연세대학교 상경대학
경제연구소
Economic Research Institute
Yonsei Universit

서울시 서대문구 연세로 50
50 Yonsei-ro, Seodaemun-gu, Seoul, Korea
TEL: (+82-2) 2123-4065 FAX: (+82-2) 364-9149
E-mail: yeri4065@yonsei.ac.kr
http://yeri.yonsei.ac.kr/new

Is Domestic Uncertainty A Local Pull Factor Driving Foreign Capital Inflows? New Cross-Country Evidence

Sangyup Choi
Yonsei Univ
Gabriele Ciminelli
OECD
Davide Furceri
IMF

April 2022
2022RWP-195

Economic Research Institute

Yonsei University

Is Domestic Uncertainty a Local Pull Factor Driving Foreign Capital Inflows? New Cross-Country Evidence•

Sangyup Choi† Gabriele Ciminelli◊ Davide Furceri‡

First version: January 2020

This version: Apil 2022

Abstract

Theory and conventional wisdom suggest that an increase in uncertainty in one country scares away foreign investment. But, due to the limited availability of cross-country uncertainty data, empirical evidence remains scarce. This paper provides a systematic analysis of how foreign capital inflows react to an increase in political and economic uncertainty, proxied using the World Uncertainty Index. We focus on bank credit, portfolio debt, and portfolio equity capital inflows into 143 countries from 51 source countries. We find that an increase in domestic uncertainty induces a substantial and persistent decrease in bank credit and portfolio debt inflows, and (to a lesser extent) in equity inflows. The effects on portfolio flows are larger for countries with more open capital markets. We also uncover important differences in the response of portfolio flows through actively-managed and passive funds. The former are similarly sensitive to changes in uncertainty that are country-specific (purely local uncertainty) and common across countries (global uncertainty), while the latter are only sensitive to global uncertainty.

JEL codes: F21; F32; F42.

Keywords: Uncertainty; Capital flows; World Uncertainty Index; Mutual funds; ETFs; COVID-19

• The views expressed in this paper are those of the authors and do not represent those of the IMF or OECD. We thank our discussants (Soyoung Kim and Ju Hyun Pyun), Jaebin Ahn, Woojin Choi, Hayato Kato, Chang Joo Lee, Inmoo Lee, and Youngjin Yun for their helpful comments. We also received valuable feedback from seminar and conference participants at KAFE SKKU International Conference on Finance, KAIST School of Business, Korea's Allied Economic Associations Annual Meeting, Korean Economic Review International Conference, Korean International Finance Conference, Seoul National University Institute of Economic Research, and World Bank, Kuala Lumpur Office. Jaehun Jeong and Seng Yong Yoo provided excellent research assistance. This research was (in part) supported by the Yonsei Signature Research Cluster Program of 2021 (2021-22-0011).

† School of Economics, Yonsei University, 50 Yonsei-ro, Seodaemun-gu, Seoul 03722, South Korea. Email address: sangyupchoi@yonsei.ac.kr

◊ Organization for Economic Co-operation and Development: OECD, 2 Rue André Pascal, 75016 Paris, France. Email address: gabriele.ciminelli@oecd.org

‡ International Monetary Fund, 700 19th street NW, 20431 Washington D.C. Email address: dfurceri@imf.org

I. INTRODUCTION

The global economy has witnessed a marked increase in international capital flows over the last three decades—largely driven by the expansion of global operations of banks for cross-border bank credit flows and financial innovations allowing for easy access to foreign bond markets or stock markets for portfolio flows. However, international capital flows significantly declined during the global financial crisis (GFC, thereafter). This slowdown was unprecedented and much sharper than the decline in the volume of international trade. Bank credit flows were the most affected, followed by portfolio bond and equity flows, while FDI flows were fairly resilient (Milesi-Ferretti and Tille, 2011; Ahmed and Zlate, 2014). More recently, international capital flows sharply reduced after the COVID-19 outbreak but recovered quite quickly (Beirne et al., 2021; Falato et al., 2021) and have recently declined again since the onset of the war in Ukraine.

Because sharp slowdowns in international flows often coincide with periods of heightened uncertainty worldwide, there has been increasing attention to risk perceptions as a potential driver of international capital flows. Several studies have established that there exists a strong and robust negative correlation between the VIX index—as well as other measures of global risk—and cross-border bank and portfolio capital flows (Forbes and Warnock, 2012; Fratzscher, 2012; Ahmed and Zlate, 2014; Bruno and Shin, 2015; Rey, 2015). Similarly, another strand of the literature has shown that higher uncertainty in one country can have important spillover effects on other countries through adjustments in capital flows (Fogli and Perri, 2015; Kollmann, 2016; Gete and Melkadze, 2018; Benhima and Cordonier, 2022).

However, while the VIX has been proven to be a strong global push factor of international capital flows, our understanding of domestic uncertainty as a pull factor driving capital into and out of countries remains limited to a few studies, covering a relatively small number countries. These studies either focus on capital flows at the aggregate level (Gourio et al., 2015) or on a particular type of international capital flows and a small number of countries (Julio and Yook, 2016; Wang, 2018; Choi and Furceri, 2019; Bénétrix and Curran, 2020; Choi et al., 2021).[1] This paper contributes to this emerging literature by providing the first systematic

[1] Julio and Yook (2016) focus on FDI outflows from only the U.S. to 43 destination countries. Choi et al. (2021) analyze the effect of local policy uncertainty on FDI inflows to 18 countries using bilateral FDI flow data from OECD. Wang (2018), Choi and Furceri (2019), and Bénétrix and Curran (2020) analyze the effect of domestic uncertainty only on bank credit flows by exploiting a dyadic structure of cross-border banking flow data from BIS.

analysis of different types of bilateral capital flows into more than a hundred recipient countries, which is far more comprehensive than previous studies.

We focus on gross (inflows to country A from country B) rather than net flows (inflows to country A from country B minus outflows from country A to country B) due to the rapid expansion of gross international asset and liability positions, which calls for a deeper understanding of the drivers of gross flows (Obstfeld, 2012; Broner et al., 2013; Avdijev et al., 2017; Davis and Van Wincoop, 2018). Indeed, gross capital flows can have important economic and financial spillovers in recipient countries: from economic growth (Aizenman et al., 2013), domestic financial development (Baltagi et al., 2009), domestic private credit (Lane and McQuade, 2014), housing prices (Cesa-Bianchi et al., 2015), to business cycle synchronization (Pyun and An, 2016).

We make three main contributions to the literature. The first is empirical. Identifying the causal link between uncertainty and international capital flows is typically challenging due to the difficulty of separating the effect of uncertainty from other demand and supply factors affecting capital flows. This is especially true when using the aggregate-level capital flow data, such as the balance of payments (BoP) statistics. In this paper, we rely on bilateral data, which allows us to obtain a cleaner identification of the effect of domestic uncertainty on capital inflows by including time fixed effects for each source country—that is, source-country-time fixed effects—and thereby controlling for credit supply factors that are known to be important determinants of capital inflows (Cerutti et al., 2019). Moreover, we estimate a static as well as a dynamic framework of uncertainty and foreign capital inflows. This helps us get a more comprehensive understanding of the persistence of the effects.

The second contribution relates to the coverage of various types of capital flows we analyze. Unlike previous studies that focus only on a particular type, we examine three types of bilateral gross capital inflows—bank, bond, and equity. To this end, we construct a large bilateral panel dataset for bank credit inflows from the Bank for International Settlements (BIS) Locational Banking Statistics (LBS) and portfolio bond and equity inflows from Emerging Portfolio Fund Research (EPFR). The EPFR data also has the advantage that we can study the effect of uncertainty on portfolio flows via exchange-traded funds (ETFs) separately from those via traditional mutual funds. This enables us to shed further light on the behavior of ETF flows, which have gained an increasing role in shaping international portfolio investment.

Our third contribution is the large sample of countries covered. We consider 143 recipient countries—all advanced and emerging markets, as well as a great majority of frontier markets and low-income countries—and 51 source countries, of which only about half are

advanced markets. Such a large cross-sectional dimension allows us to draw a complete picture of the effect of uncertainty on foreign capital flows and to uncover heterogeneities in the effect of uncertainty across different country groups, including their exchange rate regimes or capital account openness. To measure uncertainty in such a large panel of countries, we employ the World Uncertainty Index (WUI), a novel text-based measure of uncertainty recently constructed by Ahir et al. (2022). As we explain in more detail below, the WUI is very well suited for measuring domestic uncertainty in a consistent way across countries since it is constructed from the same source for all countries—the country reports of the Economist Intelligence Unit, which cover all political, policy and economic developments in the country concerned.

Our results can be summarized as follows. First, we find that a major increase in domestic uncertainty in the recipient country induces a substantial and persistent decrease in cross-border bank and portfolio bond inflows, and (to a lesser extent) in portfolio equity inflows. These results complement the earlier literature on the role of global uncertainty as a *push* factor by shedding light on the parallel role of domestic uncertainty as a local (negative) *pull* factor driving foreign capital inflows.

Second, we find significant heterogeneity across countries in the sensitivity of foreign capital inflows to domestic uncertainty. We find that capital flows into emerging and developing economies tend to be more susceptible to domestic uncertainty, especially for bank credit and equity flows, and that portfolio flows into the country with open capital markets—measured by the Chinn-Ito capital account openness index—are more sensitive to domestic uncertainty.[2]

Lastly, we uncover an important asymmetry in the response of actively-managed traditional mutual funds relative to passive funds like ETFs. While ETF bond inflows are much more sensitive to uncertainty than mutual fund bond inflows, once the global uncertainty component is controlled for, the effect of domestic uncertainty becomes statistically insignificant. This is in sharp contrast to the response to the uncertainty of mutual fund bond inflows, which is still relatively large and statistically significant also after accounting for the global component of uncertainty. In other words, ETF investors are very sensitive to increases in global uncertainty, but they do not respond to the country-specific increase in uncertainty. On the other hand, traditional mutual fund investors respond equally to global and country-specific changes in uncertainty. This finding sheds new light on understanding the behavior of

[2] In contrast, we do not find statistically significant evidence for the role of the exchange rate regime.

international mutual funds and ETFs, which bears important policy implications. The rise of ETFs might have made international financial markets more exposed to global shocks while at the same time decreasing the importance of other signals.[3]

The remainder of the paper is organized as follows. Section II describes the construction of the dataset. Section III presents the econometric methodology used to mitigate endogeneity issues and disentangle the effect of uncertainty from that of other demand and supply factors. Section IV presents the main results and a battery of robustness exercises. Section V discusses the extensions of the baseline model. Section VI concludes.

II. DATA

Our dataset covers the most comprehensive cross-sectional dimension among the existing studies on the link between uncertainty and international capital flows. The dataset includes 51 reporting (or source) jurisdictions and 143 counterpart (or recipient) countries and spans the period from the first quarter of 1996 to the fourth quarter of 2020. The period and frequency, as well as the sample of recipient countries, are constrained by the availability of uncertainty measures, while the sample of source jurisdictions depends on the availability of capital flows data.

2.1. Measure of uncertainty

A crucial step in our empirical analysis is how to measure uncertainty, which is inherently unobservable. To maximize the country sample, including many low-income countries, we use the novel World Uncertainty Index (WUI) developed by Ahir et al. (2022). This index measures the number of times the words 'uncertain, 'uncertainty' and 'uncertainties' are mentioned in the country reports of the Economist Intelligence Unit (EIU), which contain discussions of major political and economic developments in each country, along with analyses and forecasts of political, policy and economic conditions. The raw count is scaled by the total number of words in each report to allow for comparison both across countries and over time.

