_{CS}	0.05	0.05	0.08	0.23	0.26	0.26	0.22	0.24	0.24
R^2_{TS}	0.05	0.23	0.23	0.32	0.67	0.68	0.37	0.57	0.57
Weeks	1071	1071	1071	765	765	765	765	765	765
Countries	15	15	15	23	23	23	23	23	23
Emerging:									
		Δfx_t			ΔIF_t			ΔIF_t^{Debt}	
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)
f_t		3.73***	4.97***		2.06***	1.76***		2.15***	2.00***
		(0.08)	(0.19)		(0.02)	(0.06)		(0.03)	(0.07)
$nfa_{t-52}^e \times f_t$			-0.51			-0.15			0.33
			(0.57)			(0.16)			(0.20)
$nfa_{t-52}^d \times f_t$			-2.64***			-0.12			0.20
			(0.50)			(0.14)			(0.18)
$R_{t-52} \times f_t$			-8.70***			1.02***			1.19***
			(0.86)			(0.24)			(0.31)
$CA_{t-52} \times f_t$			-3.97***			-3.84***			-5.01***
			(1.27)			(0.55)			(0.70)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.13	0.14	0.20	0.45	0.46	0.20	0.39	0.39
R^2_{CS}	0.05	0.05	0.06	0.16	0.20	0.20	0.15	0.19	0.19
R^2_{TS}	0.05	0.34	0.34	0.24	0.68	0.68	0.24	0.56	0.56
Weeks	1071	1071	1071	765	765	765	765	765	765
Countries	26	26	26	24	24	24	24	24	24

Columns 1a, 1b, and 1c regress the dependent variable on its own lags and a country fixed effect. Columns 2a, 2b, and 2c add the change in the GFC factor. Columns 3a, 3b, 3c add interactions between the change in the GFC factor and the net foreign asset and current account variables defined in the notes to Table 1. The coefficients on the non-interacted net foreign asset and current account variables are insignificant and are omitted.

4.2 Results over the 2020-2021 period

Next we ask how the uneven spread of COVID-19 pandemic across countries over time affected exchange rates and capital flows. In Table 4 we add the changes in COVID cases and vaccination rates as additional explanatory variables, both as stand-alone variables and interacted with the GFC. Instead of regressing over the whole 2001-2021 sample as in Table 2, we regress over 2020 and 2021, which is the part of the sample where these COVID variables were relevant. Again we regress on each of our three dependent variables: the week-over-week log change in the nominal exchange rate (columns 1a-4a), the week-over-week change in total inflows (columns 1b-4b), the week-over-week change in debt inflows (columns 1c-4c).

Table 4: Regression of weekly log changes in the exchange rate, weekly changes in portfolio inflows, or weekly changes in portfolio debt inflows on the weekly change in the GFC factor over 2020-2021.

	Δfx_t				ΔIF_t				ΔIF_t^{Debt}			
	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)	(1c)	(2c)	(3c)	(4c)
f_t		3.29***	3.61***	3.27***		1.45***	1.34***	1.01***		2.00***	1.91***	1.49***
		(0.12)	(0.25)	(0.27)		(0.03)	(0.05)	(0.06)		(0.04)	(0.06)	(0.07)
$nfa^e_{t-52} \times f_t$			-0.53*	-0.66**			-0.36***	-0.37***			-0.07	-0.10
			(0.28)	(0.28)			(0.05)	(0.05)			(0.06)	(0.06)
$nfa^d_{t-52} \times f_t$			-1.10***	-0.87**			-0.52***	-0.49***			-0.11	-0.08
			(0.41)	(0.42)			(0.06)	(0.06)			(0.08)	(0.07)
$R_{t-52} \times f_t$			-1.01	-1.03			0.46***	0.64***			0.69***	0.92***
			(0.67)	(0.67)			(0.14)	(0.14)			(0.18)	(0.17)
$CA_{t-52} \times f_t$			-5.51**	-5.82**			-4.06***	-4.14***			-5.03***	-5.14***
			(2.66)	(2.65)			(0.85)	(0.84)			(1.08)	(1.06)
$\Delta Cases_{t-1} \times f_t$				0.36***				0.38***				0.49***
				(0.14)				(0.03)				(0.04)
$\Delta Vacc_{t-1} \times f_t$				-1.62				-1.01***				-1.99***
				(1.37)				(0.32)				(0.40)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.10	0.28	0.29	0.30	0.17	0.44	0.46	0.48	0.17	0.48	0.48	0.50
R^2_{CS}	0.11	0.14	0.16	0.16	0.11	0.17	0.20	0.21	0.10	0.15	0.16	0.17
R^2_{TS}	0.08	0.54	0.54	0.55	0.25	0.85	0.86	0.89	0.25	0.82	0.82	0.84
Weeks	104	104	104	104	104	104	104	104	104	104	104	104
Countries	41	41	41	41	47	47	47	47	47	47	47	47

Notes: columns 1a, 1b, and 1c regress on a country-fixed effect and lags of the dependent variable. Columns 2a, 2b, and 2c add the change in the GFC factor. Columns 3a, 3b, and 3c add the interaction between the change in the GFC factor and the external asset position variables defined in the notes to table 1. Columns 4a, 4b, and 4c add the interaction between the change in GFC factor and the weekly log change in number of Covid cases, $\Delta Cases_{i,t}$ or the weekly change in the vaccination rate (2nd dose), $\Delta Vacc_{i,t}$ in country i.

Coefficient Estimates: In columns 1a, 1b, and 1c of the tables, we regress on a country-fixed effect and lags of the dependent variable alone; in columns 2a, 2b, and 2c we add the change in the GFC factor; and in columns 3a, 3b, and 3c we add the interaction between the change in the GFC factor and the external asset position variables that were used in Table 2. Other than the truncated time sample, the regression specification in these nine columns in Table 4 is the same as in the nine columns of Table 2. The coefficient results in this truncated sample are broadly similar to those in the full sample. The change in the GFC factor alone has a positive and significant effect on the value of the exchange rate and total and debt capital flows. In the regression where the exchange rate is the dependent variable, the interactions between the GFC factor and the net foreign asset position in debt securities (excluding reserves) or central bank foreign exchange reserves are negative and significant, indicating that the exchange rate in a country with a positive net foreign asset position in debt securities or a high stock of central bank foreign exchange reserves tends to be less sensitive to fluctuations in the GFC.

In columns 4a, 4b, and 4c we add interactions of changes in COVID cases and vaccination rates (at least 1 dose) with the GFC as additional explanatory variables in the regression.

In the regressions with each of the three dependent variables, the coefficient on the interacted term between the change in the GFC factor and the log change in COVID cases is *positive* and highly significant. For changes in total and debt portfolio flows, the coefficient on the interacted term between the GFC factor change and the log change in vaccination rates is negative and highly significant. These results imply that exchange rates and capital flows were more sensitive to fluctuations in the GFC when COVID cases are increasing, and less sensitive when the vaccination rates are increasing.[3]

In Table 5 we run the same regressions, but we split out full sample of countries into an advanced economy subgroup and and emerging market subgroup. The coefficient differences between the advanced and emerging market subgroups that we noted in the full 2001-2021 sample period continue to hold in this truncated sample. What is interesting in this table is that the coefficients on the Covid variables in columns 4a, 4b, and 4c are always much greater in absolute value in the emerging market subsample. The same change in Covid cases or vaccination rates had a much larger effect on the elasticity of a country's exchange rate or capital flows in the emerging markets than in the advanced economies.

[3]We also collected data on cumulative COVID deaths and vaccination rates (at least 1 dose). However COVID cases are highly correlated with deaths, and vaccination rates (fully vaccinated) are highly correlated with vaccination rates (at least 1 dose), so deaths and fully-vaccinated rates would be multicolinear and add little additional information. For robustness we run the regressions replacing the weekly log change in cases numbers with weekly log changes in deaths, or 1 dose vaccination with fully vaccinated, and the results are very similar.

Table 5: Regression of weekly log changes in the exchange rate, weekly changes in portfolio inflows, or weekly changes in portfolio debt inflows on the weekly change in the GFC factor over 2020-2021. Results from dividing the sample of countries into advanced and emerging subgroups.

