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

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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 48 advanced and emerging market economies. We begin by estimating the global financial cycle at a weekly frequency with data through 2021 and observe the two standard deviation fall in our global financial cycle index over a period of four weeks in March 2020. We then estimate the country-specific sensitivities of exchange rates and capital flows to fluctuations in the global financial cycle. We show how during the pandemic crisis, high-frequency COVID-19 fundamentals like infection and vaccination rates—which differed in timing and intensity across our sample countries—were just as important as traditional, slow-moving macroeconomic fundamentals, such as the net external asset position and the current account balance, in explaining the cross-country heterogeneity in exchange rates and capital flows.

JEL Classification: F3; F4

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

[*] The views presented here are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas, the Board of Governors or the Federal Reserve System.

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1 Introduction

Over a brief four-week period from the end of February through the middle of March 2020, there was a coordinated 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 to this fall in risky asset prices in late February/early March 2020 as the COVID shock. In this paper we ask what was the effect of the COVID shock on capital flows and the balance of payments across advanced and emerging market economies, and what explains the heterogeneous effect across countries.

We know from many papers in 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 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-19 fundamentals" such as infection case numbers and vaccination rates add explanatory power to the model explaining these flows?

Writing early in the COVID-19 crisis, 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. 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 et al. (2021) discuss the related spike in local currency bond yield and spreads in emerging markets. Beirne et al. (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, but they do not consider these effects within the wider context of the global financial cycle.

In this paper we first construct an index for the global financial cycle (henceforth, GFC) at a weekly frequency and observe the large drop in early March 2020, which we then call the "COVID shock". Second, we estimate the sensitivities of exchange rates and capital flows to the GFC during the pandemic and we estimate how country-specific macroeconomic and COVID-19 fundamentals affect the elasticity of a country's exchange rate 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 factor and how this share changes when allowing for interactions with country-specific fundamentals.

[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 et al. (2017), Davis et al. (2021)

In more detail, first, we estimate the GFC factor using weekly data through the end of 2021. Like Miranda-Agrippino and Rey (2020), we estimate the GFC factor as a common component in a wide sample of advanced and emerging market asset prices. But unlike Miranda-Agrippino and Rey (2020), who estimate the GFC factor using data at a monthly frequency, we estimate the GFC using data at the weekly frequency, which is more appropriate to 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 deviations fall in the GFC factor, followed by a sizable recovery in the few weeks after the middle of March 2020.

Second, after identifying the COVID shock to the GFC in early 2020, we ask what effect that shock had on capital flows and the balance of payments 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 for the analysis and the ideal frequency for the 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.

Thus we examine the effect of the GFC and the COVID shock on the nominal exchange rate and on portfolio equity and debt flows with data from the EPFR. Using a panel of weekly log changes in the nominal exchange rate, portfolio debt flows, and portfolio equity flows across a range of up to 48 advanced and emerging market economies, we estimate the elasticity of exchange rates, debt flows, and equity flows to fluctuations in the GFC. We find that on average across countries, a downturn in the GFC is associated with a depreciation in exchange rates (relative to the U.S. dollar), and a fall in both portfolio debt and portfolio equity inflows.

After estimating the average elasticity across our full set of countries, we examine how country-specific macroeconomic and COVID-19 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, the results we find are similar to those in the literature cited earlier. The exchange rate and capital flows tend to be less sensitive to fluctuations in the GFC in countries with positive net foreign assets positions in debt securities or larger current account surpluses.

Importantly, we find that an increase in the weekly COVID-19 infection rates raised the sensitivity of a country's exchange rate and capital flows to the GFC. Interestingly, we also find that a change in vaccination rates did not affect the sensitivity of the exchange rate or capital flows to the GFC, but this is not surprising given that the main effect of the COVID shock on world asset prices was in the spring of 2020, while vaccines did not arrive until late 2020. The effect of country-specific COVID-19 fundamentals on the sensitivity of exchange rates and capital flows to the GFC is a key novel finding in our paper.

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 slow-moving macroeconomic fundamentals and high-frequency COVID-19 fundamentals—increases the explanatory power of the model.

Using the law of total variance, the variance of a panel of exchange rate or capital flow fluctuations is simply the sum of the time series variance of the cross-sectional average plus the average cross-sectional variance of individual country observations. In other words, the variance of a panel of exchange rate or capital flow fluctuations is the time-series variance of the central trend plus the average cross-sectional variance around that central trend.

Using this approach, we calculate the share of the variance of a panel of exchange rates or capital flows that can be explained by fluctuations in the GFC over the full sample period between 2001 and 2021. For exchange rate fluctuations, we find that the GFC factor alone 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 financial crisis and Euro Area crisis, and one was the 2020-2021 period, encompassing the COVID shock. For portfolio debt flows, we find that the share of the panel variance that can be explained by the GFC factor reached an all time high during the COVID shock. For portfolio equity flows, we find that the explanatory power of the GFC changed little as a result of the COVID shock.

Importantly, by interacting the GFC factor with certain country-specific macroeconomic and COVID-19 fundamentals in the panel data regressions, we allow for cross-country differences in the sensitivity of exchange rates and capital flows to the GFC. We find that allowing for interactions between the GFC and COVID-19 fundamentals like case numbers and vaccination rates more than doubles the model's ability to explain the cross-sectional variance of exchange rates and capital flows. Importantly, the improvement in the cross-sectional goodness-of-fit from allowing country-specific COVID-19 fundamentals is greater than the improvement from allowing country-specific macroeconomic fundamentals to affect the elasticity. That is to say that during the pandemic, country-specific COVID-19 fundamentals played a larger role than the traditional country-specific macroeconomic fundamentals in explaining cross-country heterogeneity in the fluctuations in the exchange rate or portfolio debt flows.

To sum up, the results suggest that the COVID-19 shock in late February/early March 2020 led to strong negative pressure the exchange rate and capital flows in many advanced and emerging market economies. During this time, COVID-19 fundamentals like the change in weekly infection rates significantly affected the sensitivity of the exchange rate or capital flows to the GFC. During the pandemic, the share of the variance of exchange rate fluctuations or fluctuations in portfolio debt flows that was due to a common trend, as opposed to idiosyncratic country-specific variation around that trend, increased and in some cases reached an all-time high, which is not surprising given the simultaneous depreciation of currencies and drop in capital flows across countries. What is surprising is that investors paid attention to high-frequency COVID-19 statistics such as infection rates, which varied in timing and intensity across the sample countries, more than to country-specific fundamentals as drivers of exchange rates and capital flows.

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 capital flows and the balance of payments. The results are presented in section 4. Finally section 5 concludes.

1.1 Literature

This paper is related to the literature on the global financial cycle. 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 and call this a global financial cycle. Using a different data and a different methodology we are able to identify a similar GFC cycle at the weekly frequency. (see Miranda-Agrippino and Rey (2021) for a review of the extensive GFC literature).

This paper is related to the literature that seeks to find the latent factors to explain international capital flows. This includes Davis et al. (2021), Cerutti et al. (2019b), Barrot and Serven (2018), Sarno et al. (2016), and Cerutti et al. (2019a). These papers however all consider capital flows at a much lower frequency, 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 suggests that we should look to higher frequency weekly data.

Finally, this paper is related to the literature on capital flow push and pull factors. There is of course an extensive literature on the fluctuations in net capital flows (see e.g. Calvo et al. (1996)). A more recent literature looking at the factors driving gross flows includes Forbes and Warnock (2012 and 2014), Milesi-Ferretti and Tille (2011), Fratzscher (2012), Broner et al. (2013), Ahmed and Zlate (2014) among others. Our contribution to this literature is to add certain certain country-specific COVID fundamentals as potential pull factors for global capital flows.