Importantly, the WUI has three main advantages over the existing measures of uncertainty for our analysis. First, it has the widest geographical coverage, as it is available for 143 countries—37 in Africa, 22 in the Americas, 22 in Asia and the Pacific, 35 in Europe, and

[3] See, for example, Borensztein and Gelos (2003), Broner et al. (2006), and Puy (2016) for the herding behavior of mutual funds and its consequence on contagion.

27 in the Middle East and Central Asia—altogether summing up to 99 percent of the world's GDP. Other existing text-based indices are typically restricted to a few advanced and emerging market economies and are thus not suited for our analysis.[4]

The second advantage relates to the type of uncertainty that is captured by the WUI. We aim to study how 'country-specific' increases in uncertainty affect foreign inflows of capital. The WUI primarily captures domestic uncertainty because the EIU country reports used to construct the WUI focus exclusively on national developments. If domestic uncertainty were interpreted as an expropriation risk that investors face when investing abroad (e.g., Gourio et al., 2015), this distinction is particularly important. The approach to constructing the WUI is different from other text-based uncertainty indexes, such as the Economic Policy Uncertainty (EPU) of Baker et al. (2016), which typically rely on newspapers also covering events in other countries that might not directly affect uncertainty in the country considered. The more 'international' nature of the uncertainty measured by the EPU is confirmed in a simple regression of the EPU and the WUI, for the same set of countries for which the EPU index is available, against time fixed effects: while time dummies account for 37 percent of the variation in the EPU, they explain only 12 percent of the variation of the WUI (Ahir et al. 2022).

The uncertainty we study is 'local' in the sense that they are specific to the destination country and are not shared with the source country. This is not to say, however, that it is unique to a destination country. It is still possible that uncertainty in one country can arise out of global events and can be synchronized with uncertainty in other countries–and indeed, the exercise just described confirms that. Moreover, as documented by Ahir et al. (2022), uncertainty spikes tend to be more synchronized within the group of advanced economies and between countries with tighter trade and financial linkages.[5] Thus, we control for changes in global uncertainty by including time-fixed effects in the empirical analysis. What matters for our analysis, however, is to have a good proxy of domestic uncertainty, regardless of whether this is caused by national or international events, rather than a measure that mixes local and global

[4] The EPU index is available for only 28 countries as of April 2022 and they are mostly advanced economies.

[5] As an example, the Brexit negotiations have increased uncertainty in a rather similar way across the other EU countries (Ahir et al., 2022). In other cases, changes in uncertainty might be confined to a single country (e.g., the recent Hong Kong political protests).

uncertainty. In this regard, the WUI does cover not only economic policy but also political and financial uncertainty, thus providing a comprehensive measure.[6]

The third advantage of the WUI is that it is constructed from a single source, the EIU country reports, which makes it well-suited for cross-country analyses like ours. Moreover, the EIU itself follows a systematic and standardized process to develop country reports. Field experts first send a draft to country experts at EIU headquarters. They integrate the draft with their inputs and check that the report is consistent with the EIU's global and regional views. In a second step, senior staff at headquarters do a thorough check of the draft. The reports then go through an editing process to ensure consistency and standardization. Unlike the WUI, other text-based uncertainty indexes, such as the EPU, are instead based on different sources both within and across countries, thus raising problems for cross-country comparability.

Ahir et al. (2022) show that the global average of the WUI spikes near the 9/11 attacks, the SARS outbreak, the Gulf War II, the Euro debt crisis, El Niño, the European border-control crisis, the U.K.'s referendum vote in favor of Brexit, the 2016 U.S. presidential election, the COVID-19 outbreak, and the war in Ukraine. Besides, cross-country comparisons reveal that the level of uncertainty varies across countries and is, on average, lower in advanced economies than in the rest of the world. The index is positively associated with other popular measures of uncertainty, such as the EPU index and stock market volatility, and negatively correlated with GDP growth, and innovations in the WUI foreshadow significant declines in output (Ahir et al., 2022).

2.2. Capital inflows

We aim to study how foreign investors react to changes in uncertainty in the recipient country. Thus, it is crucial to have a good measure of gross inflows of capital for the three types that we focus on: portfolio equity, portfolio debt, and bank credit. Portfolio equity inflows represent foreign capital flowing to the local stock market, while portfolio debt inflows denote foreign capital flowing to the local bond markets (both sovereign and corporate). Bank credit inflows are loans extended by foreign banks to the domestic sector (both public and private).

We focus on bilateral data—that is, gross inflows from country A to country B—because this allows us to include time fixed effects at the source-country level, thus controlling for both observable and unobservable factors affecting the supply of credit (refer to the methodology

[6] Stock market volatility—another popular measure of uncertainty—is known to have a high cross-country correlation due to the contagion in international financial markets (Choi and Furceri, 2019).

section for a detailed discussion). Data on portfolio inflows come from Emerging Portfolio Fund Research (EPFR), while data for bank credit inflows come from the restricted access version of the Locational Banking Statistics (LBS) dataset of the Bank for International Settlements (BIS).

2.2.1. Portfolio inflows

EPFR collects information from a large sample of mutual investment funds and then aggregates it together to provide data on total purchases, by funds domiciled in jurisdiction A, of stock and bond assets of country B. The sample covers 37 reporting (source) jurisdictions and their 118 counterpart (recipient) countries. Among the reporting countries, 23 are advanced economies, while six are offshore low-tax jurisdictions (Bermuda, British Virgin Islands, Cayman, Jersey, Guernsey, and Lichtenstein).

We classify recipient countries based on their income level according to the 2018 classification of Morgan Stanley Corporation International (MSCI). Our sample covers all 23 advanced markets, all 26 emerging markets, and 23 of the 34 frontier markets.[7] The remaining 34 are not classified by the MSCI.[8] Tables A.1 and A.2 in the appendix report the full list of reporting and recipient countries, respectively. For stock flows, data are available from the first quarter of 1996 to the last quarter of 2020, while the series for bond flows is only available starting from the first quarter of 2004.

By relying on EPFR data, we can only observe a subsample of all transactions that make up for cross-border portfolio flows. This is because EPFR only reports data on mutual fund activity, while the financial actors that engage in cross-border portfolio investment also include other actors, such as, for instance, central banks, commercial and investment banks, hedge funds and pension funds. However, bilateral data on the universe of portfolio flows do not exist, and EPFR provides the closest possible measure. The representativeness of EPFR data was first established by Jotikasthira et al. (2012), who showed in detail a close match between the EPFR portfolio flows and portfolio flows stemming from the total Balance of Payments data.

[7] We consider countries classified by MSCI as Standalone Markets (Bosnia Herzegovina, Botswana, Bulgaria, Iceland, Jamaica, Malta, Panama, Trinidad & Tobago, Ukraine, and Zimbabwe) to be Frontier Markets.

[8] These other markets generally are low-income countries. Their GDP per capita in 2018 is approximately $5,400 against 9,600, 15,000, and 51,000 in frontier, emerging, and advanced markets, respectively.

Moreover, by investigating the investment behavior of mutual funds, we can enhance our understanding of an increasingly important actor in international capital markets. At the end of 2017, the mutual fund industry managed more than $49 trillion in assets worldwide, and its share in worldwide debt and equity markets rose from 16 to 23 percent between 2010 and 2017 (ICI, 2018). In 2017, the funds reporting to EPFR cumulatively held over $24 trillion of assets under management, thus representing roughly half of the entire industry.

From EPFR, we collect data on (i) the dollar value of new purchases of country *j*'s assets made by country *i*'s funds at time *t*, which we define allocations, and (ii) the dollar value of all country *j*'s assets owned by country *i*'s funds at the end of time *t*, which we define assets. Importantly, our flow variables abstract from valuation and exchange rate changes, thus providing a pure measure of cross-border inflows. The adjustment for exchange rate movements is crucial in our setup since fluctuations in the exchange rate are influenced by changes in uncertainty regarding the recipient countries. We scale allocations by assets to have measures of flows that are comparable across countries. We use period t rather than period $t-1$ assets because, as the sample of funds reporting to EPFR varies over time, differences in assets across periods might be due to the changing composition of reporting funds rather than real cross-border transactions. Finally, since the data is at the monthly frequency, while our analysis is at the quarterly frequency, we calculate the mean of flows over each quarter. We consider bond and equity flows separately.

Our flow variables account for the behavior of both individual investors and managers. Investors buy and sell funds' shares in exchange for money, while the role of managers is typically to decide in which assets the fund should invest (with the only restriction given by the fund's mandate). An exception is exchange-traded funds (ETFs). Since they typically track an index, managers have a marginal role as they cannot choose which assets to invest in. Besides this difference, ETFs usually carry lower fees than traditional mutual funds and thus attract more short-term-oriented investors than traditional mutual funds (Lettau and Madhavan, 2018). To extend the baseline analysis, we construct separate variables for flows stemming exclusively from traditional mutual funds and ETFs.

Following Fratzscher (2012), Converse et al. (2018), and Ciminelli et al. (forthcoming), we screen observations with abnormal flows, which we define as larger than 50% or lower than -50% of assets (approximately the lower and upper percentiles of the flow distribution). We also drop country pairs for which data is not available for at least the last five years of the sample. In some robustness checks, we also exclude country pairs for which assets are less than $5 million on average.

To check that our flow variables are indeed a good proxy for overall portfolio capital flows, we aggregate gross inflows from all source jurisdictions together and compare the resulting variable with the official Balance of Payment total portfolio inflows. The correlation between the two variables is relatively high, at 0.37. For a more comprehensive assessment of the suitability of EPFR data to track official capital flows, we refer to Jotikasthira et al. (2012).

2.2.2. Bank credit inflows

Bank credit inflows data is constructed as follows. The BIS first collects information on cross-border positions of all internationally active banks, which record their positions on an unconsolidated basis, including intragroup positions between offices of the same banking group. The BIS then aggregates all information and provides cross-border data on outstanding loans and deposits of banks located in jurisdiction A against counterparties residing in country B. The counterparties considered belong to all sectors of the economy.

Overall, the LBS contains information on cross-border positions of 40 reporting jurisdictions and their 143 recipient countries. Among reporting jurisdictions, about half, 19, are advanced economies, while six are offshore low-tax jurisdictions (Bermuda, Curaçao, Guernsey, Isle of Man, Jersey, and Netherlands Antilles). We again group recipient countries according to the MSCI classification. Our sample covers all 23 advanced markets, all 26 emerging markets, and 25 of the 34 frontier markets. The remaining 69 countries are not classified by the MSCI. Tables A.3 and A.4 in the appendix report the full list of reporting jurisdictions and recipient countries, respectively. The data are available for the full sample– from the first quarter of 1996 to the last quarter of 2018.