Advanced:		Δfx_t				ΔIF_t				ΔIF_t^{Debt}		
	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)	(1c)	(2c)	(3c)	(4c)
f_t		2.90***	4.09***	4.22***		0.92***	1.01***	0.68***		1.53***	1.50***	1.14***
		(0.16)	(0.34)	(0.35)		(0.03)	(0.04)	(0.05)		(0.04)	(0.06)	(0.08)
$nfa^e_{t-52} \times f_t$			-0.62**	-0.59**			-0.15***	-0.13***			0.03	0.05
			(0.28)	(0.28)			(0.04)	(0.04)			(0.06)	(0.06)
$nfa^d_{t-52} \times f_t$			-0.74	-1.34***			-0.16***	-0.11**			0.18**	0.24***
			(0.46)	(0.51)			(0.05)	(0.04)			(0.07)	(0.07)
$R_{t-52} \times f_t$			-1.68***	-1.33**			-0.34***	-0.18*			-0.19	0.00
			(0.64)	(0.65)			(0.11)	(0.11)			(0.17)	(0.17)
$CA_{t-52} \times f_t$			-5.57	-0.61			0.98	0.12			2.94***	1.96*
			(4.99)	(5.23)			(0.73)	(0.72)			(1.17)	(1.16)
$\Delta Cases_{t-1} \times f_t$				-0.17				0.31***				0.36***
				(0.20)				(0.03)				(0.05)
$\Delta Vacc_{t-1} \times f_t$				-2.10				-0.48*				-1.63***
				(1.42)				(0.25)				(0.40)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.06	0.28	0.32	0.33	0.17	0.44	0.45	0.49	0.19	0.47	0.47	0.49
R^2_{CS}	0.06	0.12	0.21	0.22	0.11	0.19	0.21	0.24	0.10	0.16	0.17	0.19
R^2_{TS}	0.06	0.42	0.42	0.43	0.27	0.81	0.83	0.86	0.28	0.78	0.78	0.80
Weeks	104	104	104	104	104	104	104	104	104	104	104	104
Countries	15	15	15	15	23	23	23	23	23	23	23	23
Emerging:												
		Δfx_t				ΔIF_t				ΔIF_t^{Debt}		
	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)	(1c)	(2c)	(3c)	(4c)
f_t		3.50***	3.24***	2.52***		2.02***	1.59***	1.18***		2.50***	2.25***	1.72***
		(0.17)	(0.43)	(0.46)		(0.05)	(0.10)	(0.11)		(0.06)	(0.12)	(0.13)
$nfa^e_{t-52} \times f_t$			-1.63	-2.06**			-1.88***	-1.69***			-0.91***	-0.67**
			(1.01)	(1.00)			(0.27)	(0.27)			(0.32)	(0.32)
$nfa^d_{t-52} \times f_t$			-4.00***	-3.56***			-0.51	-0.63*			0.69*	0.53
			(1.22)	(1.22)			(0.33)	(0.33)			(0.39)	(0.38)
$R_{t-52} \times f_t$			-3.49*	-3.07			-0.45	-0.12			0.89*	1.31***
			(1.96)	(1.94)			(0.44)	(0.43)			(0.52)	(0.51)
$CA_{t-52} \times f_t$			0.12	2.74			-6.27***	-4.22***			-11.67***	-8.99***
			(4.51)	(4.49)			(1.66)	(1.64)			(1.96)	(1.92)
$\Delta Cases_{t-1} \times f_t$				0.69***				0.49***				0.65***
				(0.20)				(0.06)				(0.07)
$\Delta Vacc_{t-1} \times f_t$				-2.00				-1.79***				-2.56***
				(2.24)				(0.65)				(0.77)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.11	0.28	0.29	0.31	0.17	0.50	0.52	0.54	0.17	0.52	0.54	0.56
R^2_{CS}	0.12	0.15	0.16	0.17	0.10	0.16	0.18	0.21	0.09	0.14	0.16	0.19
R^2_{TS}	0.09	0.58	0.59	0.62	0.24	0.86	0.87	0.89	0.24	0.84	0.85	0.87
Weeks	104	104	104	104	104	104	104	104	104	104	104	104
Countries	26	26	26	26	24	24	24	24	24	24	24	24

Goodness of fit: The goodness of fit statistics in Table 4 show that fluctuations in the GFC factor can better explain the variance of weekly exchange rate fluctuations or changes in portfolio debt inflows over the past two years than over the full 21 year sample. Recall from the R^2 statistics in Table 2 that the model with lags and the change in the GFC factor alone (column 2 of both tables) can explain about 12 percent of the variance of the panel of weekly exchange rate fluctuations over the full 2001-2021 sample, but from Table 4 the model explains almost 30 percent in the 2020-2021 period. This is due to an increase in the share of the time-series variance explained by changes in the GFC factor, where the R^2_{TS} rose from 30 percent in the full sample to over 50 percent over the past two years.

Similarly, the share of the variance of weekly change in portfolio debt inflows that can be explained by the change in the GFC increases from around 30 percent in the full sample to almost 50 percent over the past two years. Like the model with exchange rate fluctuations, this is also due to an increase in the time-series goodness of fit, R^2_{TS} from 60 percent to more than 80 percent.

However, it is interesting to note that in the regression of portfolio debt inflows, while the overall goodness-of-fit and the time-series goodness-of-fit increased in the model with the change in the GFC factor between the full 21 year sample and the sample with the last two years, this masks about a 6 percentage point fall in the cross-section goodness-of-fit in the shortened sample. Basically, over the last two years, when regressing debt inflows, the overall explanatory power of the GFC has increased, but this is due to the ability of fluctuations in the GFC to explain the time-series fluctuations of the cross-country average of debt inflows. The ability of the GFC to explain the cross-sectional variance of debt inflows has fallen in the more recent time period.

There is little change in the goodness-of-fit statistics between the full sample and the sample that just includes the last two years for the regression of the weekly change in changes in total portfolio inflows. The change in the GFC explains more than 40 percent of the total variance of the panel of weekly changes in total inflows over both the full sample and the last two years. Similar to the results when regressing debt inflows, there was an increase in the time-series goodness of fit in the recent subsample, but a fall in the cross-section goodness-of-fit.

Adding the interaction of changes in the GFC factor with the country-specific external assets variable (columns 3a and 3b) raises the cross-sectional goodness-of-fit by a few percentage points.

Finally, adding the country-specific COVID variables raises the explanatory power in both the time series and cross sectional dimensions in the regressions where the the dependent variable is the change in total or debt portfolio flows (columns 4b and 4c). The R^2_{CS} improves once again by a few percentage points in both cases. In fact, adding the COVID metrics improves the model's ability to explain the cross-sectional variation of portfolio flows during the crisis by just as much as standard macro variables considered earlier.

Turning now to the regressions for the advanced and emerging market subgroups in Table 5. Again we see that the goodness-of-fit in the regression of portfolio flows, particularly debt portfolio flows, is higher in the emerging market subgroup, and this is entirely due to the time-series goodness-of-fit. The cross-section goodness of fit is higher in the advanced economy subgroup.

Robustness: In the Online Appendix we include the results from estimating the GFC factor with a dynamic factor model instead of a static factor model. The results are nearly identical.

In addition, all of these regression results use data at a weekly frequency, and thus rely on weekly changes in exchange rates and portfolio flows regressed on weekly changes in the GFC factor. It is possible to aggregate up to a monthly frequency and present the same results. For robustness we do this in the Online Appendix and we present the results using the same data and methodology where changes are monthly instead of weekly. The results are very similar, the only clear difference being that when regressions use monthly data, the cross-sectional goodness-of-fit, R^2_{CS} is higher. But the signs and significance of the key coefficient estimates, and the differences in the overall, time-series, and cross-sectional R^2 between various models remain unchanged with the lower data frequency.

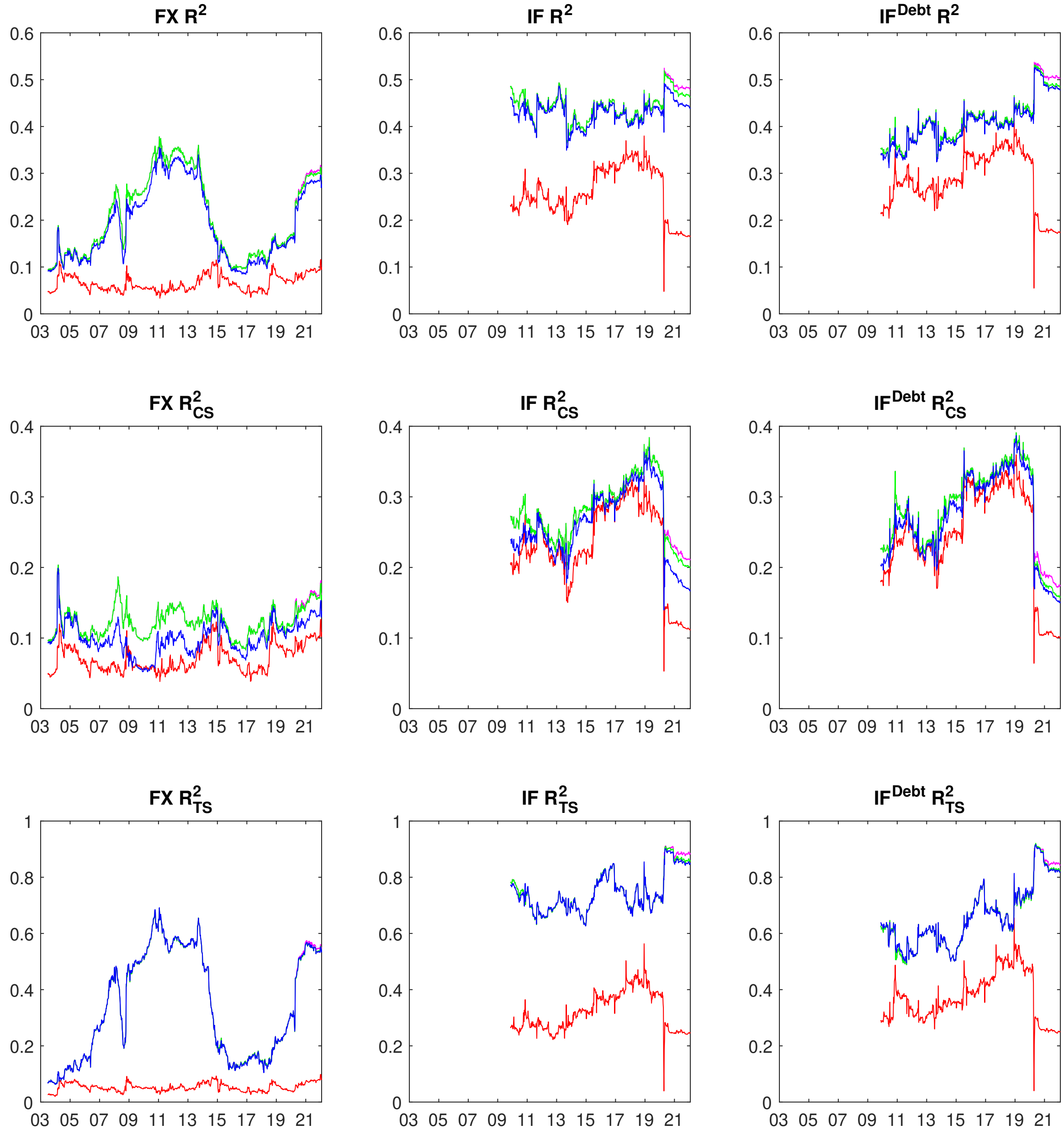
4.3 Results from rolling window regressions

Figure 4 presents the overall goodness of fit, R^2, the cross-section goodness of fit, R^2_{CS}, and the time-series goodness of fit, R^2_{TS} from the four regression specifications in Table 4 using rolling windows of 104 weeks (two years) over the full 2001-2021 sample period. The rolling window goodness of fit statistics from the regression with the change in the exchange rate as the dependent variable are plotted in the left-hand column, those from the regression with total portfolio flows as the dependent variable are plotted in the middle column, and those where debt flows is the dependent variable are plotted in the right-hand column.