2 Estimating the GFC factor

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

Specifically, the global financial cycle factor is the first principal component of these weekly stock price indices. 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, 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 value of the the weekly log change in the stock price index, $x_{i,t}$ (and thus will be the trend growth rate of the log of the stock price index over the sample). The GFC factor $F_t = \sum_{s=1}^{t} f_s$. 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. We estimate this factor using stock index data at both the weekly and monthly frequency. Weekly will be the frequency we use for the rest 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). 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. Our GFC factor at both the monthly and weekly frequency and the Miranda-Agrippino and Rey factor are plotted in 1. The chart at the monthly frequency shows the very high correlation between our factor and the Miranda-Agrippino and Rey factor at the monthly frequency. But unlike the Miranda-Agrippino and Rey sample, which ends before the COVID shock, out estimation continues through the end of 2021 and thus contains the COVID shock in February/March 2020 and subsequent recovery. We estimate the COVID shock to be about a 2 standard deviation downturn in the global financial cycle factor. At the weekly frequency, between the week of February 21 and the week of March 20, 2020, our GFC factor fell from -0.15 to -2.11. At the monthly frequency the factor fell from -0.21 to -1.46 between February and March 2020. 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 this 2 standard deviation fall in the GFC factor from September 2008 to March 2009 is part of a larger 5 standard deviation fall from July 2007 to March 2009.

What is notable about the COVID shock is the speed. The two 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 two 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). The two standard deviation fall in the GFC from the pre-pandemic local maximum to the local minimum took 5 weeks, followed by a sharp recovery, where the GFC factor regained about half a standard deviation in the 3 weeks after the local minimum the week of March 20.

The speed of the decline and subsequent recovery is why for the rest of this paper we rely on data at the weekly frequency. At the monthly frequency the factor fell from -0.21 to -1.46 between February and March 2020, a less than a 1.5 standard deviation fall. 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 frequency will conflate some of the fall in early March with some of the recovery in late March. To single out the effects of a acute crisis like the COVID shock we want to use weekly data that allows us to identify the COVID shock and its effects with much greater precision.

3 The COVID shock and the exchange rate and capital flows

After identifying the global financial cycle factor at the weekly frequency in the last section we now turn to a panel data regression to identify the effect of the global financial cycle on the exchange rate and capital flows.

3.1 Data and Methodology

For a total of 60 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 total net assets of a country's debt or equity mutual funds or ETFs as recorded by EPFR.

To that we add annual data on external asset and liability positions and the current account from IFS, and a weekly count of total COVID-19 cases and deaths as well as vaccination rates from OWID.

The 60 countries include 27 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, the United Kingdom, and the United States. 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 Euro Area aggregate, and since we consider exchange rate against the U.S. dollar, we exclude the U.S. in the regressions involving the exchange rate. 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 lose three advanced countries (Iceland, Luxembourg, and Germany), leaving 24 in the advanced country sample, and we lose 9 emerging markets (Cyprus, Malta, Latvia, Slovakia, Bulgaria, Albania, Kuwait, North Macedonia, Uruguay) leaving 24 in the emerging markets in the sample.

There are a few caveats about the data in the analysis. As mentioned in the introduction, there is a trade-off between the data we would like to use for the analysis and the 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 slow-moving and not available at a weekly frequency.

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 et al. (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. First, this data is just measuring 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 around the COVID shock.

Second, the EPFR flows are not measuring capital inflows in a balance of payments of payment 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 an American investor rebalances their portfolio by selling shares in a European fund and buying shares in an American fund, in balance of payments terms this is a negative inflow into Europe and no change in U.S. inflows. In the 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 et al. (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.

But given those data caveats, we run the following panel data regression over the full 2001 to 2021 sample:

$$y_{i,t} = \alpha_i + \beta f_t + \boldsymbol{\gamma} \boldsymbol{Z_{i,t-52}} f_t + \boldsymbol{\theta} \boldsymbol{Z_{i,t-52}} + \varepsilon_{i,t} \tag{2}$$

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 portfolio equity inflows, ΔIF^{Equity}, or the week-over-week change in portfolio debt inflows, ΔIF^{Debt}. 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 1, 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).

In this regression model, the elasticity of the dependent variable, either the change in the exchange rate or the change in capital inflows, with respect to changes in the GFC factor is given by $\beta + \boldsymbol{\gamma Z_{i,t-52}}$, and thus macroeconomic fundamentals like net external assets or the current account affect how a country's exchange rate or capital flows respond to exogenous fluctuations in the global financial cycle. Furthermore, we allow these same fundamentals to directly affect fluctuations in the exchange rate or capital flows independent of the GFC through the term $\boldsymbol{\theta Z_{i,t-52}}$. When looking at year-over-year changes in the exchange rate, Davis and Zlate (2016) show that the exchange rates of emerging market countries with poor macroeconomic fundamentals depreciate relative to their emerging market peers with better fundamentals on average over the cycle, but also show greater volatility and that relative depreciation is amplified during a global downturn.

By using the regression model in equation (2) we are implicitly assuming that the change in the level of the exchange rate or the change in the level of capital inflows is related to the change in the level of the GFC factor, f_t. Of course one can make other assumptions, like the change in the exchange rate is related to the level of the GFC factor or the level of capital flows is related to the change in the GFC factor. When the dependent variable is the exchange rate, we specifically choose the current functional form since the change in the GFC factor f is derived from the change in asset prices, and since the exchange rate is also an asset price, it's logical to relate the change in the exchange rate to the change in other asset prices. When the dependent variable is capital inflows, Davis et al. (2021) show that the first principal component of the level of gross capital flows is highly correlated with the level of the Miranda-Agrippino and Rey (2020) asset price GFC factor (the same asset price factor that we plot in Figure 1). Furthermore Davis and van Wincoop (2021) provide a theory to link the level of asset prices with the level of capital flows through the impact of the level of asset prices on portfolio shares and leverage.

To evaluate the effect of COVID on exchange rates we add a few extra variables to the previous panel data model and regress over 2020 and 2021:

$$y_{i,t} = \alpha_i + \beta f_t + \boldsymbol{\gamma Z_{i,t-52}} f_t + \boldsymbol{\delta C_{i,t}} f_t + \boldsymbol{\theta Z_{i,t-52}} + \boldsymbol{\eta C_{i,t}} + \mu_{i,t} \tag{3}$$

This regression model adds a few extra independent variables in the vector $\boldsymbol{C_{i,t}}$: the cumulative number of COVID cases in country i as of week t, $C_{i,t}$, the week-over-week change in the number of Covid cases, $\Delta C_{i,t}$, the share of the population that has been fully vaccinated with a COVID vaccine, $Vacc^f_{i,t}$, and the week-over-week change in the share of the population that has been fully vaccinated $\Delta Vacc^f_{i,t}$.

In this new specification including Covid variables, the elasticity of the dependent variable with respect to changes in the GFC factor is given by $\beta + \boldsymbol{\gamma Z_{i,t-52}} + \boldsymbol{\delta C_{i,t}}$, and thus Covid variables can affect how the dependent variable responds to fluctuations in the GFC. Through the term $\boldsymbol{\eta C_{i,t}}$ these same Covid variables directly affect the week-over-week change in the exchange rate or capital flow independent of the GFC.