Similar to the EPFR portfolio data, the BIS bank credit data is adjusted for exchange rate changes and thus provides a measure of cross-border loans after accounting for the valuation effect. The availability of a currency breakdown enables the BIS to calculate break- and exchange rate-adjusted changes in amounts outstanding.[9] The data is compiled following the residence principle that is consistent with the balance of payments (BOP) statistics. In

[9] The adjustment is done by first converting U.S. dollar-equivalent amounts outstanding into their original currency using end-of-period exchange rates, then calculating the difference in amounts outstanding in the original currency, and finally converting the difference into a U.S. dollar-equivalent change using average period exchange rates (Bank for International Settlements, 2017).

contrast to our proxies for portfolio flows, BIS data capture the universe of cross-border bank loans between countries.[10]

We construct the variable that we use in the analysis, similar to what is done for portfolio flows. We first collect data on (i) exchange rate-adjusted changes in loans and deposits of country *i*'s banks against country *j*'s agents in period *t*, and (ii) all outstanding loans and deposits of country *i*'s banks against country *j*'s agents at the end of period *t*. We define these two variables as new loans and stocks, respectively. To have a flow measure that is comparable across countries, we divide loans by stocks, using the previous period's stock data. In the case of LBS data, we do not have to use current period stocks since all banks report to the BIS. Thus, changes in stocks across periods are not affected by changes in the composition of reporting banks (as instead, it might be the case for EPFR data).

2.3. Control variables

The dataset is complemented by other variables that we use as controls. As we discuss in Section IV below, the empirical framework includes a set of fixed effects for each source country. Thus, the control variables are collected only for recipient countries. Since we have a large number of recipient countries (143), we merge data from different sources to maximize the coverage. We collect data on real GDP growth from the IMF World Economic Outlook (WEO, Spring 2021 edition), CEIC, and Oxford Economics. Inflation data come from the WEO, CEIC, Haver Analytics, and the BIS. We also collect information on the central bank policy rate from the BIS, CEIC, and Haver Analytics and the change of the foreign exchange rate versus the U.S. $ (from the WEO). We derive a measure of the growth rate of the stock market (in local currency). For all these control variables, we censor outliers and exclude observations that are above or below five times the standard deviation. Finally, we collect data on the VIX index as an additional measure of global uncertainty.

2.4. Descriptive statistics

Table 1 presents basic descriptive statistics—mean, median, standard deviation, and the number of observations—for the main variables used in the analysis: bank credit, portfolio bond, and portfolio equity flows, as well as the WUI. We also report the standard deviation of

[10] Nevertheless, the adjustment practice by the BIS cannot eliminate the possibility of under or overestimation of actual flows. Adjusted changes could still be affected by changes in valuations, writedowns, the underreporting of breaks, and differences between the exchange rate on the transaction date and the quarterly average exchange rate used for conversion. See Avdjiev and Hale (2019) for further details.

the residuals from a regression including country-pair fixed effects and time fixed effects at the source country. For portfolio bond and equity flows, we also present descriptive statistics for traditional mutual funds and ETFs separately.

Three main stylized facts emerge. The first is that both bank credit and portfolio equity flows were negative at the median during the sample considered (respectively at -0.36% and -0.45%), while portfolio bond flows were slightly positive (at 0.04%). The decline in bank credit flows and the rise in portfolio bond flows over the sample period are consistent with the observation of the shift in the composition of international capital flows (Avdjiev et al., 2014; Duca et al., 2016). The bank capital loss during the GFC and the introduction of various macroprudential policies thereafter have induced a retrenchment of global (European, in particular) banks. International bond issuance, especially by emerging market borrowers, has filled in this gap (e.g., Chang et al., 2017; Caballero et al., 2019).

Within portfolio flows, however, there are important heterogeneities. Flows through ETFs were positive and large for both bond and equity, at a stunning 3.95% and 2.24%, respectively, at the median. This indicates shifting investors' preference for using ETFs from traditional mutual funds to invest in other countries, possibly because they make it easier to repatriate money and carry lower fees.

Second, another important statistic to notice is the relatively high standard deviation of all types of flows considered, particularly bank credit flows (at 17.89%) and portfolio bond and equity flows through ETFs (at 12.62% and 10.54%, respectively). The higher volatility of ETF flows relative to traditional mutual fund flows is an indication that ETFs investors are more short-term oriented than investors in traditional mutual funds.

The third fact to highlight is the much larger importance of global factors in determining portfolio relative to bank credit inflows. The standard deviation of the residuals from a regression of the flows on country pair and source-by-time fixed effects relative to the standard deviation of the raw data is more than halved for portfolio bond flows (4.12 versus 8.72) and is reduced by about 30% for portfolio equity flows (5.61 versus 8.38), an indication that portfolio flows depend for a large part on global factors. The difference between the standard deviation before and after controlling for fixed effects is large for both ETFs and traditional mutual fund flows, but particularly so for the former.

III. EMPIRICAL FRAMEWORK

Any empirical investigation of international capital flows must note that variations in the volume of inflows reflect not only the demand condition in a recipient country but also the supply condition in a source country. Ignoring supply-side factors would bias the estimation results to the extent to which uncertainty in a recipient country affects those factors. We exploit the bilateral structure of the EPFR and LBS data to control for both observed and unobserved time-variant factors in a source country by including time-fixed effects for each source country.

Moreover, time fixed effects at the source country also control for global factors, such as changes in 'global' uncertainty, which are a robust determinant of international capital flows (e.g., Milesi-Ferretti and Tille, 2011; Forbes and Warnock, 2012; Fratzscher, 2012; Ahmed and Zlate, 2014; Bruno and Shin, 2015; Rey, 2015). Thus, our empirical strategy mitigates a criticism that countries are often subject to heightened global uncertainty at the same time, which prevents a proper identification of the role of domestic uncertainty in driving foreign capital inflows. Our uncertainty measure captures deviation from the (time-varying) global mean, thereby serving as an appropriate measure of domestic uncertainty.

We now present our econometric framework in more detail, starting from the specification used for bank credit flows. We regress our cross-border bank loan flow variables from country *i* to country *j*, in percent of cross-border positions, on the level of the WUI in country *j*. Besides the time-fixed effects for each source country *i* mentioned above, we also include cross-sectional fixed effects at the *i, j* country-pair level, which account for time-invariant characteristics, such as geographical distance, language, and institutional affinity that might influence flows between two countries. These "gravity" factors are known to be an important determinant of bilateral capital flows (Portes and Rey, 2005). Finally, we control for real GDP growth, which can be correlated with uncertainty, given the countercyclical nature of uncertainty (Bloom et al., 2018). In some robustness checks and extensions, we also include other macroeconomic and financial control variables.

Following the rest of the literature on cross-border banking flows (e.g., Bruno and Shin, 2015; Cerutti et al., 2017; Choi and Furceri, 2019), the WUI and the GDP growth rate, as well as the other control variables that we add later in the robustness checks, enter the regression with a lag. This is because new banking loans typically take time to be arranged so that the flow variables respond to macroeconomic and financial developments with some delays.

Moreover, this approach helps mitigate potential reverse causality issues between banking flows and uncertainty. The equation that we estimate for banking flows is as follows:

$$FLOW_{i,j,t} = \alpha + \mu_{i,j} + \tau_{i,t} + \beta WUI_{j,t-1} + \gamma Z_{j,t-1} + \sum_{l=1}^{4} \delta^l FLOW_{i,j,t-l} + \varepsilon_{i,j,t}, \quad (1)$$

where the subscripts i and j respectively refer to source and recipient countries, and the subscript t indicates time (in quarters). $FLOW_{i,j,t}$ measures bank debt flows from country i to country j in quarter t (in percent of claims of country i's banks against country j's agents at the end of quarter t-1); α is a constant term; $\mu_{i,j}$ is a set of country-pair fixed effects accounting for country-pair time-invariant characteristics; $\tau_{i,t}$ are source country-by-time fixed effects, accounting for time-varying factors affecting credit supply in country i as well as global shocks; $WUI_{j,t-1}$ is the main explanatory variable: the level of uncertainty in recipient country j in quarter $t-1$; $Z_{j,t-1}$ is a set of lagged control variables, which as a baseline includes GDP growth in destination country j; and $\varepsilon_{i,j,t}$ is an error term assumed to be uncorrelated with the regressors.[11] β is the main coefficient of interest. Following Abadie et al. (2017), we cluster standard errors at the treatment level, which is at the destination country-by-time level.

Next, we present the econometric framework used to estimate the effects of uncertainty on bond and equity portfolio flows. In practice, we estimate a specification that is very similar to that used for banking flows. The only difference is that the uncertainty variable, $WUI_{j,t}$, and the control variables contained in the matrix $Z_{j,t}$ enter the regression contemporaneously, which is in accordance with most of the literature using portfolio flow data (see, among others, Fratzscher, 2012, Converse et al., 2018, and Ciminelli et al., forthcoming). Stocks and bonds can be traded almost instantaneously in international financial markets, and thus portfolio flows tend to respond much faster to new developments than banking flows. Thus, the lagged framework might be problematic, especially when we work with relatively low-frequency (quarterly) data. The equation that we estimate is as follows:

$$FLOW_{i,j,t} = \alpha + \mu_{i,j} + \tau_{i,t} + \beta WUI_{j,t} + \gamma Z_{j,t} + \sum_{l=1}^{4} \delta^l FLOW_{i,j,t-l} + \varepsilon_{i,j,t} \quad (2)$$

where $FLOW_{i,j,t}$ is the purchase of either bond or equity assets of country j by mutual funds incorporated in country i at quarter t (in percent of country j's assets owned by the mutual funds

[11] We estimate equation (1) using OLS, which would result in inconsistency of the least-squares parameter estimates due to the combination of lagged dependent variables and fixed effects (Nickell, 1981). However, because the time-series dimension of the panel dataset is quite large, inconsistency is not a major concern.

domiciled in country *i*); and the rest of the specification follows Equation (1). Perhaps the most important feature of our econometric framework is the inclusion of time-fixed effects at the source country level. They not only control for global developments, such as changes in global uncertainty or appetite for risk but also for source-country-specific and time-varying factors that might affect capital flows from country *i* to country *j*, including changes in macroeconomic conditions or investor sentiment in country *i*. Thus, among others, they allow us to isolate the variations in uncertainty in the recipient country *j* that are not shared with the source country *i*.[12]

IV. RESULTS

4.1. Main results

We estimate a regression including only the WUI and real GDP growth in the recipient country and country-pair fixed effects. Following Avdijev et al. (2017), we use real GDP growth as a representative of domestic pull factors of capital flows, as our dataset includes many low-income countries, which do not necessarily have data for other pull factors at a quarterly frequency. We then extend this parsimonious specification by adding (i) the VIX index, (ii) the global component of the WUI, estimated through factor analysis, and (iii) and source-by-time fixed effects—which also capture common time fixed effects. Other controls are added later. Table 2 presents the estimated effects of heightened uncertainty, which we define as a two standard deviation increase, on cross-border bank credit flows, while Table 3 presents the same effects estimated for portfolio debt (Columns 1-4) and portfolio equity (Columns 5-8) flows.

We find higher uncertainty in recipient countries to induce foreign investors to withdraw capital. This is regardless of the type of capital considered. However, there are important quantitive differences. The effect is strongest for bank flows, intermediate for portfolio debt (bond) flows, and somewhat weaker for portfolio equity flows. When we estimate the most parsimonious specification, including only the domestic WUI and GDP growth, we find a major—two standard deviation—increase in uncertainty to induce a decline in bank inflows by 0.40 p.p. (Column 1 of Table 2) and to decrease bond and equity inflows by 0.30 p.p. and 0.16 p.p., respectively (Columns 2 and 5 of Table 3). These coefficients are

[12] To see this, think about capital flows from the United States to China during the 2017-2019 trade war between these two countries. The WUI increased in both countries as a result of the trade war. Still, by including source-by-time fixed effects, we effectively control for this common increase in uncertainty and quantify the effects that the differential impact of the trade war might have had on uncertainty in China relative to the United States.

all statistically significant at the 95% (equity) or 99% (bank and bond) confidence level. As expected, growth itself has a positive effect on flows.