The R^2 value from our first regression specification, that with lags of the dependent variable and a country fixed effect is plotted in *red*. The values from our second regression specification, the model that adds the change in the GFC factor, is plotted in *blue*. The R^2 values from our third regression specification, the model that adds interactions with the macroeconomic variables, is plotted in *green*, and that from our fourth regression specification, the model that adds interactions with the COVID variables, is plotted in *purple*.

We begin with the goodness of fit statistics for the model where the exchange rate is the dependent variable in the left-hand column. The goodness-of-fit in the regression model

Figure 4: The overall, cross-section, and time-series goodness-of-fit from the three regression specifications. Panel regression includes the full sample of advanced and emerging market countries.



Notes: The R^2 values from the regression on lags of the dependent variable and a country fixed effect are plotted in red, the model that adds the change in the GFC factor is plotted in blue, the model that adds the interaction between the change in the GFC factor and the country-specific macro variables is plotted in green, the model that adds the interaction between the change in the GFC factor and the country-specific COVID variables is plotted in purple. The results from the regression of the log change in the exchange rate are plotted in the left-hand column, the regression of the change in total portfolio flows in the middle column, and the change in portfolio debt flows in the right-hand column.

with lags of the dependent variable and a country-fixed effect (red line) is fairly steady at a little less than 10 percent. Then adding the GFC factor to the regression (blue line) leads to a major increase in the model fit during a few distinct time periods. The top row of the figure shows that over this 21 year sample period there have been two periods where the overall R^2 from our regression model was elevated, the 2008-2013 period, encompassing the global financial crisis and the Euro Area crisis, and the 2020-2021 period, encompassing the COVID shock. The bottom two rows in the figure show that this elevated R^2 during these two periods is mainly due to an increase in the time series goodness of fit, R^2_{TS}. During some periods, like the 2008 crisis, adding the GFC factor to the model actually leads to a slight fall in the cross-section goodness of fit from the model with just lags of the dependent variable.

Adding the interaction terms, either with the macroeconomic variables (green line) or both the macro and COVID variables (purple line), leads to a slight improvement in the overall R^2, especially during the 2008-2013 period. This improvement in the overall goodness-of-fit from adding the interaction between the GFC and country-specific macro variables is entirely due to improvement in the cross-section goodness of fit.

Next we discuss the statistics from the regressions where capital inflows is the dependent variable in the middle or the right-hand column. Recall that this data does not start until early 2007, so the first two year rolling window ends in early 2009.

As the decade following the global financial crisis progressed, the explanatory power of the model with just lags of the dependent variable and a country fixed effect rose (red line), and the extra explanatory power from the GFC factor fell (distance between blue line and red line). In the years leading up to the COVID crisis, the GFC was having less of an effect on capital flow fluctuations. However, this pattern reversed dramatically in early 2020, when the explanatory power of the model with just lags of the dependent variable fell sharply. The overall explanatory power of the model that includes the change in the GFC factor did not fall, and that of the model with the GCF increased in the cross-section.

Adding the macro fundamentals improves the goodness of fit somewhat (distance between green and blue lines). Importantly, adding the COVID metrics improves the goodness of fit notably over the model with only macro fundamentals (distance between purple and green lines).

5 Economic Interpretation

Our regression results highlight two important features of the empirical capital flows literature. The first is related to fluctuations in gross capital flows or exchange rates for the *average* country over time. The second has to do with the heterogeneity across countries, and the fact that some countries see a larger fall in capital inflows or larger exchange rate depreciation than others. In this section we discuss the economic significance of these two sets of results and their theoretical underpinnings.

5.1 The aggregate response of capital flows and the exchange rate

The first row of Table 4 shows the effect of the GFC shock on exchange rates against the U.S. dollar and gross portfolio inflows in the average country in the sample for the 2020-2021 period.

The response of the exchange rate in the average country following a downturn in the GFC is an example of the safe-haven flows to the U.S. dollar. As shown in Figure 1, the U.S. dollar appreciated sharply against both advanced and emerging market currencies during the Covid shock. Attempts to model and explain this safe haven appreciation in the dollar during times of crisis rely on the special role for of the U.S. dollar and U.S. dollar-denominated assets for providing liquidity during times of crisis.

Jiang, Krishnamurthy, and Lustig (2020 and 2021) explicitly introduce an exogenous convenience yield on U.S. dollar assets. Investors, both U.S. and foreign, assign a liquidity premium to U.S. dollar assets, and are willing to hold U.S. dollar assets at a lower rate of return. In the steady state, this convenience yield can explain the negative U.S. net foreign asset position and the negative U.S. current account deficit. In addition, a positive shock to this dollar convenience yield there is associated with an immediate appreciation in the dollar. Other recent papers have endogenized this convenience yield, either through including a demand for U.S. dollar bonds in the utility function and then shocking this demand (see e.g Kekre and Lenel, 2021) or by introducing uncertainty in bank funding shocks and a special role for dollar reserves (see e.g Bianchi, Bigio, and Engel, 2021).

In our empirical results over the 2020-2021 period, we find that a one standard deviation negative shock to the GFC (remember that the GFC level is normalized to have a standard deviation of 1) led to a 3.3% appreciation in the U.S. dollar on average across our sample of advanced and emerging market countries. The descriptive statistics in Table 1 show that the standard deviation of the weekly log change in the exchange rate is 1.1%, and thus a shock to the GFC of -1 during the Covid period led to about a 3 standard deviation depreciation in the exchange rate for the average country in the sample.

The large negative response of capital inflows for the average country similarly denotes retrenchment in gross capital inflows and outflows during a downturn in the GFC. This retrenchment has been well documented around the time of the Global Financial Crisis in 2008 (see e.g. Milesi-Ferretti and Tille, 2011). While with this weekly data we only observed capital inflows, since the world net flows or current account must equal zero, then presumably what happens with gross inflows for the average country must also happen with gross outflows. (In the next subsection we will discuss cross-country heterogeneity and why inflows fall by more than outflows in some countries but less in others).

Davis and van Wincoop (2021) model the retrenchment in gross flows during crises. What at first seems like a fairly intuitive idea of global retrenchment in response to a common global shock to risk aversion is actually difficult to model in a portfolio choice model. After all, if all agents are identical then a common global shock to risk aversion doesn't lead to any asset flows, just a fall in asset prices. In order to have flows, one needs heterogeneity so that after the shock some agents become buyers and some become sellers.

Therefore to model global retrenchment, Davis and van Wincoop (2021) rely on cross-investor heterogeneity in risk aversion, which then becomes household heterogeneity in the share of their portfolio devoted to risky assets, as shown in household-level administrative wealth data in Calvet, Campbell, and Sodini (2007, 2009a and 2009b). Thus in response to a common global shock that leads to a fall in risky asset prices, the investors who hold a larger share of their portfolio in risky assets face a larger drop in their wealth, and in a portfolio choice model these agents become the sellers and investors with a lower risky asset share become the buyers.

If this is then combined with cross-investor heterogeneity in the desire to hold foreign assets, where the investors who are more willing to hold risky assets are also more willing to hold foreign assets, then following a common shock, investors with the riskier portfolios sell both home and foreign risky assets, while the willing buyers in the same country have less demand for foreign assets. In equilibrium, investors with a high risky asset share in the home country end up selling their foreign assets to investors with a low risky asset share in the foreign country, and thus there is a repatriation of risky assets, a global retrenchment.

The net result of all of this, and what is important for our purposes, is the fact that on aggregate at the country level, home bias, the preference to hold home assets as opposed to foreign assets, increases following a negative shock to the GFC. The shock was a common shock that impacted all investors and all assets equally, but due to cross-investor heterogeneity in the willingness to hold foreign assets, the common global shock led to a shift in relative wealth away from investors with a low home bias and towards investors with a high home bias, leading to an aggregate increase in home bias and a global retrenchment.

Quantitatively, in Table 4, we see that a shock to the GFC of -1 led to a fall in total capital inflows of 1.45 percentage points and a fall in debt capital inflows of 2 percentage points. From the descriptive statistics in Table 1, we see that these magnitudes are equivalent to more than 4 standard deviations fall in either total or debt portfolio inflows.