Some statistics on the cross-sectional distribution of our dependent variable, and the independent variables in vectors $\boldsymbol{Z_{i,t-52}}$ and $\boldsymbol{C_{i,t}}$ are presented in Table 1. To calculate these statistics in the table, for the three dependent variables and the external asset or current account variables in the vector $\boldsymbol{Z_{i,t-52}}$ we calculate the cross-sectional mean or percentiles of the distribution each year in the sample, and then average these yearly observations. For the COVID variables in the vector $\boldsymbol{C_{i,t}}$ we simply calculate and present the cross-sectional mean and percentiles in the last week in the sample, the last week of 2021.

3.1.1 Cross-sectional and time-series goodness of fit

The R^2 of the regressions in equations 2 and 3 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 will tell us the share of the total variance that can be explained by the model, we may be interested in whether the model can better explain the time-series variance of the cross-sectional average exchange rate or capital flow fluctuations, or the cross-sectional variance around that average.

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 $y_{i,t}$:

$$var\left(y_{i,t}\right) = \overbrace{E\left(var\left(y_{i,t}|t\right)\right)}^{Cross-section} + \overbrace{var\left(E\left(y_{i,t}|t\right)\right)}^{Time-series} \tag{4}$$

.

In other words, the variance of the panel is equal to the variance of the central tendency plus the average cross-sectional variance around this central tendency. 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:

$$R^2 = \frac{var\left(\hat{y}_{i,t}\right)}{var\left(y_{i,t}\right)} = \omega_y R^2_{CS} + \left(1-\omega_y\right) R^2_{TS} \tag{5}$$

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

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 discuss the regression over the last two years of this sample, 2020-2021, to ask specifically how the GFC factor affected these dependent variables over the period of the Covid shock.

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 1 and 2), the week-over-week change in equity inflows (columns 3 and 4), the week-over-week change in debt inflows (columns 5 and 6). 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.

Columns 1, 3, and 5 in the table simply regress the dependent variable against the change in the GFC factor. A one standard deviation downturn in the GFC factor leads to about a 4 percent currency depreciation, equity mutual funds and ETFs see about a 1.2 percent fall in net inflows, and debt mutual funds and ETFs see about a 1.5 percent fall in net inflows.

Columns 2, 4, and 6 then add the interaction terms, and thus ask how the 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 looking 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 insignificant. Meanwhile the coefficients on the interaction between the GFC factor and the net foreign asset position in debt securities (excluding reserves) or the interaction between the GFC factor and central bank foreign exchange reserves are negative and significant. These results mirror those in Davis and Zlate (2016). The coefficient on the interaction term between the current account and 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 insignificant and are omitted from the table for brevity.

The results from the regressions of equity or debt inflows in columns 4 and 6 are broadly similar. The coefficients on the interaction term between 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 central bank foreign reserves and 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 to smooth exogenous fluctuations in gross capital inflows to lessen volatility in net capital flows. (see e.g. Obstfeld et al. (2010)) The coefficient of the interaction between the GFC factor and the current account balance is negative and significant, indicating that indicating that a capital inflows for a country with a current account surplus are less sensitive to fluctuations in the GFC factor.

The R^2 statistics show that the regression model with just country fixed effects and the GFC factor can explain about 8.5 percent of the variance of weekly log differences in the nominal exchange rate, about 7 percent of the weekly change in equity inflows, and 9 percent of the variance of weekly changes in debt inflows. This is mainly due to the ability of the model to explain the time-series variance of the cross-country average exchange rate change or change in capital inflows. The R^2_{TS} statistics show that GFC factor can explain 27 percent of the time-series variance of the cross-country average change in the nominal exchange rate and 27 to 30 percent of the time-series variance of the cross-country average change in capital inflows.

The model with the GFC factor explains very little of the cross-sectional variance of either weekly exchange rate fluctuations or weekly changes in capital inflows. The R^2_{CS} statistics are of course close to zero in columns 1, 3, and 5, where the common GFC factor and a country-fixed effect are the only variables in the regression. But in columns 2, 4, and 6, where the interaction between country specific external asset variables and the GFC factor are also included, the R^2_{CS} barely changes, indicating that the interaction of the GFC factor with these low frequency macro variables does little to explain the cross-sectional variation in weekly exchange rates or capital inflows.

Tables 3 and 4 look at these same regressions over the full sample period for either the subset of advanced countries or the subset of emerging markets. The results are similar across the two country subgroups, although there are a few important differences to note. First and foremost, while the coefficient on the GFC factor alone is positive and significant in all regression specifications in both sets of countries, it is larger in the emerging markets subgroup. This indicates that weekly changes in the exchange rate or capital flows are more sensitive to fluctuations in the global financial cycle in the emerging markets.

The R^2 statistics show that the model can explain 8 to 10 percent of the variance of exchange rate fluctuations in both sets of countries. However, the R^2_{TS} statistics show that the model explains less than 20 percent of the time-series variance of cross-sectional of advanced country exchange rate fluctuations but more than 30 percent of the variance of the cross-sectional average of emerging market exchange rate fluctuations. In other words, the GFC explains a much larger share of the average emerging market exchange rate fluctuation.

For capital inflows, the GFC factor only explains 4 to 6 percent of the variance of weekly fluctuations in equity or debt capital inflows in the advanced countries, but the same factor explains 15 percent of the variance of the same capital inflows in the emerging markets. There are two reasons behind this. First, the R^2_{TS} statistics indicate that the model with the GFC factor explains around 20 percent of the time-series variance of the cross-sectional average change in capital inflows in the advanced countries, but the same factor explains closer to 30 percent of the time-series variance in the emerging markets. At the same time, the ω_y statistics indicate that in the emerging markets a larger share of the total variance of the panel of capital flow fluctuations is the time series variance of the central tendency, whereas the share due to time-series variance of the central tendency is lower in the advanced economies.

4.2 Results over the 2020-2021 period

Next we ask how the spread of COVID-19 affected exchange rates and capital flows. In Table 5 we add COVID cases and vaccination rates as extra explanatory variables. Instead of regressing over the whole 2001-2021 sample as in Table 2, we regress over 2020 and 2021, 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 1-3), the week-over-week change in equity inflows (columns 4-6), the week-over-week change in debt inflows (columns 7-9).

In columns 1, 4, and 7 of the table we regress on a country-fixed effect and the GFC factor alone, and in columns 2, 5, and 8 we add the interaction between 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 six columns in Table 5 is the same as in the six columns of Table 2. The coefficient results in this truncated sample are broadly similar to those in the full sample. The GFC factor alone has a positive and significant effect on the value of the exchange rate and equity 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.

The goodness of fit statistics show that 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 country fixed effect and the GFC factor alone explain about 8.5 percent of the variance of the panel of weekly exchange rate fluctuations over the full 2001-2021 sample, but from Table 5 they explain 16 percent over the 2020-2021 period. This is due to an increase in the share of the time-series variance explained by the GFC factor, where the R^2_{TS} rose from 27 percent in the full sample to 42 percent over the past two years, and a slight decrease in the ω_y from 72 percent in the full sample to 67 percent in the two-year sample.

Similarly, the share of the variance of weekly change in debt capital inflows that can be explained by the GFC increases from around 9 percent in the full sample to 25 percent over the past two years. Like the model with exchange rate fluctuations, this is due to both a increase in the time-series goodness of fit, R^2_{TS} from 25 percent to 50 percent, and an fall in the share of the total panel variance that is due to country-specific fluctuations, ω_y.

Interestingly, there is little change in the goodness-of-fit statistics between the full 21 year sample and the sample that just includes the last two years for the regression of the weekly change in portfolio equity inflows. The GFC explains about 7 percent of the total variance of the panel of weekly changes in portfolio equity inflows over the full 21 year sample and about 6 percent over the last two years. From this we would conclude that the role of the GFC in explaining the variance of fluctuations in the exchange rate or fluctuations in debt capital inflows has increased sharply in the same period that focuses on the Covid shock, the Covid shock had little effect on the ability of the GFC to explain fluctuations in equity capital inflows.