Importantly, the effects of domestic uncertainty on gross inflows discussed above are in addition to those caused by spikes in global uncertainty, measured through the VIX index and the global WUI component. They have themselves important effects, as found by the extant literature—with the VIX, in particular, having large adverse effects on portfolio flows—but the coefficients estimated for the effect of the WUI in recipient countries are similar to the first parsimonious specification and still highly statistically significant (Columns 2-3 in Table 2 and 2-3, 6-7 in Table 3).

Once we introduce source-by-country time fixed effects, the effect of the WUI is slightly reduced, at -0.33 p.p., for bank flows (Column 4 of Table 2) and about halved, at -0.13 p.p. and -0.08 p.p., for respectively bond and equity flows (Columns 4 and 8 of Table 3), but still highly statistically significant. At the same time, the coefficient estimated for GDP growth in the recipient country becomes statistically insignificantly different from zero for portfolio flows and is substantially reduced in absolute value for bank flows. The R-squared of the bond and equity flows regressions increases considerably. These results are an indication that global factors are important in driving portfolio inflows, as documented by a large body of literature, although so far limited to emerging markets (Fratzscher, 2012; Ahmed and Zlate, 2014; Sarno et al., 2016).

We draw three main insights from these results. The first is that an increase in uncertainty in a given country that is not global in nature induces foreign investors to withdraw bank loans rather meaningfully. Inflows decrease by about a third of a percentage point after a major increase in uncertainty. The effect on portfolio debt flows is roughly half that on bank debt flows, while the effect on portfolio equity flows is marginal, about half that on portfolio debt flows. The fact that portfolio bond inflows are more responsive to domestic uncertainty than equity inflows can be understood by the different natures of end investors (bond investors being more risk-averse than equity investors). The second insight is that domestic uncertainty is more important than domestic GDP growth in determining foreign capital inflows. Finally, global events, including global uncertainty, are important determinants of all types of flows.

In what follows, we augment the model by including other control variables in addition to GDP growth and source-by-time fixed effects. We consider the inflation rate, the central bank policy rate, the stock market growth, and the nominal exchange rate (NER) growth (positive values indicating a depreciation of the local currency), which previous literature has found to affect capital flows and might be correlated with uncertainty. All control variables

enter the regression in percent. Tables A.5, A.6, and A.7 in the appendix report the results for bank, bond, and equity flows, respectively, when the controls are introduced both one at a time and jointly in the regression. In Table 4, we summarize key results when the controls enter the regression jointly. Columns 1, 3, and 5 report the baseline results without controls, while Columns 2, 4, and 6 report the results when the controls are included, for the bank, bond, and equity flows, respectively.

Despite the decrease in the sample size due to the limited availability of some control variables, our main results remain robust. Cross-border banking flows continue to be most affected by country-specific uncertainty. The estimated effect of a two standard deviation increase in uncertainty changes from -0.32 p.p. estimated in the baseline model to -0.27 p.p. estimated in the model including all controls. The effect estimated for bond flows remains unchanged, at -0.13 p.p., while the one estimated for equity flows becomes larger in absolute value, at -0.11 p.p.

Among the controls, we find stock growth to be positively associated with all types of inflows considered. Not surprisingly, the coefficient is quantitatively larger for equity flows. We also find a depreciation of the local currency to be associated with a decline in bank inflows, in line with Choi and Furceri (2019), and consistent with the risk-taking channel of global banks described in Bruno and Shin (2015). The central bank's interest rate, instead, is negatively associated with bond inflows, as in Fratzscher (2012). In the rest of the analysis, since we lose between 15% and 35% of the sample when we include our full set of control variables, we use the model controlling only for GDP growth as our baseline. [13]

4.2. Robustness checks

We check the sensitivity of our findings to a battery of alternative specifications. All the results from these robustness checks are reported in the appendix. We first check the robustness of our econometric specification and estimate alternatives containing 2 and 8 lags of the dependent variable. The results, shown in Table A.8, are roughly similar to the baseline.

[13] We also estimate our baseline specification for the periods before and after the GFC. We find that bank credit inflows have become less sensitive to increases in domestic uncertainty after the GFC while both portfolio debt and equity inflows have increased sensitivity (results available upon request). This is in line with Avdjiev et al. (2020), who find that the responsiveness of international bank lending to global uncertainty, measured by the VIX, declined considerably post-crisis and became similar to that of international debt securities using aggregate capital flow data. These authors attribute the post-crisis fall in the sensitivity of international bank lending to global uncertainty to a compositional effect, driven by increases in the lending market shares of better-capitalized national banking systems.

Second, we check whether our results are driven by particular groups of source countries. Our sample contains nine offshore low-tax jurisdictions among the source countries that host a large number of global banks and mutual investment funds (Bermuda, British Virgin Islands, Cayman, Curaçao, Guernsey, Isle of Man, Jersey, Lichtenstein, and Netherlands Antilles). It might be that financial intermediaries in these countries serve as a vehicle for domestic investors to invest in assets of their own country while incurring less monetary and non-monetary costs (consider a mutual fund investing predominantly in German assets and with a predominantly German shareholding that is incorporated in Guernsey for fiscal or administrative advantages).

Similarly, there are other countries that, although they are not offshore jurisdictions, have an outsized mutual fund or banking industry relative to GDP. Countries with an outsized banking industry are Cyprus, The Bahamas, Panama, Macao, and Bahrain, while those with an outsized mutual fund industry are Hong Kong, Ireland, and Luxembourg. Thus, we estimate the baseline model on the restricted samples, excluding all offshore low-tax jurisdictions and all global financial and banking centers. The results are reported in Table A.9 and are again roughly similar to the baseline for both bank and bond flows while they are not significant for equity flows.

As a third robustness exercise, we examine whether our results are driven by a single source or recipient country and repeat the estimation, dropping, in turn, one source and one recipient country at a time. The results are displayed in Figure A.1 and again show that the results for bank and bond flows are very robust, while those for equity flows are less robust. Lastly, we re-estimate the baseline model censoring observations in which the underlying assets (loans in the case of bank flows and bond or equity in the case of portfolio flows) of source country i in recipient country j at time t are less than five million USD. The results, shown in Table A.10, are very similar to the full sample baseline.

We conclude that our baseline results for bank and bond flows are quite robust. In contrast, those for equity flows are less robust and might not be statistically different from zero, depending on the specification used.

V. Extensions of the Baseline Model

5.1. Dynamic framework

Are the effects of heightened uncertainty on foreign capital inflows persistent, or do they die off in a relatively short time? To answer this question, we derive five-quarter impulse response

functions (IRFs), which include the quarter of the shock plus the entire year after it. To estimate IRFs from a large bilateral panel dataset, we make use of the local projection method which was first proposed by Jordà (2005) and has been frequently used thereafter (Jordà and Taylor, 2016; Ramey and Zubairy, 2018, among others) as a flexible alternative to autoregressive distributed lag specifications since it does not impose a dynamic structure on the response to be estimated.

We adopt the local projection method over commonly used VAR models for the following three reasons. First, our estimation entails a large international panel dataset with a constellation of fixed effects, which makes a direct application of standard VAR models more difficult. In addition, the local projection method obviates the need to estimate the equations for dependent variables other than the variable of interest, thereby significantly economizing on the number of estimated parameters. Second, it allows for incorporating various time-varying features of source (recipient) economies directly and allows for their endogenous response to changes in uncertainty. Third, the error term in the following panel estimations is likely to be correlated across countries. This correlation would be difficult to address in the context of VAR models, but it is easy to handle in the local projection method by clustering standard errors at the recipient country and time level.[14]

In practice, our approach entails regressing the cumulative flows over the $t+k$ horizon onto the uncertainty variable at time $t-1$ (for bank flows) and time t (for portfolio flows). Starting with bank credit flows, for each $k = 0, \dots, 4$, we estimate the following specification:

$$\frac{\sum_{k=0}^{4} LOANS_{i,j,t+k}}{ASSETS_{i,j,t-1}} = \alpha + \mu_{i,j} + \tau_{i,t} + \beta^k WUI_{j,t-1} + \gamma^k Z_{j,t-1} + \\ + \sum_{l=1}^{4} \delta^l \frac{LOANS_{i,j,t-l}}{ASSETS_{i,j,t-1-l}} + \sum_{h=1}^{k} \vartheta^h WUI_{j,t-1+h} + \varepsilon_{i,j,t+h}, \quad (3)$$

where the subscripts i and j again indicate source and recipient country respectively; the subscript t denotes time (in quarters); $LOANS_{i,j,t}$ is new loans made by banks of country i to counterparty country j during quarter t; $ASSETS_{i,j,t-1}$ is the stock of existing loans made by

[14] Despite the advantages mentioned above, the local projection method has also some drawbacks compared to structural VARs. First, since the iterated VAR method produces more efficient parameter estimates than the local projection method, the impulse response function estimated by local projections is often associated with large confidence intervals. This problem of less precise estimates is exacerbated as the forecast horizon increases due to the decreasing sample size in each estimation. Second, compared to a single equation framework in the local projection method, structural VARs allow tracing the dynamic endogenous response of various macroeconomic variables in the system to changes in uncertainty, which in turn can also affect the dynamics of foreign capital inflows.

banks of country *i* to counterparty country *j* at the end of period $t-1$; and the rest of the notation is as in Equation (1). In essence, the dependent variable is cumulative flows over the $t+k$ period in percent of initial assets.

We further include forward uncertainty variables ($\sum_{h=1}^{k} WUI_{j,t-1+h}$) to control for the uncertainty that arises within the response horizon $t+k$ (for $k>1$) that is not captured by $WUI_{j,t-1}$. As shown by Teulings and Zubanov (2014), not doing so would leave the model misspecified and bias our estimates. In our context, this is particularly important because the rise in uncertainty is sometimes correlated over time. We estimate Equation (3) through OLS. The β^k are the main coefficients of interest. They denote the quarter $t+k$ response of the foreign bank inflows after a two-standard deviation increase in uncertainty in the recipient country. We obtain IRFs by plotting the β^k coefficients for $k=0,\dots,4$, together with 90% confidence bands that we compute using the standard errors clustered at the recipient-country-time level.

For portfolio bond and equity flows, we estimate a specification similar to Equation (3). The only two differences stem from the dependent variable and the fact that the explanatory variables (the WUI, GDP growth, and the other controls) enter the regression contemporaneously at time *t*:

$$\sum_{k=0}^{4} FLOW_{i,j,t+k} = \alpha + \mu_{i,j} + \tau_{i,t} + \beta^k WUI_{j,t-1} + \gamma Z_{j,t-1} + \\ + \sum_{l=1}^{4} \delta^l FLOW_{i,j,t-l} + \sum_{1}^{k} \vartheta^h WUI_{j,t-1+h} + \varepsilon_{i,j,t+h} \quad (4)$$

where $FLOW_{i,j,t}$ are quarter *t* net purchases of either equity or bond securities of country *j* by investment funds domiciled in country *i*, in percent of assets of country *j* owned by investment funds of country *i*; and the rest of the notation is as before. The difference in the dependent variable is that we cumulate the $t+k$ percent flows, rather than calculating net purchases over the $t+k$ period and divide them by period $t-1$ assets. This is because funds reporting to EPFR change over time, and thus variations in total assets might be due to changes in the composition of reporting funds (see Section II for more details). We estimate Equation (4) through OLS and construct IRFs in the same manner as for bank inflows.