5.2 Cross-country heterogeneity in the response of capital flows and exchange rates

Regression specifications 3 and 4 in Table 4 show the effect of cross-country heterogeneity on the exchange rate and capital inflows. The basic insight across all three dependent variables is that countries with a negative net foreign asset position, a current account deficit, fast growth in Covid cases, or slow growth in the Covid vaccination rate, see greater exchange rate depreciation and a greater drop in capital inflows.

This can be seen as evidence that during a downturn in the GFC, countries with these risk factors face a fall in net capital inflows. A positive shift in net capital inflows puts upward pressure on the value of the exchange rate, so when one currency depreciated relative to another, that is a sign that the depreciating country faced a greater fall in net capital inflows. Similarly, while in the capital flows data we only observe inflows and not outflows, the relatively larger drop in capital inflows in the country with greater risk factors will most likely translate into a larger fall in net capital inflows.

Davis and van Wincoop (2021) think about the effect of a country's net foreign asset position on the response of their net capital flows. They model net capital flows with a portfolio choice model, and a country's net foreign asset position is a sign of the aggregate desire to hold risky assets. The argument is analogous to the one given in the previous subsection when describing how a retrenchment in gross capital flows is driven by heterogeneity in the risky asset share among investors within a country. When this same reasoning is applied to the country-level data, a country with a negative net foreign asset position (and thus a country that is more leveraged) faces a larger drop in wealth following a common global fall in risky asset prices. By the permanent income hypothesis, that greater fall in wealth leads to a greater increase in savings, and savings minus investment is equal to the current account is equal to the negative of net capital inflows. Thus following a negative shock to the GFC, savings increases in the more leveraged country and thus their current account increases and net capital inflows decrease.

Alternatively one can view these risk factors as leading to a greater probability of default in the case of a crisis. In this channel, a negative net foreign asset position is a sign that a country is highly leveraged, and a current account deficit is a sign that a country relies on net foreign borrowing to sustain domestic demand. In Davis, Devereux, and Yu (2020), countries with a high initial level of debt or that rely on foreign financing are susceptible to the reversal of that financing during a downturn in the GFC. The reversal of that financing can lead to the tightening of borrowing constraints and a "sudden stop" in net capital inflows, leading to depreciation in the exchange rate and a fall in capital inflows relative to countries that do not display the same risk factors.

Davis et al. (2020) do not consider the role of the Covid shock, but as discussed earlier, Kalemli-Ozcan (2020), Akinci et al. (2020), Corsetti and Marin (2020) all described the potential for capital flight, sudden stops, and currency depreciation in emerging market economies as a result of the pandemic when writing early in the Covid crisis. The fact that a surge in new Covid cases makes a country's exchange rate and capital inflows more sensitive to fluctuations in the GFC is a sign that the surge in Covid cases increases country-specific risk. Likewise, an increase in the vaccination rate reduces this country-specific risk and lessens the sensitivity of a country's exchange rate and capital inflows to fluctuations in the GFC.

Recall that in the last subsection we discussed how a shock to the GFC of -1 led to a 3.3% currency depreciation in the average country in the sample. Notice also that in Table 4 the coefficient on the interaction term between the current account and the GFC factor is -5.8. From the descriptive statics in Table 1, a country in the 25th percentile of current account balances has a current account of -1.5% and a country in the 75th percentile of current account balances has a current account of 3.8%. Putting all of this together, following a shock to the GFC of -1, the currency of the country in the 25th percentile of current account balances should depreciate relative to the currency of the country in the 75th percentile by 0.3%. Likewise, the same negative shock to the GFC should lead to a 0.27 percentage point greater fall in debt inflows in the 25th percentile current account country relative to the 75th percentile country.[4]

Similarly, in Table 4 the coefficient on the interaction term between new Covid cases and the GFC factor is 0.004 in the regression of the exchange rate and 0.48 in the regression of debt inflows. Take a country with a weekly log change in Covid cases of 100% (which was very common early in the crisis when all countries were starting from a low base and cases would double weekly at the onset of a new wave). In response to a shock to the GFC of -1, a country with this weekly growth rate in cases would see a depreciation in the exchange rate of 0.4% and a 0.48 percentage point greater fall in debt inflows relative to a country that did not see any growth in Covid cases.[5] Thus, the cross-sectional differences in the behavior of exchange rates and capital flows explained by traditional macro fundamentals such as current accounts were roughly similar in magnitude to the differences explained by COVID fundamentals in countries experiencing new waves.

6 Conclusion

The COVID shock led to a downturn in global risky asset prices similar in magnitude to the fall between October 2008 and March 2009, but in over a period of only four weeks rather

[4] $-0.3 = -1 \times (-0.015 - .0.038) \times -5.8$ and $-0.21 = -1 \times (-0.015 - .0.038) \times -5.135$

[5] $-0.4 = -1 \times 1 \times 0.04$ and $-0.48 = -1 \times 1 \times 0.48$

than five months. The fast-paced developments during the pandemic crisis require the use of high-frequency, country-specific data to understand the unusually large movements in capital flows and exchange rates over a narrow time interval.

In this paper we set out to find the effect of the COVID shock to the GFC on exchange rates and capital flows, while also taking the fast-changing country-specific conditions into account. Given the speed of the deterioration in financial markets during the pandemic, we estimate a GFC factor at a weekly frequency and then evaluate its effect on the weekly log changes in exchange rates and portfolio flows.

We find that on average, across our sample of advanced and emerging market countries, a downturn in the GFC was associated with currency depreciation (relative to the U.S. dollar) and a fall in portfolio equity and debt flows. Furthermore, we find that country-specific macroeconomic and COVID-19 fundamentals affected the sensitivity of a country's exchange rate or capital flows to fluctuations in the GFC. The effect of macroeconomic fundamentals is already well known in the literature, but the effect of the COVID-19 fundamentals on sensitivity to the GFC is particularly interesting and novel. We find that an increase in a country's COVID-19 infection rates made the exchange rate or capital flows more sensitive to adverse fluctuations in the GFC. Thus, during the COVID-19 shock when there was a sharp fall in the GFC, exchange rates and capital flows fell across the board, but they fell by more for countries and during episodes with larger increases in COVID-19 cases.

Finally, we ask what share of the variance of a panel of exchange rates or capital flow fluctuations can be explained by the GFC and country-specific macro or COVID fundamentals. In rolling window regressions, we find this explanatory power fluctuates, rising during crisis times and falling during more tranquil times. Importantly, we find that while the GFC predictably explained a higher share of the panel variation during the COVID-19 downturn, country-specific COVID-19 indicators mattered just as much as traditional macroeconomic fundamentals in explaining the cross-sectional variation of exchange rates and capital flows.

Our finding suggests the literature should look beyond the traditional macroeconomic fundamentals and deploy factors that are better aligned in frequency and relevance with the cross-border capital flows to be explained, such as the fast-moving epidemiological indicators during the COVID-19 pandemic.

References

Ahmed, S., Coulibaly, B., Zlate, A., 2017. International financial spillovers to emerging market economies: How important are economic fundamentals? Journal of International Money and Finance 76, 133–152.
https://doi.org/10.1016/j.jimonfin.2017.05.001

Ahmed, S., Hoek, J., Kamin, S., Smith, B., Yoldas, E., 2020. The impact of covid-19 on emerging market economies' financial conditions. FED Notes.
https://doi.org/10.17016/2380-7172.2749

Ahmed, S., Zlate, A., 2014. Capital flows to emerging market economies: a brave new world? Journal of International Money and Finance 48, 221–248.
https://doi.org/10.1016/j.jimonfin.2014.05.015

Akinci, O., Benigno, G., Queraltó, A., 2020. Modeling the global effects of the covid-19 sudden stop in capital flows. FEDS Notes (2020-07), 02.
https://doi.org/10.17016/2380-7172.2586

Avdjiev, S., Hardy, B., Kalemli-Özcan, Servén, L., 2017. Gross capital flows by banks, corporates and sovereigns. NBER Working Paper No. 23116.
https://doi.org/10.3386/w23116

Bai, J., Ng, S., 2004. A panic attack on unit roots and cointegration. Econometrica 72 (4), 1127–1177.
https://doi.org/10.1111/j.1468-0262.2004.00528.x

Barrot, L.-D., Serven, L., 2018. Gross capital flows, common factors, and the global financial cycle. World Bank Policy Research Working Paper (8354).