Adding the interaction of the GFC factor with the country-specific external asset variable raises the cross-sectional goodness-of-fit a few percentage points in the regression of changes in the exchange rate. It makes less of a change for the cross-sectional goodness of fit for regressions of capital inflows.

Next we ask whether adding adding additional country- and week-specific information on Covid cases and vaccination rates can increase either the cross-sectional or time-series explanatory power of the GFC. In columns 3, 6, and 9 we add interactions with COVID cases and vaccination rates as additional variables in the regression. In the regression of the weekly change in the exchange rate, the interaction term between the GFC factor and the log level of cases is positive and highly significant. Similarly the coefficient on the interaction between the weekly log change in Covid cases and the GFC factor is positive and significant. This implies that exchange rates are more sensitive to fluctuations in the GFC when COVID cases are high and increasing.[2]

[2] As shown in Table 1 we also have data on cumulative COVID deaths and vaccination rates (at least 1 dose). However COVID cases are highly correlated with COVID deaths and vaccination rates (at least 1 dose) are highly correlated with vaccination rates (fully vaccinated), so to avoid multicollinearity, we drop COVID deaths and the share that has received at least 1 dose of a vaccine as variables in this regression.

In the regression of equity or debt capital inflows, the coefficient on the interaction term between the GFC factor and the log level of Covid cases is negative and significant but the coefficient on the interaction between the GFC factor and the weekly log change in Covid cases is positive and significant and much larger in absolute value. So countries with a large week-over-week increase in Covid cases tend to have capital inflows that are more sensitive to fluctuations in the GFC.

The coefficient on the interaction between COVID vaccination rates and the GFC factor is generally not significant. As discussed earlier, the COVID shock to the GFC came in late February/early March of 2020, yet vaccines were not available until December, and by December the COVID shock had largely dissipated.

The goodness of fit statistics in column 3 show that adding the COVID cases and vaccinations variables raises the R^2 by a little more than 2 percentage points to the regression of the weekly change in the exchange rate, slightly more than the improvement to the R^2 that came from adding the interaction with the net external asset variables in column 2. Adding the country-specific COVID variables raises the cross-section goodness of fit by about 1.5 percentage points. Adding these COVID variables adds nearly 5 percentage points to the time-series goodness of fit.

Adding the Covid variables adds about 2 percentage points to the goodness of fit for the regression of equity inflows in column 6, which is due to a little more than 1 percentage point increase in cross-sectional goodness of fit and about a 5 percentage point increase in time-series goodness of fit, a modest improvement in the explanatory power of the model. However adding the same Covid variables raises the overall goodness of fit for debt inflows by 11 percentage points in column 9, and this is due to a nearly 8 percentage point increase in cross-sectional goodness of fit and 15 percentage point increase in time-series goodness of fit. So while adding the Covid variables had a modest effect on the explanatory power of the model when regressing equity inflows, adding the same variables had a large effect on the explanatory power of the model when regressing debt inflows.

It is interesting to compare the ω_y statistics from the full 2001-2021 sample in Table 2 with those from the 2020-2021 sample in Table 5. For the exchange rate, the share of the total panel variance that is due to cross-sectional variation around a central trend falls from 72 percent in the 21 year sample to 66 percent over the last two years. For equity inflows the ω_y falls as well, but only from 78 percent to 76 percent. But interestingly the ω_y statistic for debt inflows falls from 68 percent for the full 21 year sample to 52 percent for the last two years, indicating that over the last two years, a much larger share of the variance of debt inflows has been due to the time-series variance of a common trend.

Tables 6 and 7 present the same regression results over the same 2 year sample, but for the subsample of 24 advanced or 24 emerging market economies. The results are similar to what we see for the full sample of countries. The most interesting thing to note is that the goodness-of-fit, particularly the time series goodness of fit, is much higher for the emerging market sample.

4.3 Results from rolling window regressions

Figure 2 plots the ω_y statistic for our 3 dependent variables in 104 week 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 varies across time, and 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 portfolio equity inflows in the middle panel of the figure shows that over the sample period there has been little change in the share of the variance in portfolio equity fluctuations that is due to a common trend. There has been a slight upward drift, from between 60 and 70 percent in the early part of the sample to close to 80 percent now, indicating that idiosyncratic variation around the mean is playing a larger role in equity flow variation now that at the beginning of the sample period, but there have been no abrupt changes to ω_y, up or down, over the sample period.

The ω_y statistic for portfolio debt inflows 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 80 percent to close to 50 percent, during the COVID shock. The share of the panel variance of portfolio debt inflows that is explained by a common trend is currently the highest on record (admittedly the sample is short and only begins in 2007).

Figure 3 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 three regression specifications in Table 3 in 104 week rolling window regressions over our full 2001-2021 sample. 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 equity inflows as the dependent variable are plotted in the middle column, and those where debt inflows is the dependent variable are plotted in the right-hand column.

The R^2 values from the regression on the GFC factor and a country fixed effect are plotted in red (columns 1, 4, and 7 of Table 5), the model that adds the interaction between the GFC factor and the COVID variables is plotted in blue (columns 2, 5, and 8 of Table 5), and the model that adds the interaction between the GFC factor and the COVID variables is plotted in green (columns 3, 6, and 9 of Table 5).

We begin with the statistics from the regression where the exchange rate is the dependent variable in the left-hand column. 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}. Furthermore the bottom row of the figure shows that this high goodness of fit during these two crisis periods is mainly due to the explanatory power of the GFC factor alone, and that there is very little difference in the R^2_{TS} between the three regression models, where the blue line lies on top of the red line for most of the sample, and the green line lies only slightly above the red/blue line, indicating that the addition of the COVID explanatory variables in the last two years of the rolling window regressions only slightly improves the time series goodness of fit.

However, the middle row of the figure shows that adding explanatory variables raises the cross-section goodness of fit, R^2_{CS}. In the red line, the model with only the country-fixed effect and the GFC factor, the country-fixed effect is the only source of cross-section heterogeneity. The difference between the blue and red lines shows the additional R^2_{CS} that comes from adding the interaction between the GFC factor and the net external asset variables. This gap between the blue and red lines increased during the the period around the 2008 financial crisis and Euro Area crisis. The distance between the green and blue lines then shows the additional R^2_{CS} that comes from adding the interaction between the GFC factor and the country-specific COVID variables to the model. This is of course only relevant in the end of the sample, but the figure shows that the additional COVID variables led to an increase in the cross-section goodness of fit and the overall 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. For equity inflows, the overall R^2 is fairly constant across the sample, and this is true for both the cross-sectional R^2_{CS} and the time-series R^2_{TS}. The addition of the Covid variables at the end of the sample period adds a little to the cross-sectional, time-series, and overall R^2, but not much.

This is not the case for debt inflows. There was a sharp increase in the explanatory power of the model with the GFC factor during the Covid shock in early 2020, and the overall, cross-sectional, and time series goodness of fit over the 2020-2021 window is the higher than at any other point during the sample. Interestingly the external asset and current account variables add little to the explanatory power, and the blue line is very close to the red line. But during the last few years of the sample, the addition of the Covid variables has a large effect on the explanatory power of the model.

5 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 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 asset prices over a narrow time interval.