Figure 1 shows the results for each type of foreign capital inflows. The blue solid and red dotted lines report the response and associated confidence bands. The main finding is that the negative effect of heightened uncertainty on bank credit persists for more than one year and it tends to increase over time; reaching -1.17 p.p. in the latest horizon considered. The negative response of bond inflows following an increase in domestic uncertainty also tends to increase

over time, but this increase is less pronounced and not statistically significant at standard confidence levels. The response of equity inflows, instead, tends to flatten around zero over the horizon considered.

5.2. Cross-country Heterogeneity

Next, we investigate whether the impact of higher uncertainty varies across countries depending on their income levels. We classify recipient countries into advanced economies vs. emerging and developing economies, using the IMF World Economic Outlook country classification. To estimate the differential effect of uncertainty, we interact the WUI variable in Equations (1) and (2) with country group dummies and estimate four different coefficients.[15]

The results reported in Table 5 suggest that capital flows into emerging and developing economies are more vulnerable to domestic uncertainty than those into advanced economies, especially for bank credit and equity flows. For these types of flows, the adverse effect of domestic uncertainty is only statistically significant for emerging and developing economies. To the extent that foreign investors in emerging and developing economies are more exposed to expropriation risk than those in advanced economies, they are more likely to be concerned about uncertainty in their investment destination (Gourio et al., 2015).

This finding can also provide an underlying mechanism for the finding that uncertainty shocks have more negative real effects in emerging and developing economies (e.g., Carrière-Swallow Céspedes, 2013; Choi, 2018). These authors claim that the financial channel plays an important role in amplifying the adverse effect of uncertainty shocks, and emerging and developing economies are characterized by more financial frictions. For bond flows, the negative uncertainty effect is statistically significant for both groups and the difference is not statistically significant (p-value of 0.18).

We further investigate cross-country heterogeneity through the lens of the Mundellian trilemma. To the extent that the trilemma establishes the impossibility of the coexistence of a fixed exchange rate, free capital movements, and independent monetary policy, it would provide us a natural benchmark to think of which types of country characteristics determine the sensitivity of foreign capital inflows to domestic uncertainty. To do so, we add augment equations (1) and (2) with the recipient country's trilemma index constructed by Aizenman et

[15] We do not run a subsample analysis because of the time-fixed effects in our baseline model. Whereas in the full sample specification, they capture truly global developments, in the restricted sample specification, they only capture developments that are common among countries of the particular group concerned.

al. (2010) and its interaction with the WUI.[16] Equation (5) corresponds to the estimation of bank credit flows, whereas equation (6) corresponds to that of portfolio flows:

$$FLOW_{i,j,t} = \alpha + \mu_{i,j} + \tau_{i,t} + \beta WUI_{j,t-1} + \theta WUI_{j,t-1} \times Tri_{j,t-1} + \vartheta Tri_{j,t-1} + \gamma Z_{j,t-1} + \sum_{l=1}^{4} \delta^{l} FLOW_{i,j,t-l} + \varepsilon_{i,j,t}, \quad (5)$$

$$FLOW_{i,j,t} = \alpha + \mu_{i,j} + \tau_{i,t} + \beta WUI_{j,t} + \theta WUI_{j,t} \times Tri_{j,t-1} + \vartheta Tri_{j,t-1} + \gamma Z_{j,t-1} + \sum_{l=1}^{4} \delta^{l} FLOW_{i,j,t-l} + \varepsilon_{i,j,t}, \quad (6)$$

where our main interest is the sign of the interaction term θ, which tells us whether a certain characteristic amplifies or dampens the adverse effect of domestic uncertainty on foreign capital inflows. To mitigate any reverse causality, the trilemma index enters the regression with a lag.

The trilemma index by Aizenman et al. (2010) quantifies the degree of achievement along the three dimensions of the trilemma hypothesis: exchange rate stability, monetary policy independence, and financial openness, thereby providing a comprehensive and consistent overview of an individual recipient country's trilemma status. The trilemma index has three sub-components. First, annual standard deviations of the monthly exchange rate between the home country and the base country are calculated to measure exchange rate stability, then the index is normalized between zero and one. Second, the extent of monetary independence is measured as the reciprocal of the annual correlation of the monthly money market rates between the home country and the base country and normalized between zero and one. Lastly, the updated version of the Chinn-Ito index (KAOPEN) is used to measure capital account openness (Chinn and Ito, 2008). Since KAOPEN is based upon reported restrictions, it is a de jure index of capital account openness.

Since a recipient country fixed effect would absorb any time-invariant recipient country characteristic in our specification, it is important to note that what we identify is the within variation in the time-varying trilemma index. To the extent that the exchange rate regime or capital account openness varies over time, using the time-invariant characteristics could bias the results toward finding less stark differences across country groups. Nevertheless, we confirm that the narrative of the results remains the same when taking the average value of the

[16] We download the 2020 updated version from http://web.pdx.edu/~ito/trilemma_indexes.htm.

trilemma index over time (allowing for the estimation of only the interaction term). This result is available upon request.

Table 6 reports the results when (i) adding the interaction terms one by one and (ii) at the same time to account for the correlation among the three components of the index. First, the effect of domestic uncertainty on foreign capital inflows does not significantly vary with the exchange rate regime and the degree of monetary policy independence. This finding can be reconciled by the dilemma not trilemma narrative of Rey (2015), who asserted that the floating exchange rate regime does not moderate capital flows in response to external shocks. In our context, adopting the floating exchange rate regime is not sufficient to dampen the adverse effect of domestic uncertainty, regardless of the types of flows. On the other hand, we find a statistically significant interaction term on KAOPEN for both portfolio bond and equity flows, suggesting that capital controls do ameliorate the adverse effect of domestic uncertainty on portfolio inflows.

5.3. Traditional Mutual Funds vs. Exchange-traded Funds

Exchange-traded funds (ETFs) represent one of the most important financial innovations in decades. Globally, assets of ETFs under management were $4.3 trillion in September 2017 (exceeding the hedge fund industry), while the global total market value of equity and fixed income securities was over $160 trillion (Lettau and Madhavan, 2018). An ETF is an investment vehicle that typically seeks to track the performance of a specific index, similar to an index mutual fund. But an ETF differs from a mutual fund in fundamental ways. For example, exchange-traded funds offer greater transparency because their investment strategies are specified in advance, and their holdings are listed daily. The ability to trade ETFs intraday also makes them attractive to hedge funds and other institutions seeking to hedge risks or gain exposure based on macroeconomic and other news events. The ETF structure also enables lower fees than traditional active mutual funds. Relative to open-ended index mutual funds, ETFs can offer significant tax advantages. Most importantly, mutual funds hold a portfolio of assets, whereas an ETF does not interact with capital markets directly.

Ignoring such differences between mutual funds and ETFs might lead to a mixed conclusion about the effect of uncertainty on portfolio flows. In this section, we investigate this possibility by estimating the effect of domestic uncertainty on portfolio inflows for mutual funds and ETFs, respectively. Due to the inherent passive nature of ETFs compared to mutual funds, they might pay less attention to country-specific shocks, including domestic uncertainty. If this were true, ETFs would respond more strongly to global uncertainty and weaklier to

domestic uncertainty. To gauge the relative role of global and domestic uncertainty, we estimate responses for the mutual fund and ETF sample with and without the time-fixed effect, respectively.

The results presented in Table 7 point to significant heterogeneity in the way these bond inflows respond to uncertainty. First, by comparing Column 1 with Column 3, ETF bond inflows are much more sensitive to the WUI than mutual fund bond inflows. However, once the time-fixed effect is controlled for, the effect of the WUI on ETF bond inflows becomes statistically insignificant (Column 4), while that on mutual fund bond inflows is still statistically significant (Column 2). Second, similar to the case of portfolio bond inflows, ETF equity inflows are much more sensitive to uncertainty than mutual fund equity inflows (Column 5 and Column 7). Once time fixed effects are included, however, both the responses of mutual fund and ETF equity inflows to domestic uncertainty are statistically insignificant.

Our findings suggest an important asymmetry between the type of investment fund as well as the type of capital inflows. In general, flows through ETFs are more responsive to global factors, including global uncertainty, but they are less responsive to country-specific uncertainty than traditional mutual funds. To the extent that previous studies finding an important role of domestic pull factors of portfolio flows did not distinguish ETFs from traditional mutual funds (e.g., Chuhan et al., 1998; Portes and Rey, 2005), our finding sheds new light on understanding the behavior of international portfolio flows. This result also squares well with the finding of Converse et al. (2018) that ETFs respond more to the VIX than traditional mutual funds. However, Converse et al. (2018) do not investigate the response of ETFs to country-specific uncertainty. Here we show that flows through these types of funds are generally not responsive to country-specific uncertainty.

VI. CONCLUSION

Despite the theoretical prediction and conventional wisdom that an increase in domestic uncertainty in one country would discourage foreign capital investment, identifying an independent role of domestic uncertainty in driving foreign capital inflows from other confounding factors is empirically challenging. Using a comprehensive dataset covering three types of bilateral foreign capital inflows—bank credit, portfolio debt, and portfolio equity—as well as a large number of source and destination countries, we have documented systematic

evidence regarding the role of domestic uncertainty as a pull factor driving foreign capital inflows.

Although domestic uncertainty reduces foreign capital inflows, the size of this effect differs across types of capital flows. Bank credit inflows are the most sensitive to domestic uncertainty, while portfolio equity inflows are the least sensitive, with portfolio bond inflows being an intermediate case. We further discover interesting heterogeneity in response to uncertainty between traditional mutual funds and ETFs. The response of ETFs is typically larger than that of mutual funds bonds. At the same time, while mutual fund bond inflows respond both to global and domestic uncertainty, ETF bonds tend to respond to global uncertainty only. Our findings shed new light on understanding the distinct behavior of ETFs, which represent one of the most important financial investment vehicles these days as well as a source of instability in international financial markets.

Taken together, the rich heterogeneity we discovered in the paper has important implications for both the design of policy to deal with capital inflow surges or sudden stops and the research on theoretical modeling of the effect of uncertainty on capital flows.

TABLES AND FIGURES

Table 1. Descriptive Statistics

	Mean	Median	S.d.	S.d. after fixed effects	Observations
Bank credit	-0.88	-0.36	17.89	17.34	152,968
Portfolio bond – total	-0.14	0.04	8.72	4.12	103,648
Portfolio bond – MFs	-0.33	-0.04	8.65	4.13	101,052
Portfolio bond – ETFs	5.66	3.95	12.62	5.45	27,477
Portfolio equity – total	-0.66	-0.45	8.38	5.61	147,323
Portfolio equity – MFs	-0.95	-0.74	8.16	5.38	141,330
Portfolio equity – ETFs	3.30	2.24	10.54	7.06	43,349
World Uncertainty Index	0.48	0.34	0.51	0.44	308,681

Notes: This table provides descriptive statistics of the main dependent variables (three types of bilateral capital inflows) and the WUI.