Beirne, J., Renzhi, N., Sugandi, E., Volz, U., 2021. Covid-19, asset markets and capital flows. Pacific Economic Review 26 (4), 498–538.
https://doi.org/10.1111/1468-0106.12368

Bianchi, J., Bigio, S., Engel, C., 2021. Scrambling for dollars: International liquidity, banks and exchange rates.
https://doi.org/10.3386/w29457

Broner, F., Didier, T., Erce, A., Schmukler, S. L., 2013. Gross capital flows: Dynamics and crises. Journal of Monetary Economics 60 (1), 113–133.
https://doi.org/10.1016/j.jmoneco.2012.12.004

Bussiere, M., Fratzscher, M., 2006. Towards a new early warning system of financial crises. journal of International Money and Finance 25 (6), 953–973.
https://doi.org/10.1016/j.jimonfin.2006.07.007

Calvet, L. E., Campbell, J. Y., Sodini, P., 2007. Down or out: Assessing the welfare costs of household investment mistakes. Journal of Political Economy 115 (5), 707–747.
https://doi.org/10.1086/524204

Calvet, L. E., Campbell, J. Y., Sodini, P., 2009a. Fight or flight? portfolio rebalancing by individual investors. The Quarterly journal of economics 124 (1), 301–348.
https://doi.org/10.1162/qjec.2009.124.1.301

Calvet, L. E., Campbell, J. Y., Sodini, P., 2009b. Measuring the financial sophistication of households. American Economic Review 99 (2), 393–98.
https://doi.org/10.1257/aer.99.2.393

Calvo, G. A., Leiderman, L., Reinhart, C. M., 1996. Inflows of capital to developing countries in the 1990s. The Journal of Economic Perspectives 10 (2), 123–139.
https://doi.org/10.1257/jep.10.2.123

Catão, L. A., Milesi-Ferretti, G. M., 2014. External liabilities and crises. Journal of International Economics 94 (1), 18–32.
https://doi.org/10.1016/j.jinteco.2014.05.003

Cerutti, E., Claessens, S., Puy, D., 2019a. Push factors and capital flows to emerging markets: why knowing your lender matters more than fundamentals. Journal of international economics 119, 133–149.
http://doi.org/10.1016/j.jinteco.2019.04.006

Cerutti, E., Claessens, S., Rose, A. K., 2019b. How important is the global financial cycle? evidence from capital flows. IMF Economic Review 67 (1), 24–60.
http://doi.org/10.1057/s41308-019-00073-5

Chari, A., Dilts-Stedman, K., Forbes, K., 2022. Spillovers at the extremes: The macroprudential stance and vulnerability to the global financial cycle. Journal of International Economics 136, 103582.
https://doi.org/10.1016/j.jinteco.2022.103582

Corsetti, G., Marin, E., 2020. The dollar and international capital flows in the covid-19 crisis. VOX CEPR Policy Portal.

Crucini, M. J., Telmer, C. I., 2020. Microeconomic sources of real exchange rate variation. Review of Economic Dynamics 38, 22–40.
https://doi.org/10.1016/j.red.2020.02.001

Davis, J. S., Devereux, M. B., Yu, C., 2020. Sudden stops and optimal foreign exchange intervention. NBER Working Paper No. 28079.
https://doi.org/10.3386/w29217

Davis, J. S., Valente, G., van Wincoop, E., 2021. Global drivers of gross and net capital flows. Journal of International Economics 128, 103397.
https://doi.org/10.1016/j.jinteco.2020.103397

Davis, J. S., van Wincoop, E., 2018. Globalization and the increasing correlation between capital inflows and outflows. Journal of Monetary Economics 100, 83–100.
https://doi.org/10.1016/j.jmoneco.2018.07.009

Davis, J. S., van Wincoop, E., 2021. A theory of the global financial cycle. NBER Working Paper No.29217.
https://doi.org/10.3386/w29217

Davis, J. S., Zlate, A., 2016. Financial performance and macroeconomic fundamentals in emerging market economies over the global financial cycle. Federal Reserve Bank of Dallas, Globalization and Monetary Policy Institute Working Paper no. 288.
http://dx.doi.org/10.24149/gwp288

Eichengreen, B., Gupta, P., 2015. Tapering talk: The impact of expectations of reduced federal reserve security purchases on emerging markets. Emerging Markets Review 25, 1–15.
https://doi.org/10.1016/j.ememar.2015.07.002

Forbes, K., Warnock, F. E., 2012. Capital flow waves: Surges, stops, flight, and retrenchment. Journal of International Economics 88, 235–251.
https://doi.org/10.1016/j.jinteco.2012.03.006

Forbes, K., Warnock, F. E., 2014. Debt- and equity-flow led capital flow episodes. In: Fuentes, M., Reinhart, C. M. (Eds.), Capital Mobility and Monetary Policy. Central Bank of Chile.

Forbes, K. J., Warnock, F. E., 2021. Capital flow waves—or ripples? extreme capital flow movements since the crisis. Journal of International Money and Finance 116, 102394.
https://doi.org/10.1016/j.jimonfin.2021.102394

Frankel, J. A., Rose, A. K., 1996. Currency crashes in emerging markets: An empirical treatment. Journal of international Economics 41 (3), 351–366.
https://doi.org/10.1016/S0022-1996(96)01441-9

Frankel, J. A., Saravelos, G., 2012. Can leading indicators assess country vulnerability? evidence from the 2008-09 global financial crisis. Journal of International Economics 87 (2), 216–231.
https://doi.org/10.1016/j.jinteco.2011.12.009

Fratzscher, M., 2012. Capital flows, push versus pull factors and the global financial crisis. Journal of International Economics 88 (2), 341–356.
https://doi.org/10.1016/j.jinteco.2012.05.003

Gourinchas, P.-O., Obstfeld, M., 2012. Stories of the twentieth century for the twenty-first. American Economic Journal: Macroeconomics 4 (1), 226–265.
https://doi.org/10.1257/mac.4.1.226

Hofmann, B., Shim, I., Shin, H. S., 2021. Emerging market economy exchange rates and local currency bond markets amid the covid-19 pandemic. BIS Bulletin No. 5.

Hördahl, P., Shim, I., 2020. Eme bond portfolio flows and long-term interest rates during the covid-19 pandemic. BIS Bulletin (18).

Ilzetzki, E., Reinhart, C. M., Rogoff, K. S., 2019. Exchange arrangements entering the twenty-first century: Which anchor will hold? The Quarterly Journal of Economics 134 (2), 599–646.
https://doi.org/10.1093/qje/qjy033

Jiang, Z., Krishnamurthy, A., Lustig, H., 2020. Dollar safety and the global financial cycle. NBER Working Paper No. 27682.
https://doi.org/10.3386/w27682

Jiang, Z., Krishnamurthy, A., Lustig, H., 2021. Foreign safe asset demand and the dollar exchange rate. The Journal of Finance 76 (3), 1049–1089.
https://doi.org/10.1111/jofi.13003

Kalemli-Ozcan, S., 2020. Emerging market capital flows under covid: what to expect given what we know. IMF Research Special Series on COVID 19.

Kekre, R., Lenel, M., 2021. The flight to safety and international risk sharing.
https://doi.org/10.3386/w29238

Koepke, R., Paetzold, S., 2020. Capital flow data–a guide for empirical analysis and real-time tracking. IMF WP/20/171.

Milesi-Ferretti, G. M., Tille, C., 2011. The great retrenchment: International capital flows during the global financial crisis. Economic Policy 26 (66), 285–342.
https://doi.org/10.1111/j.1468-0327.2011.00263.x

Miranda-Agrippino, S., Rey, H., 2020. Us monetary policy and the global financial cycle. The Review of Economic Studies 87 (6), 2754–2776.
https://doi.org/10.1093/restud/rdaa019

Miranda-Agrippino, S., Rey, H., 2021. The global financial cycle. NBER Working Paper No. 29327.
https://doi.org/10.3386/w29327

Obstfeld, M., Shambaugh, J. C., Taylor, A. M., 2010. Financial stability, the trilemma, and international reserves. American Economic Journal: Macroeconomics 2 (2), 57–94.
https://doi.org/10.1257/mac.2.2.57

Rey, H., 2015. Dilemma not trilemma: The global financial cycle and monetary policy independence. NBER Working Paper No. 21162.
https://doi.org/10.3386/w21162

Rey, H., 2016. International channels of transmission of monetary policy and the mundellian trilemma. IMF Economic Review 64 (1), 6–35.
https://doi.org/10.1057/imfer.2016.4

Ritchie, H., Mathieu, E., Rodés-Guirao, L., Appel, C., Giattino, C., Ortiz-Ospina, E., Hasell, J., Macdonald, B., Beltekian, D., Roser, M., 2020. Coronavirus pandemic (covid-19). Our World in DataHttps://ourworldindata.org/coronavirus.

Rose, A. K., Spiegel, M. M., 2011. Cross-country causes and consequences of the crisis: An update. European Economic Review 55 (3), 309–324.
https://doi.org/10.1016/j.euroecorev.2010.12.006

Sarno, L., Tsiakas, I., Ulloa, B., 2016. What drives international portfolio flows? Journal of International Money and Finance 60, 53–72.
https://doi.org/10.1016/j.jimonfin.2015.03.006

A Online Appendix - Not for Publication

In this online appendix we present some extra results and robustness tests that were not included in the main text. First we reproduce the results in the paper using a dynamic factor model to estimate the GFC factor instead of a static factor model. Second, we reproduce the results of the paper where the regressions are at a monthly frequency, not a weekly frequency.

A.1 Results using a dynamic factor model to estimate GFC

In the main text we presented the results from estimating the GFC with a static factor model, which assumes that the week-over-week changes in the GFC f_t are distributed i.i.d.. Alternatively we can estimate the GFC with a dynamic factor model, where the model estimates an AR(p) process for f_t and the innovations to that AR process are distributed i.i.d.

Tables A1 and A3 present the regression results tables in the model where the GFC is estimated with a dynamic factor model. Figure A1 presents the moving window R^2 figure from the paper where the GFC is estimated with a dynamic factor model.

Table A1: Regression of weekly log changes in the exchange rate, weekly changes in portfolio inflows, or weekly changes in portfolio debt inflows on the weekly change in the GFC factor over full 2001-2021 sample. The GFC is estimated with a dynamic factor model.