In this paper we set out to find the effect of the COVID shock to the GFC on the exchange rate and capital flows, while also taking the fast-changing country-specific conditions into account. Given the speed of the COVID downturn to the GFC, we estimate a GFC factor at a weekly frequency and then evaluate its effect on the weekly log changes in the exchange rate or weekly changes in portfolio equity or debt 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 rate or capital flow fluctuations can be explained by the GFC and country-specific 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 explained a higher share of the panel variation than the traditional macroeconomic fundamentals such as the net foreign asset position and current account balances. 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.

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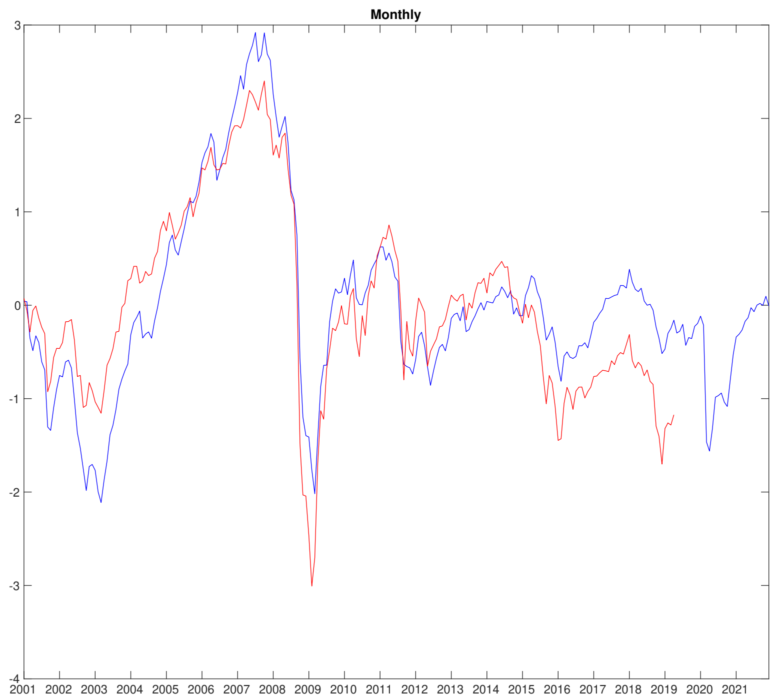
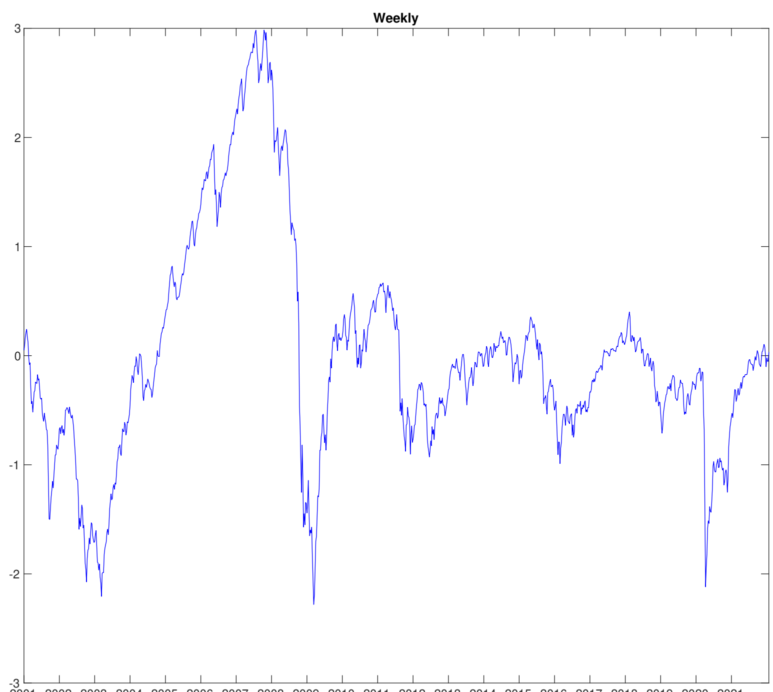
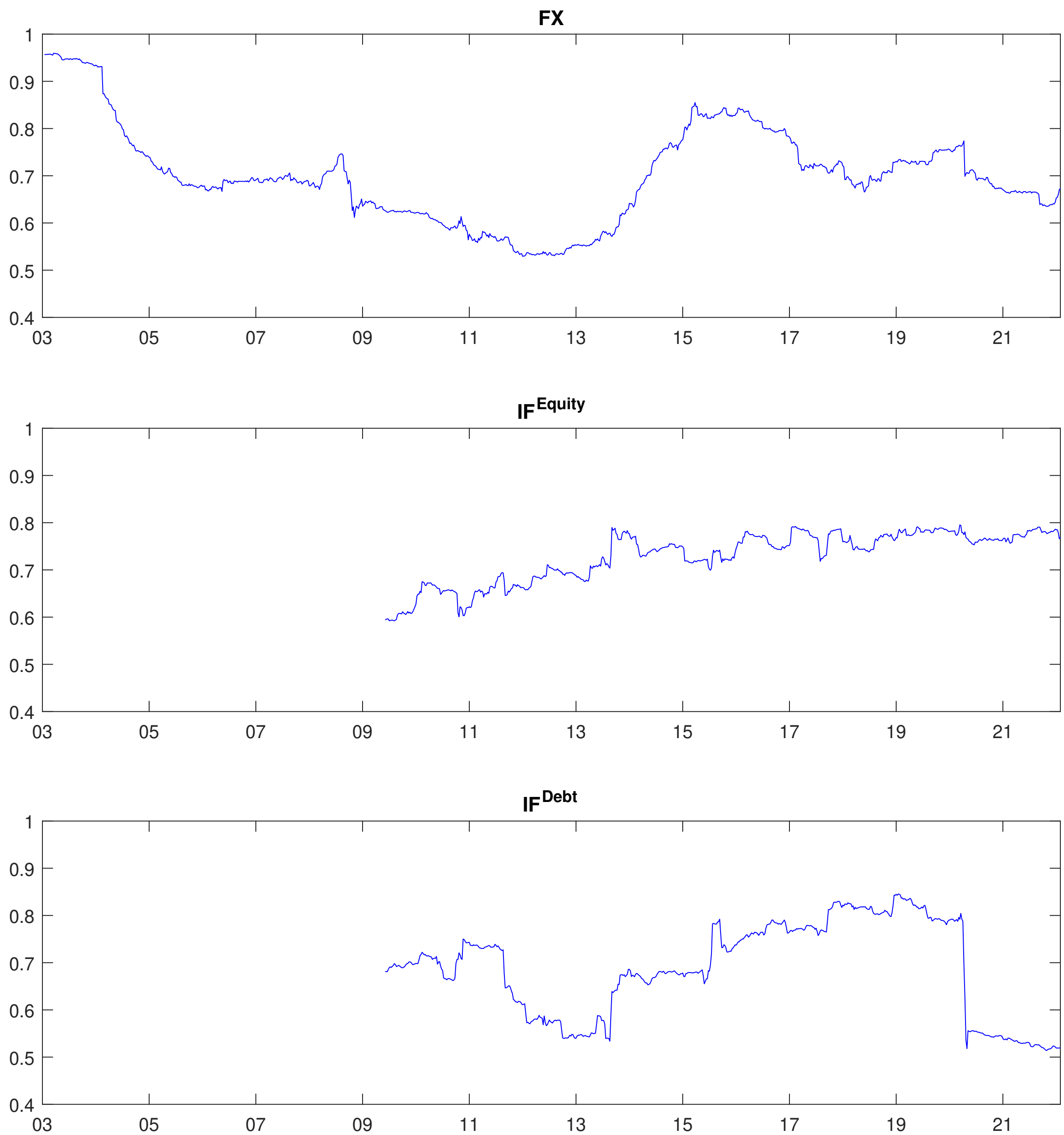
Figure 1: Estimated first global factor from panel of stock market returns across 52 countries.