Table 2. Uncertainty and Cross-Border Banking Flows

	(1) Bank	(2) Bank	(3) Bank	(4) Bank
WUI	-0.36***	-0.38***	-0.32***	-0.33***
	(0.12)	(0.12)	(0.12)	(0.12)
VIX		-0.17***	-0.17***	
		(0.06)	(0.06)	
WUI global factor			-0.21*	
			(0.12)	
GDP	0.26***	0.26***	0.25***	0.14***
	(0.04)	(0.04)	(0.04)	(0.04)
Constant	-0.92***	-0.91***	-0.92***	-0.83***
	(0.09)	(0.08)	(0.08)	(0.08)
Observations	138,943	138,943	138,943	138,942
R-squared	0.03	0.03	0.03	0.06
Source-by-time f.e.	NO	NO	NO	YES

Notes: The specification includes four lags of the dependent variable and country-pair fixed effects and all independent variables are lagged by one period. Standard errors are clustered at the destination-time level. *, ** and *** indicate significance at the 90%, 95% and 99% confidence level, respectively. The sample spans the 1996Q1-2018Q4 period and covers 39 source countries and 144 recipient countries.

Table 3. Uncertainty and Cross-Border Portfolio Flows

	(1) Bond	(2) Bond	(3) Bond	(4) Bond	(5) Equity	(6) Equity	(7) Equity	(8) Equity
WUI	-0.30***	-0.30***	-0.26***	-0.13***	-0.16**	-0.18***	-0.15**	-0.08**
	(0.09)	(0.08)	(0.08)	(0.04)	(0.06)	(0.06)	(0.06)	(0.04)
VIX		-1.36***	-1.37***			-0.75***	-0.75***	
		(0.05)	(0.05)			(0.03)	(0.03)	
WUI global factor			-0.19*				-0.10	
			(0.11)				(0.06)	
GDP	0.22***	0.06***	0.06**	-0.00	0.14***	0.07***	0.07***	0.01
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
Constant	-0.19***	-0.02	0.05	-0.14***	-0.77***	-0.69***	-0.68***	-0.71***
	(0.07)	(0.07)	(0.08)	(0.03)	(0.05)	(0.05)	(0.05)	(0.03)
Observations	85,292	85,292	85,292	85,241	126,653	126,653	126,653	126,553
R-squared	0.13	0.16	0.16	0.76	0.08	0.09	0.09	0.55
Source-by-time f.e.	NO	NO	NO	YES	NO	NO	NO	YES

Notes: The specification includes four lags of the dependent variable and country-pair fixed effects. Standard errors are clustered at the destination-time level. *, ** and *** indicate significance at the 90%, 95% and 99% confidence level, respectively. For bond flows, the sample spans the 2004Q1-2020Q4 period and covers 37 source countries and 98 recipient countries. For equity flows, the sample spans the 1996Q1-2020Q4 period and covers 39 source countries and 101 recipient countries.

Table 4. Controlling for Additional Variables

	(1) Bank baseline	(2) Bank controls	(3) Bond baseline	(4) Bond controls	(5) Equity baseline	(6) Equity controls
WUI	-0.33***	-0.27*	-0.13***	-0.13***	-0.08**	-0.11**
	(0.12)	(0.15)	(0.04)	(0.04)	(0.04)	(0.04)
GDP	0.14***	0.08	-0.00	0.01	0.01	-0.01
	(0.04)	(0.06)	(0.01)	(0.01)	(0.01)	(0.01)
CPI		0.03		0.02**		-0.01
		(0.03)		(0.01)		(0.01)
CB rate		-0.01		-0.03***		0.02**
		(0.03)		(0.01)		(0.01)
Stock growth		0.02**		0.01***		0.03***
		(0.01)		(0.00)		(0.00)
Exchange rate		-0.07***		0.00		-0.01
		(0.02)		(0.01)		(0.01)
Constant	-0.83***	-0.81***	-0.14***	-0.07	-0.71***	-0.82***
	(0.08)	(0.17)	(0.03)	(0.05)	(0.03)	(0.05)
Observations	138,942	90,179	85,241	66,767	126,553	102,887
R-squared	0.06	0.08	0.76	0.75	0.55	0.55
Source countries	39	39	36	36	37	37
Recipient countries	142	82	108	80	102	78

Notes: The specification includes four lags of the dependent variable and country-pair fixed effects and source-by-time fixed effects. For banking flows, the independent variables are lagged by one period. Standard errors are clustered at the destination-time level. *, ** and *** indicate significance at the 90%, 95% and 99% confidence level, respectively.

Table 5. Country Heterogeneity across Income Groups

	(1) Bank baseline	(2) Bank groups	(3) Bond baseline	(4) Bond groups	(5) Equity baseline	(6) Equity groups
WUI	-0.33***		-0.13***		-0.08**	
	(0.12)		(0.04)		(0.04)	
WUI - AEs		-0.31		-0.22**		-0.01
		(0.23)		(0.08)		(0.06)
WUI - EMDEs		-0.33**		-0.09**		-0.11**
		(0.13)		(0.04)		(0.05)
GDP	0.14***	0.14***	-0.00	-0.00	0.01	0.01
	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.83***	-0.83***	-0.14***	-0.14***	-0.71***	-0.71***
	(0.08)	(0.08)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	138,942	138,942	85,241	85,241	126,553	126,553
R-squared	0.06	0.06	0.76	0.76	0.55	0.55

Notes: The specification includes four lags of the dependent variable and country-pair fixed effects and source-by-time fixed effects. For banking flows, the independent variables are lagged by one period. The country classification follows that of the IMF World Economic Outlook. Standard errors are clustered at the destination-time level. *, ** and *** indicate significance at the 90%, 95% and 99% confidence level, respectively.

Table 6. Role of Trillema in Understanding Cross-country Heterogeneity

	(1) Bank ERS	(2) Bank MI	(3) Bank OPEN	(4) Bank All	(5) Bond ERS	(6) Bond MI	(7) Bond OPEN	(8) Bond All	(9) Equity ERS	(10) Equity MI	(11) Equity OPEN	(12) Equity All
WUI	-0.40	-0.06	-0.13	0.09	-0.14*	-0.18**	0.08	0.04	-0.04	-0.17**	0.03	-0.02
	(0.27)	(0.27)	(0.31)	(0.58)	(0.07)	(0.07)	(0.08)	(0.12)	(0.07)	(0.07)	(0.09)	(0.14)
WUI X ERS	0.32			0.37	0.01			0.08	-0.13			-0.04
	(0.48)			(0.54)	(0.14)			(0.17)	(0.12)			(0.16)
WUI X MI		-0.42		-0.54		0.12		0.00		0.15		0.14
		(0.60)		(0.72)		(0.15)		(0.17)		(0.17)		(0.21)
WUI X OPEN			-0.18	-0.44			-0.35***	-0.36***			-0.25**	-0.22*
			(0.41)	(0.46)			(0.19)	(0.13)			(0.12)	(0.13)
ERS	1.44**			1.35*	0.34*			0.43*	0.24			0.14
	(0.67)			(0.71)	(0.20)			(0.24)	(0.19)			(0.22)
MI		1.09*		1.29*		0.06		0.15		-0.11		-0.17
		(0.63)		(0.67)		(0.17)		(0.18)		(0.17)		(0.20)
OPEN			0.37	0.61			0.18	0.19			-0.21	-0.26
			(0.67)	(0.69)			(0.23)	(0.23)			(0.23)	(0.24)
GDP	0.06	0.08	0.06	0.06	0.00	0.01	0.01	0.01	-0.00	-0.00	0.00	0.00
	(0.06)	(0.06)	(0.06)	(0.06)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-1.69***	-1.22***	-1.06**	-2.54***	-0.28**	-0.06	-0.09	-0.41*	-0.95***	-0.77***	-0.70***	-0.69***
	(0.44)	(0.27)	(0.53)	(0.75)	(0.13)	(0.07)	(0.18)	(0.24)	(0.12)	(0.07)	(0.18)	(0.23)
Observations	89,474	87,494	88,974	86,642	66,426	62,589	59,672	56,882	102,132	99,189	94,435	92,010
R-squared	0.03	0.03	0.03	0.03	0.74	0.74	074	0.74	0.53	0.53	0.53	0.53

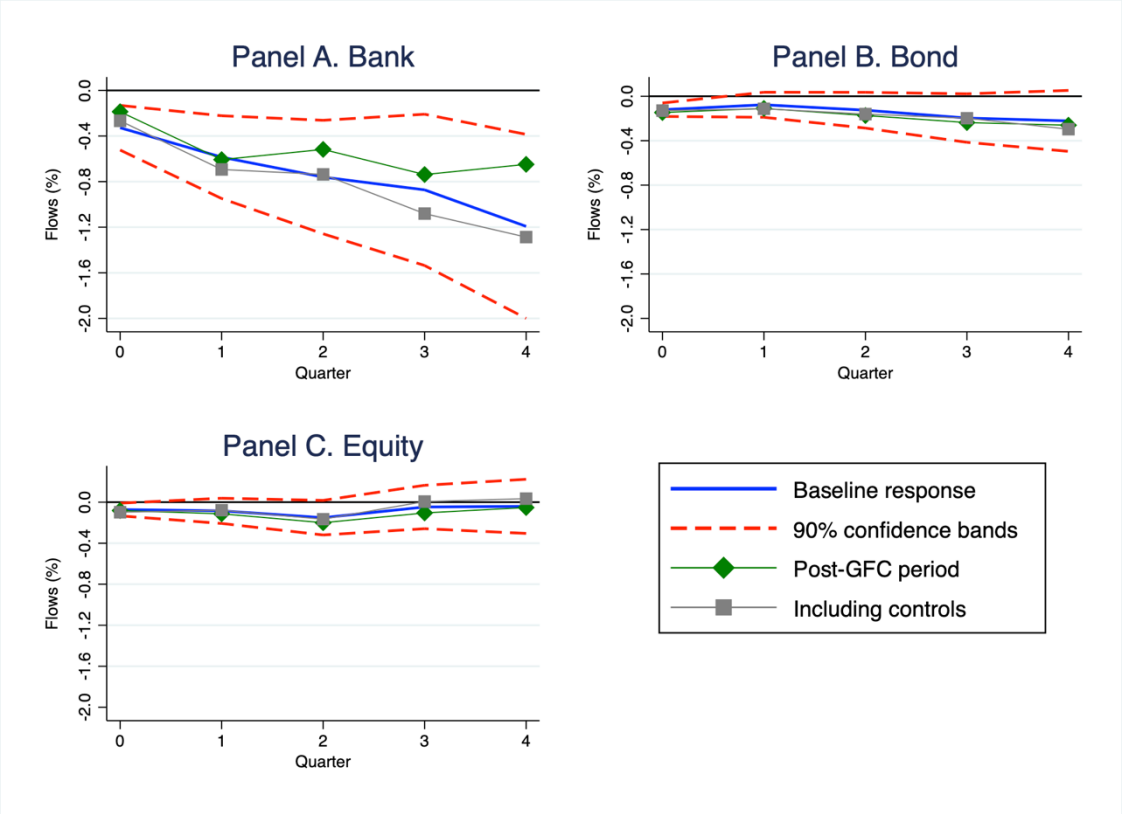
Notes: The specification includes four lags of the dependent variable and country-pair fixed effects and source-by-time fixed effects. For banking flows, the independent variables are lagged by one period. ERS, MI, and OPEN denote exchange rate stability, monetary policy independence, and capital openness, respectively. Standard errors are clustered at the destination-time level. *, ** and *** indicate significance at the 90%, 95% and 99% confidence level, respectively.