	Δfx_t			ΔIF_t			ΔIF_t^{Debt}		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)
f_t		2.64***	3.12***		1.22***	0.95***		1.24***	1.06***
		(0.05)	(0.09)		(0.01)	(0.02)		(0.02)	(0.03)
$nfa^e_{t-52} \times f_t$			-0.08			-0.31***			-0.15***
			(0.16)			(0.03)			(0.04)
$nfa^d_{t-52} \times f_t$			-0.35***			-0.35***			-0.16***
			(0.08)			(0.03)			(0.04)
$R_{t-52} \times f_t$			-1.93***			0.91***			0.73***
			(0.25)			(0.07)			(0.10)
$CA_{t-52} \times f_t$			-7.33***			-1.72***			-3.06***
			(0.74)			(0.26)			(0.38)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.11	0.12	0.22	0.38	0.39	0.22	0.31	0.32
R^2_{CS}	0.05	0.06	0.07	0.19	0.19	0.20	0.18	0.18	0.19
R^2_{TS}	0.05	0.25	0.25	0.26	0.71	0.71	0.31	0.58	0.58
Weeks	1071	1071	1071	765	765	765	765	765	765
Countries	41	41	41	47	47	47	47	47	47

Notes: Columns 1a, 1b, and 1c regress the dependent variable on its own lags and a country fixed effect. Columns 2a, 2b, and 2c add the change in the GFC factor. Columns 3a, 3b, 3c add interactions between the change in the GFC factor and the net foreign asset and current account variables defined in the notes to Table 1. The coefficients on the non-interacted net foreign asset and current account variables are insignificant and are omitted.

Table A2: Regression of weekly log changes in the exchange rate, weekly changes in portfolio inflows, or weekly changes in portfolio debt inflows on the weekly change in the GFC factor over full 2001-2021 sample. The GFC is estimated with a dynamic factor model. Results from dividing the sample of countries into advanced and emerging subgroups.

Advanced:		Δfx_t			ΔIF_t			ΔIF_t^{Debt}	
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)
f_t		2.30***	2.84***		0.83***	0.74***		0.89***	0.88***
		(0.07)	(0.10)		(0.01)	(0.02)		(0.03)	(0.04)
$nfa^e_{t-52} \times f_t$			-0.45**			-0.14***			0.01
			(0.21)			(0.03)			(0.05)
$nfa^d_{t-52} \times f_t$			-0.28***			-0.16***			0.04
			(0.08)			(0.03)			(0.06)
$R_{t-52} \times f_t$			-0.34			0.32***			0.15
			(0.28)			(0.07)			(0.13)
$CA_{t-52} \times f_t$			-13.52***			0.75***			-0.85
			(1.47)			(0.30)			(0.53)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.11	0.13	0.26	0.38	0.39	0.26	0.31	0.31
R^2_{CS}	0.05	0.06	0.09	0.23	0.23	0.24	0.22	0.22	0.22
R^2_{TS}	0.05	0.19	0.19	0.32	0.69	0.69	0.37	0.54	0.54
Weeks	1071	1071	1071	765	765	765	765	765	765
Countries	15	15	15	23	23	23	23	23	23
Emerging:									
		Δfx_t			ΔIF_t			ΔIF_t^{Debt}	
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)
f_t		2.84***	3.78***		1.59***	1.40***		1.61***	1.52***
		(0.07)	(0.15)		(0.02)	(0.05)		(0.03)	(0.06)
$nfa^e_{t-52} \times f_t$			-0.67			-0.15			0.24
			(0.48)			(0.14)			(0.18)
$nfa^d_{t-52} \times f_t$			-1.75***			0.08			0.23
			(0.41)			(0.12)			(0.15)
$R_{t-52} \times f_t$			-6.79***			0.70***			0.76***
			(0.72)			(0.21)			(0.27)
$CA_{t-52} \times f_t$			-3.49***			-3.24***			-4.58***
			(1.08)			(0.48)			(0.62)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.12	0.13	0.20	0.42	0.42	0.20	0.35	0.35
R^2_{CS}	0.05	0.06	0.07	0.16	0.16	0.16	0.15	0.16	0.16
R^2_{TS}	0.05	0.28	0.28	0.24	0.64	0.64	0.24	0.51	0.51
Weeks	1071	1071	1071	765	765	765	765	765	765
Countries	26	26	26	24	24	24	24	24	24

Columns 1a, 1b, and 1c regress the dependent variable on its own lags and a country fixed effect. Columns 2a, 2b, and 2c add the change in the GFC factor. Columns 3a, 3b, 3c add interactions between the change in the GFC factor and the net foreign asset and current account variables defined in the notes to Table 1. The coefficients on the non-interacted net foreign asset and current account variables are insignificant and are omitted.

Table A3: Regression of weekly log changes in the exchange rate, weekly changes in portfolio inflows, or weekly changes in portfolio debt inflows on the weekly change in the GFC factor over 2020-2021. The GFC is estimated with a dynamic factor model.

	Δfx_t				ΔIF_t				ΔIF_t^{Debt}			
	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)	(1c)	(2c)	(3c)	(4c)
f_t		2.60***	2.89***	2.63***		1.15***	1.08***	0.80***		1.56***	1.50***	1.13***
		(0.11)	(0.22)	(0.23)		(0.03)	(0.04)	(0.05)		(0.03)	(0.05)	(0.06)
$nfa^e_{t-52} \times f_t$			-0.41*	-0.55**			-0.28***	-0.29***			-0.05	-0.08
			(0.25)	(0.25)			(0.04)	(0.04)			(0.06)	(0.06)
$nfa^d_{t-52} \times f_t$			-0.84**	-0.58			-0.40***	-0.38***			-0.09	-0.06
			(0.36)	(0.36)			(0.05)	(0.05)			(0.07)	(0.07)
$R_{t-52} \times f_t$			-0.92	-0.99*			0.28**	0.44***			0.47***	0.70***
			(0.58)	(0.58)			(0.12)	(0.12)			(0.16)	(0.15)
$CA_{t-52} \times f_t$			-4.52*	-5.17**			-3.16***	-3.44***			-4.10***	-4.50***
			(2.32)	(2.31)			(0.75)	(0.74)			(0.96)	(0.95)
$\Delta Cases_{t-1} \times f_t$				0.28**				0.30***				0.39***
				(0.12)				(0.03)				(0.04)
$\Delta Vacc_{t-1} \times f_t$				-1.51				-0.98***				-1.84***
				(1.19)				(0.29)				(0.36)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.10	0.26	0.27	0.28	0.17	0.41	0.43	0.45	0.17	0.44	0.44	0.46
R^2_{CS}	0.11	0.16	0.18	0.18	0.11	0.13	0.16	0.18	0.10	0.11	0.12	0.15
R^2_{TS}	0.08	0.45	0.45	0.47	0.25	0.84	0.84	0.85	0.25	0.78	0.78	0.79
Weeks	104	104	104	104	104	104	104	104	104	104	104	104
Countries	41	41	41	41	47	47	47	47	47	47	47	47

Notes: columns 1a, 1b, and 1c regress on a country-fixed effect and lags of the dependent variable. Columns 2a, 2b, and 2c add the change in the GFC factor. Columns 3a, 3b, and 3c add the interaction between the change in the GFC factor and the external asset position variables defined in the notes to table 1. Columns 4a, 4b, and 4c add the interaction between the change in GFC factor and the weekly log change in number of Covid cases, $\Delta Cases_{i,t}$ or the weekly change in the vaccination rate (2nd dose), $\Delta Vacc_{i,t}$ in country i.

Table A4: Regression of weekly log changes in the exchange rate, weekly changes in portfolio inflows, or weekly changes in portfolio debt inflows on the weekly change in the GFC factor over 2020-2021. The GFC is estimated with a dynamic factor model. Results from dividing the sample of countries into advanced and emerging subgroups.