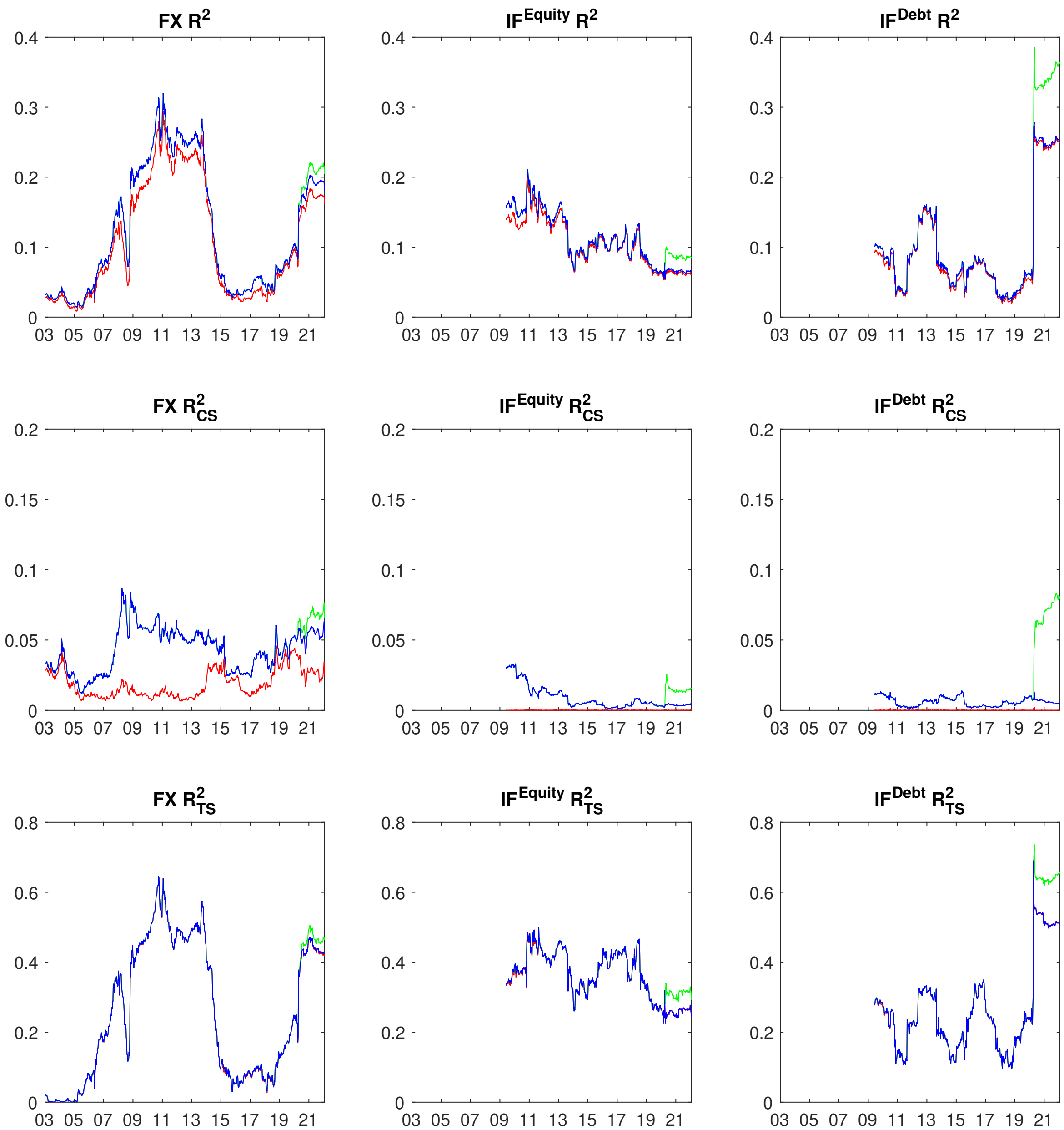
Notes: Our factor estimated from either monthly or weekly data is in blue. For comparison the global financial cycle factor from Marianda-Agrippino and Rey (2020) is plotted in red in the monthly frequency plot.

Figure 2: 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.



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 from the regression of the log change in the exchange rate are plotted in the top panel, the regression of the change in portfolio equity flows in the middle panel, and the change in portfolio debt flows in the bottom panel.

Figure 3: 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 the GFC factor and a country fixed effect are plotted in red, the model that adds the interaction between the GFC factor and the COVID variables is plotted in blue, and the model that adds the interaction between the GFC factor and the COVID variables is plotted in green. The results from the regression of the log change in the exchange rate are plotted in the left-hand column, the regression of the chnge in portfolio equity flows in the middle column, and the change in portfolio debt flows in the right-hand column.

Table 1: Descriptive statistics for the variables in the model.

	$Mean$	$Median$	$25th$	$75th$	Min	Max
			All Countries			
Δfx	0	0	-0.005	0.005	-0.221	0.684
nfa^e	-0.152	-0.171	-0.331	-0.026	-0.918	1.116
nfa^d	-0.193	-0.196	-0.354	-0.045	-7.264	1.994
Res	0.23	0.193	0.111	0.266	0.017	1.44
CA	0.01	-0.003	-0.032	0.034	-0.258	0.455
$Cases$	84507	91269	31169	121298	70	230847
$Deaths$	1639	1454	402	2551	3	6076
$Vacc^1$	67	74	57	79	28	90
$Vacc^f$	62	66	47	77	26	86
			Advanced			
Δfx	0	0	-0.005	0.004	-0.221	0.131
nfa^e	0.022	0.026	-0.139	0.232	-0.918	1.116
nfa^d	-0.198	-0.222	-0.462	0.164	-7.264	1.994
Res	0.263	0.193	0.06	0.315	0.017	1.44
CA	0.024	0.022	-0.026	0.057	-0.258	0.271
$Cases$	81487	73372	14432	135872	714	190089
$Deaths$	949	552	103	1481	10	4488
$Vacc^1$	75	78	76	82	28	87
$Vacc^f$	71	75	67	78	28	86
			Emerging			
Δfx	0.001	0	-0.005	0.005	-0.16	0.684
nfa^e	-0.257	-0.277	-0.378	-0.149	-0.774	0.485
nfa^d	-0.191	-0.196	-0.297	-0.095	-0.93	0.562
Res	0.211	0.193	0.128	0.26	0.031	0.677
CA	0.001	-0.012	-0.035	0.018	-0.156	0.455
$Cases$	86319	94028	50913	108217	70	230847
$Deaths$	2053	2074	863	2939	3	6076
$Vacc^1$	62	64	50	77	29	90
$Vacc^f$	56	56	42	68	26	86

Notes: Δfx is the weekly log-change in the exchange rate (LCU/USD), 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. For these macroeconomic variables we calculate the cross-sectional mean or percentiles for each year in the sample and then average across years. $Cases$ is cumulative number of COVID cases per million, $Deaths$ is cumulative number of COVID deaths per million, $Vacc^1$ is the share of the population that has received at least one dose of a COVID vaccine, $Vacc^f$ is the share of the population that is fully vaccinated. The table reports the cross-sectional means and percentiles for all COVID variables in the last week of 2021.