Table 7. Exchange-traded Funds vs. Traditional Mutual Funds

	(1) Bond MF no f.e.	(2) Bond MF f.e.	(3) Bond ETF no f.e.	(4) Bond ETF f.e.	(5) Equity MF no f.e.	(6) Equity MF f.e.	(7) Equity ETF no f.e.	(8) Equity ETF f.e.
WUI	-0.30***	-0.14***	-1.10***	-0.10	-0.07	-0.03	-0.63***	0.07
	(0.09)	(0.04)	(0.20)	(0.11)	(0.06)	(0.04)	(0.12)	(0.09)
GDP	0.23***	0.00	0.13***	-0.00	0.16***	0.02*	0.19***	0.02
	(0.02)	(0.01)	(0.03)	(0.02)	(0.02)	(0.01)	(0.03)	(0.03)
Constant	-0.38***	-0.31***	5.85***	5.34***	-1.13***	-1.05***	3.06***	2.98***
	(0.07)	(0.03)	(0.16)	(0.08)	(0.05)	(0.03)	(0.10)	(0.08)
Observations	83,407	83,372	22,205	22,144	121,769	121,683	36,560	36,524
R-squared	0.12	0.76	0.10	0.77	0.07	0.57	0.11	0.51

Notes: The specification includes four lags of the dependent variable and country-pair fixed effects and source-by-time fixed effects. Standard errors are clustered at the destination-time level. *, ** and *** indicate significance at the 90%, 95% and 99% confidence level, respectively.

Figure 1. Dynamic Response of Foreign Capital Inflows



Notes: The estimates are based on Equation 3. T=0 in the x-axis denotes the time of the uncertainty shocks.

References

Abadie, Alberto, Susan Athey, Guido W. Imbens, and Jeffrey Wooldridge. "When should you adjust standard errors for clustering?" No. w24003. National Bureau of Economic Research, 2017.

Ahir, Hites, Nicholas Bloom, and Davide Furceri. "The world uncertainty index." No. w29763. National Bureau of Economic Research, 2022.

Ahmed, Shaghil, and Andrei Zlate. "Capital flows to emerging market economies: A brave new world?" Journal of International Money and Finance 48 (2014): 221-248.

Aizenman, Joshua, Menzie D. Chinn, and Hiro Ito. "The emerging global financial architecture: Tracing and evaluating new patterns of the trilemma configuration." Journal of International Money and Finance 29, no. 4 (2010): 615-641.

Avdjiev, Stefan, Michael KF Chui, and Hyun Song Shin. "Non-financial corporations from emerging market economies and capital flows." BIS Quarterly Review December (2014).

Avdjiev, Stefan, Leonardo Gambacorta, Linda S. Goldberg, and Stefano Schiaffi. "The shifting drivers of global liquidity." Journal of International Economics (2020): 103324.

Avdjiev, Stefan, and Galina Hale. "US monetary policy and fluctuations of international bank lending." Journal of International Money and Finance 95 (2019): 251-268.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis. "Measuring economic policy uncertainty." Quarterly Journal of Economics 131.4 (2016): 1593-1636.

Baltagi, Badi H., Panicos O. Demetriades, and Siong Hook Law. "Financial development and openness: Evidence from panel data." Journal of Development Economics 89.2 (2009): 285-296.

Bank of International Settlement. "BIS Quarterly Review." 2017

Beirne, John, Nuobu Renzhi, Eric Sugandi, and Ulrich Volz. "COVID-19, asset markets and capital flows." Pacific Economic Review 26, no. 4 (2021): 498-538.

Bénétrix, Agustın, and Michael Curran. "Uncertainty Shocks and the Cross-Border Funding of Banks: Unmasking Heterogeneity." No. tep0920. Trinity College Dublin, Department of Economics, 2020.

Benhima, Kenza, and Rachel Cordonier. "News, Sentiment and Capital Flows." (2022). Working Paper

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J. Terry. "Really uncertain business cycles." Econometrica 86, no. 3 (2018): 1031-1065.

Borensztein, Eduardo, and R. Gaston Gelos. "A panic-prone pack? The behavior of emerging market mutual funds." IMF Staff papers 50.1 (2003): 43-63.

Broner, Fernando A., R. Gaston Gelos, and Carmen M. Reinhart. "When in peril, retrench: Testing the portfolio channel of contagion." Journal of International Economics 69.1 (2006): 203-230.

Broner, Fernando, Tatiana Didier, Aitor Erce, and Sergio L. Schmukler. "Gross capital flows: Dynamics and crises." Journal of Monetary Economics 60, no. 1 (2013): 113-133.

Bruno, Valentina, and Hyun Song Shin. "Cross-border banking and global liquidity." Review of Economic Studies 82.2 (2015): 535-564.

Caballero, Julián, Andrés Fernández, and Jongho Park. "On corporate borrowing, credit spreads and economic activity in emerging economies: An empirical investigation." Journal of International Economics 118 (2019): 160-178.

Carrière-Swallow, Yan, and Luis Felipe Céspedes. "The impact of uncertainty shocks in emerging economies." Journal of International Economics 90, no. 2 (2013): 316-325.

Cerutti, Eugenio, Stijn Claessens, and Lev Ratnovski. "Global liquidity and cross-border bank flows." Economic Policy 32.89 (2017): 81-125.

Cerutti, Eugenio, Stijn Claessens, and Damien Puy. "Push factors and capital flows to emerging markets: why knowing your lender matters more than fundamentals." Journal of International Economics 119 (2019): 133-149.

Cesa-Bianchi, Ambrogio, Luis Felipe Cespedes, and Alessandro Rebucci. "Global liquidity, house prices, and the macroeconomy: Evidence from advanced and emerging economies." Journal of Money, Credit and Banking 47.S1 (2015): 301-335.

Chang, Roberto, Andrés Fernández, and Adam Gulan. "Bond finance, bank credit, and aggregate fluctuations in an open economy." Journal of Monetary Economics 85 (2017): 90-109.

Choi, Sangyup. "The impact of US financial uncertainty shocks on emerging market economies: an international credit channel." Open Economies Review 29, no. 1 (2018): 89-118.

Choi, Sangyup, and Davide Furceri. "Uncertainty and cross-border banking flows." Journal of International Money and Finance 93 (2019): 260-274.

Choi, Sangyup, Davide Furceri, and Chansik Yoon. "Policy uncertainty and foreign direct investment." Review of International Economics 29, no. 2 (2021): 195-227.

Chuhan, Punam, Stijn Claessens, and Nlandu Mamingi. "Equity and bond flows to Latin America and Asia: the role of global and country factors." Journal of Development Economics 55, no. 2 (1998): 439-463.

Ciminelli, Gabriele, John Rogers and Wenbin Wu. "The Effects of U.S. Monetary Policy on International Mutual Fund Investment." Journal of International Money and Finance (forthcoming).

Converse, Nathan, Eduardo Levy-Yeyati, and Tomas Williams. "How ETFs amplify the global financial cycle in emerging markets." Institute for International Economic Policy Working Paper 1 (2018).

Davis, J. Scott, and Eric Van Wincoop. “Globalization and the increasing correlation between capital inflows and outflows.” Journal of Monetary Economics 100 (2018): 83-100.

Duca, Marco Lo, Giulio Nicoletti, and Ariadna Vidal Martinez. “Global corporate bond issuance: what role for US quantitative easing?” Journal of International Money and Finance 60 (2016): 114-150.

European Central Bank. “Financial Integration in Europe.” 2007.

Falato, Antonio, Itay Goldstein, and Ali Hortaçsu. “Financial fragility in the COVID-19 crisis: The case of investment funds in corporate bond markets.” Journal of Monetary Economics 123 (2021): 35-52.

Fogli, Alessandra, and Fabrizio Perri. “Macroeconomic volatility and external imbalances.” Journal of Monetary Economics 69 (2015): 1-15.

Forbes, Kristin J., and Francis E. Warnock. “Capital flow waves: Surges, stops, flight, and retrenchment.” Journal of International Economics 88.2 (2012): 235-251.

Fratzscher, Marcel. “Capital flows, push versus pull factors and the global financial crisis.” Journal of International Economics 88.2 (2012): 341-356.

Gete, Pedro, and Givi Melkadze. “Aggregate volatility and international dynamics. The role of credit supply.” Journal of International Economics 111 (2018): 143-158.

Gourio, Francois, Michael Siemer, and Adrien Verdelhan. “Uncertainty and international capital flows.” Working paper (2015).

ICI 2018. Investment company factbook Technical report, Investment Company Institute.

Jordà, Òscar. “Estimation and inference of impulse responses by local projections.” American Economic Review 95.1 (2005): 161-182.

Jordà, Òscar, and Alan M. Taylor. “The time for austerity: estimating the average treatment effect of fiscal policy.” Economic Journal 126.590 (2016): 219-255.

Jotikasthira, Chotibhak, Christian Lundblad, and Tarun Ramadorai. “Asset fire sales and purchases and the international transmission of funding shocks.” Journal of Finance 67.6 (2012): 2015-2050.

Julio, Brandon, and Youngsuk Yook. “Policy uncertainty, irreversibility, and cross-border flows of capital.” Journal of International Economics 103 (2016): 13-26.

Kollmann, Robert. “International business cycles and risk sharing with uncertainty shocks and recursive preferences.” Journal of Economic Dynamics and Control 72 (2016): 115-124.

Lane, Philip R., and Peter McQuade. “Domestic credit growth and international capital flows.” Scandinavian Journal of Economics 116.1 (2014): 218-252.

Lettau, Martin, and Ananth Madhavan. “Exchange-traded funds 101 for economists.” Journal of Economic Perspectives 32.1 (2018): 135-54.

Milesi-Ferretti, Gian-Maria, and Cédric Tille. “The great retrenchment: international capital flows during the global financial crisis.” Economic Policy 26.66 (2011): 289-346.

Nickell, Stephen. “Biases in dynamic models with fixed effects.” Econometrica (1981): 1417-1426.

Obstfeld, Maurice. “Financial flows, financial crises, and global imbalances.” Journal of International Money and Finance 31.3 (2012): 469-480.

Portes, Richard, and Helene Rey. “The determinants of cross-border equity flows.” Journal of International Economics 65, no. 2 (2005): 269-296.

Puy, Damien. “Mutual funds flows and the geography of contagion.” Journal of International Money and Finance 60 (2016): 73-93.

Ramey, Valerie A., and Sarah Zubairy. “Government spending multipliers in good times and in bad: evidence from US historical data.” Journal of Political Economy 126.2 (2018): 850-901.

Rey, Hélène. “Dilemma not trilemma: the global financial cycle and monetary policy independence.” National Bureau of Economic Research, 2015.

Sarno, Lucio, Ilias Tsiakas, and Barbara Ulloa. “What drives international portfolio flows?” Journal of International Money and Finance 60 (2016): 53-72.

Teulings, Coen N., and Nikolay Zubanov. “Is economic recovery a myth? Robust estimation of impulse responses.” Journal of Applied Econometrics 29.3 (2014): 497-514.