			Δfx_t				ΔIF_t				ΔIF_t^{Debt}	
Advanced:												
	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)	(1c)	(2c)	(3c)	(4c)
f_t		2.24***	3.24***	3.32***		0.72***	0.80***	0.54***		1.16***	1.15***	0.84***
		(0.14)	(0.30)	(0.31)		(0.02)	(0.03)	(0.04)		(0.04)	(0.05)	(0.07)
$nfa^e_{t-52} \times f_t$			-0.44*	-0.43*			-0.12***	-0.11***			0.02	0.04
			(0.25)	(0.25)			(0.03)	(0.03)			(0.06)	(0.06)
$nfa^d_{t-52} \times f_t$			-0.49	-0.76*			-0.13***	-0.08**			0.13**	0.19***
			(0.41)	(0.44)			(0.04)	(0.04)			(0.07)	(0.06)
$R_{t-52} \times f_t$			-1.49***	-1.32**			-0.34***	-0.22**			-0.21	-0.05
			(0.57)	(0.57)			(0.09)	(0.09)			(0.15)	(0.15)
$CA_{t-52} \times f_t$			-4.77	-2.72			1.06*	0.35			2.46**	1.50
			(4.40)	(4.57)			(0.64)	(0.63)			(1.05)	(1.03)
$\Delta Cases_{t-1} \times f_t$				-0.14				0.23***				0.27***
				(0.17)				(0.03)				(0.04)
$\Delta Vacc_{t-1} \times f_t$				-1.70				-0.46**				-1.50***
				(1.25)				(0.23)				(0.37)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.06	0.25	0.29	0.29	0.17	0.41	0.43	0.46	0.19	0.42	0.42	0.45
R^2_{CS}	0.06	0.14	0.21	0.22	0.11	0.14	0.17	0.21	0.10	0.12	0.13	0.17
R^2_{TS}	0.06	0.35	0.35	0.35	0.27	0.81	0.82	0.84	0.28	0.72	0.72	0.74
Weeks	104	104	104	104	104	104	104	104	104	104	104	104
Countries	15	15	15	15	23	23	23	23	23	23	23	23
Emerging:												
			Δfx_t				ΔIF_t				ΔIF_t^{Debt}	
	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)	(1c)	(2c)	(3c)	(4c)
f_t		2.79***	2.62***	2.02***		1.59***	1.26***	0.90***		1.96***	1.77***	1.29***
		(0.15)	(0.38)	(0.39)		(0.04)	(0.09)	(0.10)		(0.05)	(0.11)	(0.12)
$nfa^e_{t-52} \times f_t$			-1.29	-1.63*			-1.51***	-1.30***			-0.80***	-0.55*
			(0.88)	(0.87)			(0.24)	(0.24)			(0.29)	(0.28)
$nfa^d_{t-52} \times f_t$			-3.47***	-3.07***			-0.42	-0.55*			0.51	0.34
			(1.06)	(1.05)			(0.30)	(0.29)			(0.35)	(0.34)
$R_{t-52} \times f_t$			-3.17*	-2.76*			-0.51	-0.20			0.49	0.87*
			(1.70)	(1.68)			(0.39)	(0.38)			(0.47)	(0.45)
$CA_{t-52} \times f_t$			0.73	2.81			-5.25***	-3.49**			-9.57***	-7.31***
			(3.93)	(3.88)			(1.48)	(1.45)			(1.76)	(1.71)
$\Delta Cases_{t-1} \times f_t$				0.68***				0.47***				0.61***
				(0.17)				(0.05)				(0.06)
$\Delta Vacc_{t-1} \times f_t$				-2.01				-1.78***				-2.43***
				(1.96)				(0.58)				(0.68)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.11	0.27	0.28	0.30	0.17	0.46	0.48	0.51	0.17	0.48	0.49	0.52
R^2_{CS}	0.12	0.17	0.18	0.18	0.10	0.11	0.14	0.18	0.09	0.10	0.12	0.16
R^2_{TS}	0.09	0.49	0.50	0.55	0.24	0.83	0.84	0.85	0.24	0.79	0.80	0.82
Weeks	104	104	104	104	104	104	104	104	104	104	104	104
Countries	26	26	26	26	24	24	24	24	24	24	24	24

A.2 Results using monthly changes

The results in the text regress weekly changes in exchange rates on weekly changes in the GFC. Here we simply change the frequency to monthly and regress monthly changes in exchange rates or capital flows on monthly changes in the GFC. Furthermore the COVID variables (which are measured in differences) are monthly changes in COVID cases or vaccination rates.

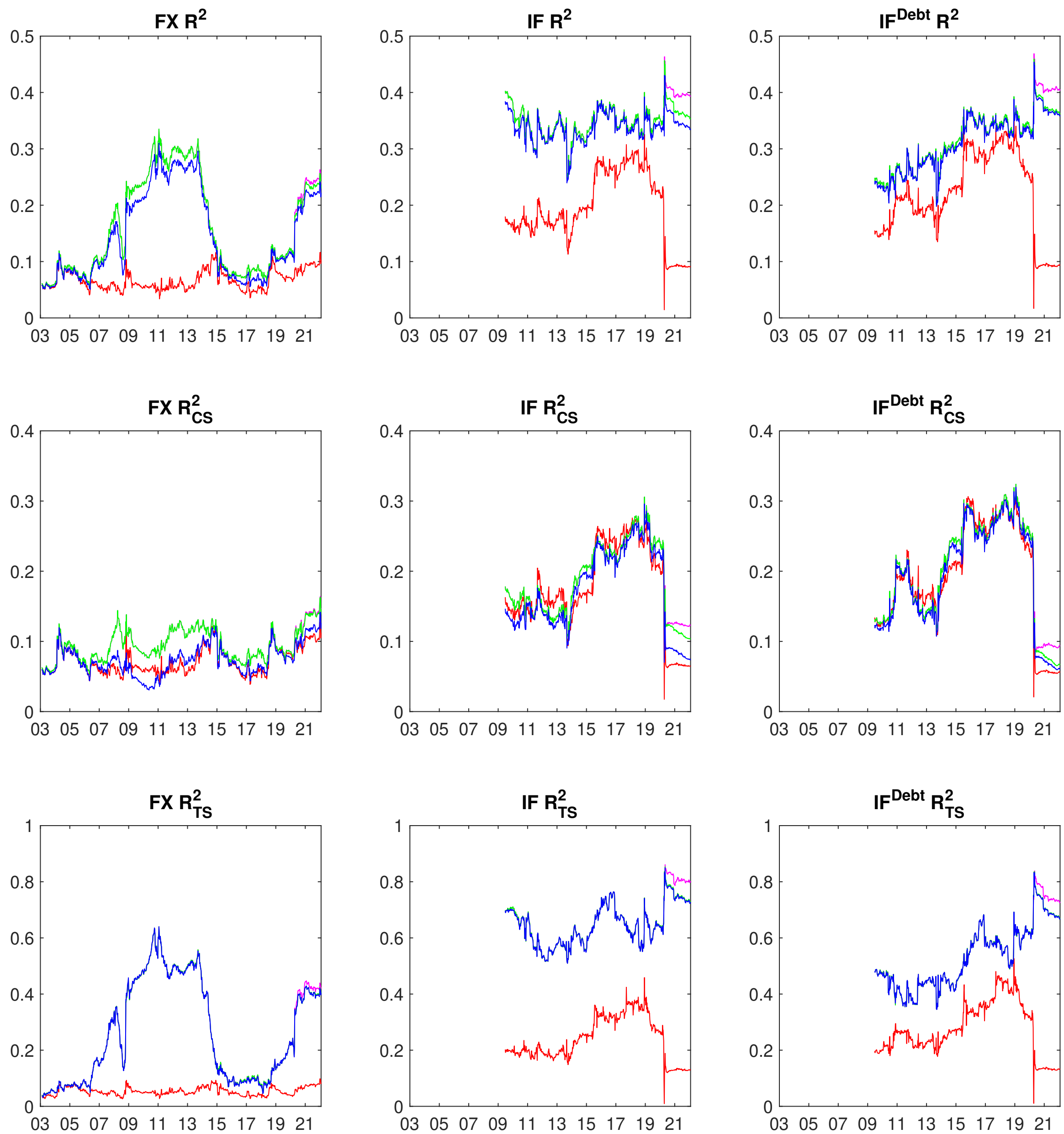
Tables A5 to A8 and present the regression results tables in the model where the frequency has been changed from weekly to monthly.

Table A5: Regression of **monthly** log changes in the exchange rate, **monthly** changes in portfolio inflows, or **monthly** changes in portfolio debt inflows on the **monthly** change in the GFC factor over full 2001-2021 sample.

	Δfx_t			ΔIF_t			ΔIF_t^{Debt}		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)
f_t		4.88***	6.36***		0.72***	0.48***		1.11***	0.93***
		(0.15)	(0.25)		(0.02)	(0.03)		(0.03)	(0.04)
$nfa^e_{t-52} \times f_t$			0.57			-0.25***			-0.18***
			(0.45)			(0.04)			(0.05)
$nfa^d_{t-52} \times f_t$			0.15			-0.31***			-0.19***
			(0.25)			(0.04)			(0.06)
$R_{t-52} \times f_t$			-4.95***			0.91***			0.70***
			(0.73)			(0.10)			(0.14)
$CA_{t-52} \times f_t$			-13.11***			-2.57***			-1.50***
			(2.01)			(0.36)			(0.49)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.14	0.15	0.33	0.47	0.48	0.29	0.45	0.46
R^2_{CS}	0.02	0.04	0.06	0.35	0.51	0.53	0.26	0.41	0.41
R^2_{TS}	0.00	0.30	0.30	0.32	0.43	0.43	0.32	0.49	0.49
Weeks	227	227	227	176	176	176	176	176	176
Countries	41	41	41	47	47	47	47	47	47

Notes: Columns 1a, 1b, and 1c regress the dependent variable on its own lags and a country fixed effect. Columns 2a, 2b, and 2c add the change in the GFC factor. Columns 3a, 3b, 3c add interactions between the change in the GFC factor and the net foreign asset and current account variables defined in the notes to Table 1. The coefficients on the non-interacted net foreign asset and current account variables are insignificant and are omitted.

Figure A1: The overall, cross-section, and time-series goodness-of-fit from the three regression specifications. Panel regression includes the full sample of advanced and emerging market countries. The GFC is estimated with a dynamic factor model.



Notes: The R^2 values from the regression on lags of the dependent variable and a country fixed effect are plotted in red, the model that adds the change in the GFC factor is plotted in blue, the model that adds the interaction between the change in the GFC factor and the country-specific macro variables is plotted in green, the model that adds the interaction between the change in the GFC factor and the country-specific COVID variables is plotted in purple. The results from the regression of the log change in the exchange rate are plotted in the left-hand column, the regression of the change in total portfolio flows in the middle column, and the change in portfolio debt flows in the right-hand column.

Table A6: Regression of **monthly** log changes in the exchange rate, **monthly** changes in portfolio inflows, or **monthly** changes in portfolio debt inflows on the **monthly** change in the GFC factor over full 2001-2021 sample.