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

	ΔFX		ΔIF^{Equity}		ΔIF^{Debt}	
	(1)	(2)	(3)	(4)	(5)	(6)
f_t	0.037***	0.045***	1.213***	0.906***	1.440***	1.175***
	(0.001)	(0.001)	(0.018)	(0.032)	(0.024)	(0.042)
$nfa^{eq}_{i,t-52} \times f_t$		-0.001		-0.357***		-0.306***
		(0.002)		(0.040)		(0.053)
$nfa^{de}_{i,t-52} \times f_t$		-0.004***		-0.415***		-0.327***
		(0.001)		(0.045)		(0.059)
$R_{i,t-52} \times f_t$		-0.030***		1.058***		0.941***
		(0.003)		(0.105)		(0.138)
$CA_{i,t-52} \times f_t$		-0.097***		-1.778***		-2.017***
		(0.009)		(0.390)		(0.510)
R^2	0.084	0.095	0.106	0.111	0.089	0.092
R^2_{CS}	0.006	0.022	0.000	0.007	0.000	0.004
R^2_{TS}	0.271	0.272	0.310	0.310	0.270	0.270
ω_y	0.725	0.725	0.672	0.672	0.683	0.683
$Weeks$	1094	1094	765	765	765	765
$Countries$	41	41	48	48	48	48

Notes: Columns 1, 3, and 5 regress the dependent variable on GFC factor and a country fixed effect. Columns 2, 4, 6 add interactions between 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 3: Regression of weekly log changes in the exchange rate, weekly changes in portfolio equity inflows, or weekly changes in portfolio debt inflows on the GFC factor over full 2001-2021 sample. Panel regression only includes the advanced countries in the sample.

	ΔFX		ΔIF^{Equity}		ΔIF^{Debt}	
	(1)	(2)	(3)	(4)	(5)	(6)
f_t	0.033***	0.041***	0.803***	0.694***	1.008***	0.955***
	(0.001)	(0.001)	(0.024)	(0.034)	(0.034)	(0.049)
$nfa^{eq}_{i,t-52} \times f_t$		-0.007***		-0.196***		-0.067
		(0.003)		(0.047)		(0.067)
$nfa^{de}_{i,t-52} \times f_t$		-0.003***		-0.206***		-0.056
		(0.001)		(0.054)		(0.076)
$R_{i,t-52} \times f_t$		-0.010***		0.353***		0.270
		(0.003)		(0.121)		(0.172)
$CA_{i,t-52} \times f_t$		-0.160***		1.840***		-0.240
		(0.018)		(0.497)		(0.710)
R^2	0.083	0.104	0.059	0.061	0.046	0.047
R^2_{CS}	0.001	0.038	0.000	0.002	0.000	0.000
R^2_{TS}	0.184	0.186	0.223	0.223	0.167	0.167
ω_y	0.591	0.591	0.765	0.765	0.752	0.752
$Weeks$	1094	1094	765	765	765	765
$Countries$	15	15	24	24	24	24

Notes: Columns 1, 3, and 5 regress the dependent variable on GFC factor and a country fixed effect. Columns 2, 4, 6 add interactions between 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 4: Regression of weekly log changes in the exchange rate, weekly changes in portfolio equity inflows, or weekly changes in portfolio debt inflows on the GFC factor over full 2001-2021 sample. Panel regression only includes the emerging market countries in the sample.

	ΔFX		ΔIF^{Equity}		ΔIF^{Debt}	
	(1)	(2)	(3)	(4)	(5)	(6)
f_t	0.040***	0.054***	1.623***	1.440***	1.873***	1.749***
	(0.001)	(0.002)	(0.028)	(0.070)	(0.034)	(0.085)
$nfa^{eq}_{i,t-52} \times f_t$		-0.003		0.263		0.161
		(0.006)		(0.199)		(0.242)
$nfa^{de}_{i,t-52} \times f_t$		-0.030***		-0.900***		0.089
		(0.005)		(0.171)		(0.208)
$R_{i,t-52} \times f_t$		-0.095***		0.234		0.814**
		(0.009)		(0.298)		(0.364)
$CA_{i,t-52} \times f_t$		-0.050***		-3.074***		-2.951***
		(0.013)		(0.682)		(0.831)
R^2	0.084	0.095	0.156	0.161	0.143	0.144
R^2_{CS}	0.007	0.021	0.000	0.010	0.000	0.002
R^2_{TS}	0.300	0.301	0.291	0.291	0.261	0.261
ω_y	0.766	0.766	0.483	0.483	0.472	0.472
$Weeks$	1094	1094	765	765	765	765
$Countries$	26	26	24	24	24	24

Notes: Columns 1, 3, and 5 regress the dependent variable on GFC factor and a country fixed effect. Columns 2, 4, 6 add interactions between 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 5: Regression of weekly log changes in the exchange rate, weekly changes in portfolio equity inflows, or weekly changes in portfolio debt inflows on the GFC factor over 2020-2021.

	ΔFX			ΔIF^{Equity}			ΔIF^{Debt}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
f_t	0.035***	0.039***	0.042***	0.413***	0.436***	0.508***	1.730***	1.600***	1.629***
	(0.001)	(0.003)	(0.005)	(0.023)	(0.038)	(0.093)	(0.042)	(0.070)	(0.160)
$nfa^{eq}_{i,t-52} \times f_t$		-0.006*	-0.010***		-0.089**	-0.082**		-0.108	-0.106
		(0.003)	(0.003)		(0.042)	(0.042)		(0.077)	(0.071)
$nfa^{de}_{i,t-52} \times f_t$		-0.010**	-0.002		-0.089*	-0.081*		-0.114	-0.056
		(0.004)	(0.004)		(0.049)	(0.049)		(0.090)	(0.083)
$R_{i,t-52} \times f_t$		-0.015**	-0.023***		-0.188*	-0.250**		0.640***	0.575***
		(0.007)	(0.007)		(0.114)	(0.114)		(0.209)	(0.195)
$CA_{i,t-52} \times f_t$		-0.065**	-0.101***		0.353	1.041		-2.562**	0.210
		(0.029)	(0.029)		(0.699)	(0.700)		(1.283)	(1.200)
$Cases_{i,t} \times f_t$			0.002***			-0.026***			-0.114***
			(0.000)			(0.006)			(0.010)
$\Delta Cases_{i,t} \times f_t$			0.003*			0.091***			0.768***
			(0.002)			(0.026)			(0.044)
$Vacc_{i,t} \times f_t$			0.001**			0.001			0.012
			(0.001)			(0.012)			(0.020)
$\Delta Vacc_{i,t} \times f_t$			-0.005			0.410			0.071
			(0.015)			(0.263)			(0.450)
$Cases_{i,t}$			0.000***			0.000			-0.006***
			(0.000)			(0.001)			(0.001)
$\Delta Cases_{i,t}$			-0.003***			0.097***			0.460***
			(0.001)			(0.011)			(0.018)
$Vacc_{i,t}$			0.000***			0.001			0.006***
			(0.000)			(0.001)			(0.001)
$\Delta Vacc_{i,t}$			-0.001			-0.010			-0.008
			(0.001)			(0.014)			(0.024)
R^2	0.162	0.181	0.205	0.061	0.064	0.084	0.251	0.253	0.365
R^2_{CS}	0.025	0.052	0.065	0.000	0.005	0.016	0.000	0.005	0.081
R^2_{TS}	0.424	0.428	0.473	0.245	0.245	0.294	0.510	0.510	0.658
ω_y	0.673	0.673	0.673	0.769	0.769	0.769	0.519	0.519	0.519
$Weeks$	104	104	104	104	104	104	104	104	104
$Countries$	41	41	41	48	48	48	48	48	48

Notes: Columns 1,4, and 7 regress the dependent variable on GFC factor and a country fixed effect. Columns 2, 5, and 8 add interactions between the GFC factor and the net foreign asset and current account variables defined in the notes to table 1. Columns 3, 6, and 9 add the interaction between the GFC factor and the natural log of COVID-19 cases, $Cases_{i,t}$, the natural log of vaccination rates, $Vacc_{i,t}$, and the week-over-week difference in these two variables. The coefficients on the non-interacted macroeconomic variables are insignificant and are omitted from this table.

Table 6: Regression of weekly log changes in the exchange rate, weekly changes in portfolio equity inflows, or weekly changes in portfolio debt inflows on the GFC factor over 2020-2021. Panel regression only includes the advanced countries in the sample.

		ΔFX			ΔIF^{Equity}			ΔIF^{Debt}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
f_t	0.029***	0.041***	0.032***	0.336***	0.381***	0.421***	1.283***	1.266***	1.192***
	(0.002)	(0.004)	(0.007)	(0.031)	(0.045)	(0.130)	(0.049)	(0.070)	(0.193)
$nfa^{eq}_{i,t-52} \times f_t$		-0.006*	-0.006**		-0.080*	-0.087*		0.053	0.055
		(0.003)	(0.003)		(0.048)	(0.048)		(0.075)	(0.071)
$nfa^{de}_{i,t-52} \times f_t$		-0.007	-0.006		-0.048	-0.061		0.190**	0.222***
		(0.005)	(0.005)		(0.056)	(0.056)		(0.087)	(0.083)
$R_{i,t-52} \times f_t$		-0.018***	-0.020***		-0.315**	-0.343***		-0.206	-0.125
		(0.007)	(0.007)		(0.131)	(0.131)		(0.205)	(0.194)
$CA_{i,t-52} \times f_t$		-0.065	-0.088		1.491*	1.974**		2.713**	3.254**
		(0.053)	(0.057)		(0.887)	(0.887)		(1.384)	(1.315)
$Cases_{i,t} \times f_t$			0.003***			-0.032***			-0.089***
			(0.001)			(0.009)			(0.014)
$\Delta Cases_{i,t} \times f_t$			-0.003			0.111***			0.682***
			(0.002)			(0.036)			(0.053)
$Vacc_{i,t} \times f_t$			0.000			-0.011			-0.006
			(0.001)			(0.016)			(0.024)
$\Delta Vacc_{i,t} \times f_t$			-0.012			0.720			0.265
			(0.014)			(0.478)			(0.709)
$Cases_{i,t}$			0.000***			0.000			-0.004**
			(0.000)			(0.001)			(0.002)
$\Delta Cases_{i,t}$			0.000			0.108***			0.357***
			(0.001)			(0.016)			(0.023)
$Vacc_{i,t}$			0.000***			0.000			0.003*
			(0.000)			(0.001)			(0.002)
$\Delta Vacc_{i,t}$			0.000			-0.021			-0.020
			(0.001)			(0.023)			(0.034)
R^2	0.168	0.215	0.249	0.044	0.051	0.074	0.218	0.224	0.315
R^2_{CS}	0.005	0.102	0.113	0.000	0.008	0.020	0.000	0.011	0.074
R^2_{TS}	0.309	0.312	0.366	0.203	0.204	0.268	0.438	0.438	0.558
ω_y	0.496	0.496	0.496	0.816	0.816	0.816	0.524	0.524	0.524
$Weeks$	104	104	104	104	104	104	104	104	104
$Countries$	15	15	15	24	24	24	24	24	24

Notes: Columns 1,4, and 7 regress the dependent variable on GFC factor and a country fixed effect. Columns 2, 5, and 8 add interactions between the GFC factor and the net foreign asset and current account variables defined in the notes to table 1. Columns 3, 6, and 9 add the interaction between the GFC factor and the natural log of COVID-19 cases, $Cases_{i,t}$, the natural log of vaccination rates, $Vacc_{i,t}$, and the week-over-week difference in these two variables. The coefficients on the non-interacted macroeconomic variables are insignificant and are omitted from this table.

Table 7: Regression of weekly log changes in the exchange rate, weekly changes in portfolio equity inflows, or weekly changes in portfolio debt inflows on the GFC factor over 2020-2021. Panel regression only includes the emerging market countries in the sample.

	ΔFX			ΔIF^{Equity}			ΔIF^{Debt}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
f_t	0.038***	0.039***	0.041***	0.491***	0.504***	0.601***	2.178***	1.854***	1.596***
	(0.002)	(0.005)	(0.008)	(0.034)	(0.075)	(0.146)	(0.068)	(0.151)	(0.270)
$nfa^{eq}_{i,t-52} \times f_t$		-0.014	-0.026**		0.111	0.095		-0.734*	-0.665*
		(0.011)	(0.011)		(0.198)	(0.198)		(0.397)	(0.366)
$nfa^{de}_{i,t-52} \times f_t$		-0.036***	-0.025*		-0.441*	-0.378		0.911*	1.096**
		(0.013)	(0.013)		(0.241)	(0.240)		(0.482)	(0.444)
$R_{i,t-52} \times f_t$		-0.044**	-0.059***		-0.258	-0.218		1.468**	1.901***
		(0.021)	(0.021)		(0.318)	(0.318)		(0.637)	(0.589)
$CA_{i,t-52} \times f_t$		-0.006	0.024		0.014	0.274		-7.492***	-4.302*
		(0.049)	(0.048)		(1.195)	(1.205)		(2.395)	(2.232)
$Cases_{i,t} \times f_t$			0.002***			-0.021***			-0.095***
			(0.000)			(0.008)			(0.015)
$\Delta Cases_{i,t} \times f_t$			0.008***			0.076*			0.865***
			(0.002)			(0.039)			(0.072)
$Vacc_{i,t} \times f_t$			0.002*			0.014			0.006
			(0.001)			(0.018)			(0.034)
$\Delta Vacc_{i,t} \times f_t$			0.010			0.284			-0.010
			(0.033)			(0.346)			(0.641)
$Cases_{i,t}$			0.000***			-0.001			-0.008***
			(0.000)			(0.001)			(0.002)
$\Delta Cases_{i,t}$			-0.005***			0.089***			0.524***
			(0.001)			(0.015)			(0.027)
$Vacc_{i,t}$			0.000***			0.001			0.008***
			(0.000)			(0.001)			(0.003)
$\Delta Vacc_{i,t}$			-0.001			-0.008			-0.001
			(0.001)			(0.021)			(0.039)
R^2	0.160	0.172	0.210	0.078	0.080	0.096	0.290	0.296	0.410
R^2_{CS}	0.025	0.039	0.062	0.000	0.003	0.010	0.000	0.012	0.081
R^2_{TS}	0.454	0.460	0.531	0.227	0.228	0.261	0.531	0.532	0.682
ω_y	0.711	0.711	0.711	0.687	0.687	0.687	0.473	0.473	0.473
$Weeks$	104	104	104	104	104	104	104	104	104
$Countries$	26	26	26	24	24	24	24	24	24

Notes: Columns 1,4, and 7 regress the dependent variable on GFC factor and a country fixed effect. Columns 2, 5, and 8 add interactions between the GFC factor and the net foreign asset and current account variables defined in the notes to table 1. Columns 3, 6, and 9 add the interaction between the GFC factor and the natural log of COVID-19 cases, $Cases_{i,t}$, the natural log of vaccination rates, $Vacc_{i,t}$, and the week-over-week difference in these two variables. The coefficients on the non-interacted macroeconomic variables are insignificant and are omitted from this table.