Advanced:		Δfx_t			ΔIF_t			ΔIF_t^{Debt}	
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)
f_t		4.32***	5.85***		0.38***	0.34***		0.78***	0.76***
		(0.21)	(0.31)		(0.02)	(0.03)		(0.03)	(0.05)
$nfa^e_{t-52} \times f_t$			0.64			-0.08**			0.04
			(0.60)			(0.04)			(0.06)
$nfa^d_{t-52} \times f_t$			0.24			-0.09**			0.06
			(0.26)			(0.04)			(0.07)
$R_{t-52} \times f_t$			-3.05***			0.17*			0.05
			(0.81)			(0.10)			(0.15)
$CA_{t-52} \times f_t$			-19.73***			0.59			0.09
			(4.15)			(0.39)			(0.63)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.14	0.17	0.37	0.45	0.45	0.34	0.44	0.44
R^2_{CS}	0.01	0.04	0.09	0.37	0.47	0.47	0.31	0.41	0.41
R^2_{TS}	0.00	0.25	0.26	0.37	0.42	0.42	0.37	0.48	0.48
Weeks	227	227	227	176	176	176	176	176	176
Countries	15	15	15	23	23	23	23	23	23
Emerging:		Δfx_t			ΔIF_t			ΔIF_t^{Debt}	
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)
f_t		5.18***	7.26***		1.07***	0.72***		1.45***	1.18***
		(0.19)	(0.46)		(0.03)	(0.07)		(0.04)	(0.09)
$nfa^e_{t-52} \times f_t$			-0.44			-0.25			-0.10
			(1.38)			(0.20)			(0.25)
$nfa^d_{t-52} \times f_t$			-2.17*			-0.59***			0.27
			(1.24)			(0.18)			(0.22)
$R_{t-52} \times f_t$			-11.76***			0.65**			1.28***
			(2.07)			(0.30)			(0.38)
$CA_{t-52} \times f_t$			-7.48**			-4.37***			-3.44***
			(3.01)			(0.68)			(0.85)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.02	0.14	0.15	0.32	0.51	0.52	0.27	0.49	0.49
R^2_{CS}	0.02	0.04	0.06	0.33	0.56	0.58	0.22	0.41	0.42
R^2_{TS}	0.01	0.32	0.32	0.32	0.49	0.50	0.29	0.52	0.52
Weeks	227	227	227	176	176	176	176	176	176
Countries	26	26	26	24	24	24	24	24	24

Notes: Columns 1a, 1b, and 1c regress the dependent variable on its own lags and a country fixed effect. Columns 2a, 2b, and 2c add the change in the GFC factor. Columns 3a, 3b, 3c add interactions between the change in the GFC factor and the net foreign asset and current account variables defined in the notes to Table 1. The coefficients on the non-interacted net foreign asset and current account variables are insignificant and are omitted.

Table A7: Regression of **monthly** log changes in the exchange rate, **monthly** changes in portfolio inflows, or **monthly** changes in portfolio debt inflows on the **monthly** change in the GFC factor over 2020-2021.

	Δfx_t				ΔIF_t				ΔIF_t^{Debt}			
	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)	(1c)	(2c)	(3c)	(4c)
f_t		4.22***	5.24***	5.95***		0.76***	0.62***	0.62***		1.09***	0.96***	0.85***
		(0.29)	(0.55)	(0.64)		(0.03)	(0.04)	(0.05)		(0.03)	(0.05)	(0.05)
$nfa^e_{t-52} \times f_t$			-0.56	-0.30			-0.19***	-0.19***			-0.05	-0.10*
			(0.58)	(0.59)			(0.04)	(0.04)			(0.05)	(0.05)
$nfa^d_{t-52} \times f_t$			-0.99	-0.43			-0.27***	-0.26***			-0.06	-0.11*
			(0.85)	(0.89)			(0.05)	(0.05)			(0.06)	(0.06)
$R_{t-52} \times f_t$			-2.56*	-3.23**			0.51***	0.50***			0.56***	0.58***
			(1.40)	(1.43)			(0.11)	(0.11)			(0.14)	(0.14)
$CA_{t-52} \times f_t$			-10.55*	-10.88**			-0.89	-0.80			-0.97	-0.96
			(5.41)	(5.40)			(0.70)	(0.70)			(0.85)	(0.84)
$\Delta Cases_{t-1} \times f_t$				-0.40**				0.01				0.10***
				(0.20)				(0.02)				(0.02)
$\Delta Vacc_{t-1} \times f_t$				-1.65				-0.88***				0.00
				(3.06)				(0.33)				(0.42)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.11	0.40	0.43	0.44	0.37	0.69	0.70	0.71	0.38	0.75	0.76	0.76
R^2_{CS}	0.14	0.23	0.28	0.28	0.30	0.56	0.59	0.57	0.33	0.63	0.64	0.62
R^2_{TS}	0.07	0.69	0.70	0.70	0.44	0.85	0.84	0.88	0.41	0.84	0.84	0.86
Weeks	24	24	24	24	24	24	24	24	24	24	24	24
Countries	41	41	41	41	47	47	47	47	47	47	47	47

Notes: columns 1a, 1b, and 1c regress on a country-fixed effect and lags of the dependent variable. Columns 2a, 2b, and 2c add the change in the GFC factor. Columns 3a, 3b, and 3c add the interaction between the change in the GFC factor and the external asset position variables defined in the notes to table 1. Columns 4a, 4b, and 4c add the interaction between the change in GFC factor and the weekly log change in number of Covid cases, $\Delta Cases_{i,t}$ or the weekly change in the vaccination rate (2nd dose), $\Delta Vacc_{i,t}$ in country i.

Table A8: Regression of **monthly** log changes in the exchange rate, **monthly** changes in portfolio inflows, or **monthly** changes in portfolio debt inflows on the **monthly** change in the GFC factor over 2020-2021.

Advanced:		Δfx_t				ΔIF_t				ΔIF_t^{Debt}		
	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)	(1c)	(2c)	(3c)	(4c)
f_t		3.01***	4.81***	5.89***		0.44***	0.43***	0.45***		0.84***	0.82***	0.74***
		(0.38)	(0.71)	(1.01)		(0.02)	(0.03)	(0.04)		(0.04)	(0.05)	(0.06)
$nfa^e_{t-52} \times f_t$			-0.66	-0.70			-0.02	0.00			0.10**	0.07
			(0.54)	(0.54)			(0.03)	(0.03)			(0.05)	(0.05)
$nfa^d_{t-52} \times f_t$			-1.24	-0.40			-0.02	-0.01			0.17***	0.14***
			(0.89)	(1.04)			(0.04)	(0.04)			(0.05)	(0.05)
$R_{t-52} \times f_t$			-1.65	-2.58*			0.04	0.02			0.02	0.04
			(1.25)	(1.39)			(0.08)	(0.08)			(0.12)	(0.12)
$CA_{t-52} \times f_t$			-10.60	-17.04			-0.16	-0.22			0.50	0.70
			(9.62)	(10.47)			(0.57)	(0.56)			(0.85)	(0.85)
$\Delta Cases_{t-1} \times f_t$				-0.31				0.00				0.06***
				(0.22)				(0.01)				(0.02)
$\Delta Vacc_{t-1} \times f_t$				1.20				-0.85***				0.64
				(3.17)				(0.25)				(0.43)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.04	0.43	0.51	0.51	0.36	0.66	0.66	0.68	0.41	0.77	0.78	0.79
R^2_{CS}	0.05	0.30	0.43	0.43	0.31	0.55	0.55	0.51	0.43	0.66	0.68	0.64
R^2_{TS}	0.03	0.56	0.58	0.58	0.41	0.79	0.79	0.87	0.40	0.83	0.84	0.86
Weeks	24	24	24	24	24	24	24	24	24	24	24	24
Countries	15	15	15	15	23	23	23	23	23	23	23	23
Emerging:		Δfx_t				ΔIF_t				ΔIF_t^{Debt}		
	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)	(1c)	(2c)	(3c)	(4c)
f_t		4.76***	5.68***	6.10***		1.17***	0.80***	0.69***		1.46***	1.17***	0.93***
		(0.41)	(0.96)	(1.00)		(0.05)	(0.08)	(0.09)		(0.06)	(0.10)	(0.10)
$nfa^e_{t-52} \times f_t$			-0.73	0.24			-0.49**	-0.74***			0.07	-0.47*
			(2.11)	(2.17)			(0.21)	(0.22)			(0.24)	(0.24)
$nfa^d_{t-52} \times f_t$			-3.45	-2.52			0.16	-0.09			0.96***	0.43
			(2.56)	(2.62)			(0.26)	(0.26)			(0.30)	(0.29)
$R_{t-52} \times f_t$			-6.46	-4.66			1.24***	0.76**			2.22***	1.17***
			(4.09)	(4.19)			(0.34)	(0.36)			(0.40)	(0.41)
$CA_{t-52} \times f_t$			-5.47	-7.95			-0.63	-1.10			-2.78*	-3.79***
			(9.30)	(9.39)			(1.28)	(1.27)			(1.48)	(1.42)
$\Delta Cases_{t-1} \times f_t$				-0.64				0.18***				0.36***
				(0.40)				(0.04)				(0.05)
$\Delta Vacc_{t-1} \times f_t$				-3.91				-0.90				-0.66
				(4.95)				(0.60)				(0.68)
Lags & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.13	0.41	0.44	0.44	0.37	0.77	0.78	0.79	0.37	0.79	0.81	0.82
R^2_{CS}	0.15	0.23	0.25	0.26	0.28	0.63	0.67	0.69	0.28	0.66	0.70	0.76
R^2_{TS}	0.08	0.75	0.75	0.75	0.44	0.88	0.87	0.87	0.43	0.87	0.87	0.86
Weeks	24	24	24	24	24	24	24	24	24	24	24	24
Countries	26	26	26	26	24	24	24	24	24	24	24	24