Wang, Yabin. “Fickle capital flows and retrenchment: Evidence from bilateral banking data.” Journal of International Money and Finance 87 (2018): 1-21.

APPENDIX

Table A.1. Source Jurisdictions – Portfolio Flows

Australia	Finland	Japan	Singapore
Austria	France	Jersey	South Africa
The Bahamas	Germany	Korea	Spain
Belgium	Greece	Sweden	Sweden
Bermuda	Guernsey	Luxembourg	Switzerland
British Virgin Islands	Hong Kong SAR	Mauritius	Thailand
Canada	India	Turkey	Turkey
Cayman	Ireland	Netherlands	United Kingdom
Denmark	Israel	New Zealand	United States
Estonia	Italy	Norway	

Notes: This table includes the list of source countries for portfolio debt and equity flows.

Table A.2. Recipient Countries – Portfolio Flows

Advanced Markets	Emerging Markets	Frontier Markets	Others
Australia	Argentina	Bangladesh	Algeria
Austria	Brazil	Botswana	Angola
Belgium	Chile	Bulgaria	Bolivia
Canada	China	Cote D'Ivoire	Cambodia
Denmark	Colombia	Croatia	Costa Rica
Finland	Czech Republic	Jordan	Dominican Republic
France	Egypt	Kazakhstan	Ecuador
Germany	Greece	Kenya	El Salvador
Hong Kong SAR	Hungary	Kuwait	Georgia
Ireland	India	Lebanon	Ghana
Israel	Indonesia	Lithuania	Guatemala
Italy	Korea	Morocco	Iran
Japan	Malaysia	Nigeria	Iraq
Netherlands	Mexico	Oman	Latvia
New Zealand	Pakistan	Panama	Liberia
Norway	Peru	Romania	Madagascar
Portugal	Philippines	Slovenia	Malawi
Singapore	Poland	Sri Lanka	Mongolia
Spain	Qatar	Tunisia	Mozambique
Sweden	Russia	Ukraine	Myanmar
Switzerland	Saudi Arabia	Vietnam	Namibia
United Kingdom	South Africa	Zimbabwe	Nepal
United States	Taiwan		Papua New Guinea
	Thailand		Paraguay
	Turkey		Rwanda
	U.A.E.		Slovak Republic
			Tajikistan
			Tanzania
			Turkmenistan
			Uganda
			Uruguay
			Venezuela
			Zambia

Notes: This table includes the list of recipient countries for portfolio debt and equity flows.

Table A.3. Source Jurisdictions – Banking Flows

Australia	Cyprus	Isle of Man	Philippines
Austria	Denmark	Italy	Portugal
The Bahamas	Finland	Jersey	Singapore
Bahrain	France	Korea	South Africa
Belgium	Greece	Luxembourg	Spain
Bermuda	Guernsey	Macao SAR	Sweden
Brazil	Hong Kong SAR	Mexico	Switzerland
Canada	India	Netherlands	Taiwan
Chile	Indonesia	Netherlands Antilles	United Kingdom
Curacao	Ireland	Panama	United States

Notes: This table includes the list of source countries for bank credit flows.

Table A.4. Recipient Countries – Banking Flows

Advanced	Emerging	Frontier	Others
Australia	Argentina	Bangladesh	Afghanistan
Austria	Brazil	Bosnia Herzegovina	Albania
Belgium	Chile	Botswana	Algeria
Canada	China	Bulgaria	Angola
Denmark	Colombia	Burkina Faso	Armenia
Finland	Czech Republic	Croatia	Azerbaijan
France	Egypt	Jamaica	Belarus
Germany	Greece	Jordan	Benin
Hong Kong SAR	Hungary	Kazakhstan	Bolivia
Ireland	India	Kenya	Burundi
Israel	Indonesia	Kuwait	Cambodia
Italy	Korea	Lebanon	Cameroon
Japan	Malaysia	Lithuania	Central African Rep.
Netherlands	Mexico	Morocco	Chad
New Zealand	Pakistan	Nigeria	Congo, Dem. Rep.
Norway	Peru	Oman	Congo, Rep.
Portugal	Philippines	Panama	Costa Rica
Singapore	Poland	Romania	Cote D'Ivoire
Spain	Qatar	Senegal	Dominican Republic
Sweden	Russia	Slovenia	Ecuador
Switzerland	Saudi Arabia	Sri Lanka	El Salvador
United Kingdom	South Africa	Tunisia	Eritrea
United States	Taiwan	Ukraine	Ethiopia
	Thailand	Vietnam	FYR Macedonia
	Turkey	Zimbabwe	Gabon
	U.A.E.		The Gambia
			Georgia
			Ghana
			Guatemala
			Guinea
			Guinea-Bissau
			Haiti
			Honduras
			Iran
			Iraq
			Kyrgyz Republic
			Lao P.D.R.
			Latvia
			Lesotho
			Liberia
			Libya

	Madagascar
	Malawi
	Mali
	Mauritania
	Moldova
	Mongolia
	Mozambique
	Myanmar
	Namibia
	Nepal
	Nicaragua
	Niger
	Papua New Guinea
	Paraguay
	Rwanda
	Sierra Leone
	Slovak Republic
	Sudan
	Tajikistan
	Tanzania
	Togo
	Turkmenistan
	Uganda
	Uruguay
	Uzbekistan
	Venezuela
	Yemen
	Zambia

Notes: This table includes the list of recipient countries for bank credit flows.

Table A.5. Control Variables – Bank Flows

	(1) Baseline	(2) CPI	(3) CB rate	(4) Stock	(5) NER	(6) All
WUI	-0.32***	-0.35***	-0.32**	-0.35**	-0.34***	-0.25*
	(0.12)	(0.12)	(0.13)	(0.14)	(0.12)	(0.15)
GDP	0.17***	0.18***	0.19***	0.22***	0.17***	0.18***
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.06)
CPI		-0.00***				0.02
		(0.00)				(0.02)
CB rate			0.03			0.01
			(0.02)			(0.03)
Stock growth				0.02***		0.02*
				(0.01)		(0.01)
Forex					-0.00	-0.07***
					(0.00)	(0.02)
Constant	-0.86***	-0.80***	-1.01***	-0.82***	-0.86***	-0.92***
	(0.08)	(0.09)	(0.15)	(0.10)	(0.09)	(0.17)
Observations	138,655	125,176	109,837	102,938	135,573	90,976
R-squared	0.06	0.07	0.07	0.07	0.06	0.08
Source countries	39	39	39	39	39	39
Recipient countries	142	115	111	92	141	82

Notes: The specification includes four lags of the dependent variable and country-pair fixed effects and source-by-time fixed effects. The independent variables are lagged by one period. Standard errors are clustered at the destination-time level. *, ** and *** indicate significance at the 90%, 95% and 99% confidence level, respectively.

Table A.6. Control Variables – Bond Flows

	(1) Baseline	(2) CPI	(3) CB rate	(4) Stock	(5) NER	(6) All
WUI	-0.13***	-0.14***	-0.15***	-0.11***	-0.13***	-0.13***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
GDP	-0.00	-0.00	-0.00	0.00	-0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CPI		0.00				0.02**
		(0.00)				(0.01)
CB rate			-0.02**			-0.03***
			(0.01)			(0.01)
Stock growth				0.01***		0.01***
				(0.00)		(0.00)
Forex					-0.00***	0.00
					(0.00)	(0.01)
Constant	-0.14***	-0.13***	-0.05	-0.16***	-0.13***	-0.07
	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)	(0.05)
Observations	85,241	83,124	76,726	70,911	84,102	66,767
R-squared	0.76	0.76	0.75	0.75	0.76	0.75
Source countries	36	36	36	36	36	36
Recipient countries	108	102	94	86	107	80

Notes: The specification includes four lags of the dependent variable and country-pair fixed effects and source-by-time fixed effects. The independent variables are lagged by one period. Standard errors are clustered at the destination-time level. *, ** and *** indicate significance at the 90%, 95% and 99% confidence level, respectively.

Table A.7. Control Variables – Equity Flows

	(1) Baseline	(2) CPI	(3) CB rate	(4) Stock	(5) NER	(6) All
WUI	-0.08**	-0.10**	-0.10**	-0.09**	-0.10**	-0.11**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
GDP	0.01	0.00	-0.00	-0.01	0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CPI		0.00				-0.01
		(0.00)				(0.01)
CB rate			0.01*			0.02**
			(0.01)			(0.01)
Stock growth				0.03***		0.03***
				(0.00)		(0.00)
Forex					0.00	-0.01
					(0.00)	(0.01)
Constant	-0.71***	-0.71***	-0.75***	-0.76***	-0.71***	-0.82***
	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)	(0.05)
Observations	126,553	123,755	112,962	112,774	124,036	102,887
R-squared	0.55	0.55	0.55	0.55	0.56	0.55
Source countries	37	37	37	37	37	37
Recipient countries	102	95	87	84	100	78

Notes: The specification includes four lags of the dependent variable and country-pair fixed effects and source-by-time fixed effects. Standard errors are clustered at the destination-time level. *, ** and *** indicate significance at the 90%, 95% and 99% confidence level, respectively.

Table A.8. Robustness Check on Lag Structure

	(1) Bank 2 lags	(2) Bank 8 lags	(3) Bond 2 lags	(4) Bond 8 lags	(5) Equity 2 lags	(6) Equity 8 lags
WUI	-0.34***	-0.33***	-0.11***	-0.15***	-0.08**	-0.07*
	(0.12)	(0.12)	(0.04)	(0.04)	(0.04)	(0.04)
GDP	0.13***	0.14***	0.00	-0.00	0.01	0.01
	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.81***	-0.83***	-0.13***	-0.21***	-0.69***	-0.67***
	(0.08)	(0.09)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	144,872	127,750	92,587	72,696	134,980	111,698
R-squared	0.06	0.07	0.77	0.75	0.55	0.55

Notes: The specification includes different lags of the dependent variable and country-pair fixed effects and source-by-time fixed effects. For banking flows, the independent variables are lagged by one period. Standard errors are clustered at the destination-time level. *, ** and *** indicate significance at the 90%, 95% and 99% confidence level, respectively.

Table A.9. Robustness Check on Offshore Low Tax Jurisdictions and Financial Centers

	(1) Bank	(2) Bank	(3) Bank	(4) Bond	(5) Bond	(6) Bond	(7) Equity	(8) Equity	(9) Equity
WUI	-0.33***	-0.33***	-0.35***	-0.13***	-0.15***	-0.17***	-0.08**	-0.04	-0.05
	(0.12)	(0.12)	(0.13)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
GDP	0.14***	0.14***	0.15***	-0.00	0.00	-0.01	0.01	-0.00	0.00
	(0.04)	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.83***	-0.77***	-0.78***	-0.14***	0.17***	-0.42***	-0.71***	-0.38***	-0.85***
	(0.08)	(0.09)	(0.09)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	138,942	130,981	110,851	85,241	72,984	75,067	126,553	104,817	111,508
R-squared	0.06	0.06	0.06	0.76	0.74	0.75	0.55	0.56	0.56
Tax havens	YES	NO	YES	YES	NO	YES	YES	NO	YES
Financial centers	YES	YES	NO	YES	YES	NO	YES	YES	NO
Source countries	39	33	31	35	29	32	37	31	34
Recipient countries	142	142	142	107	107	107	101	101	101

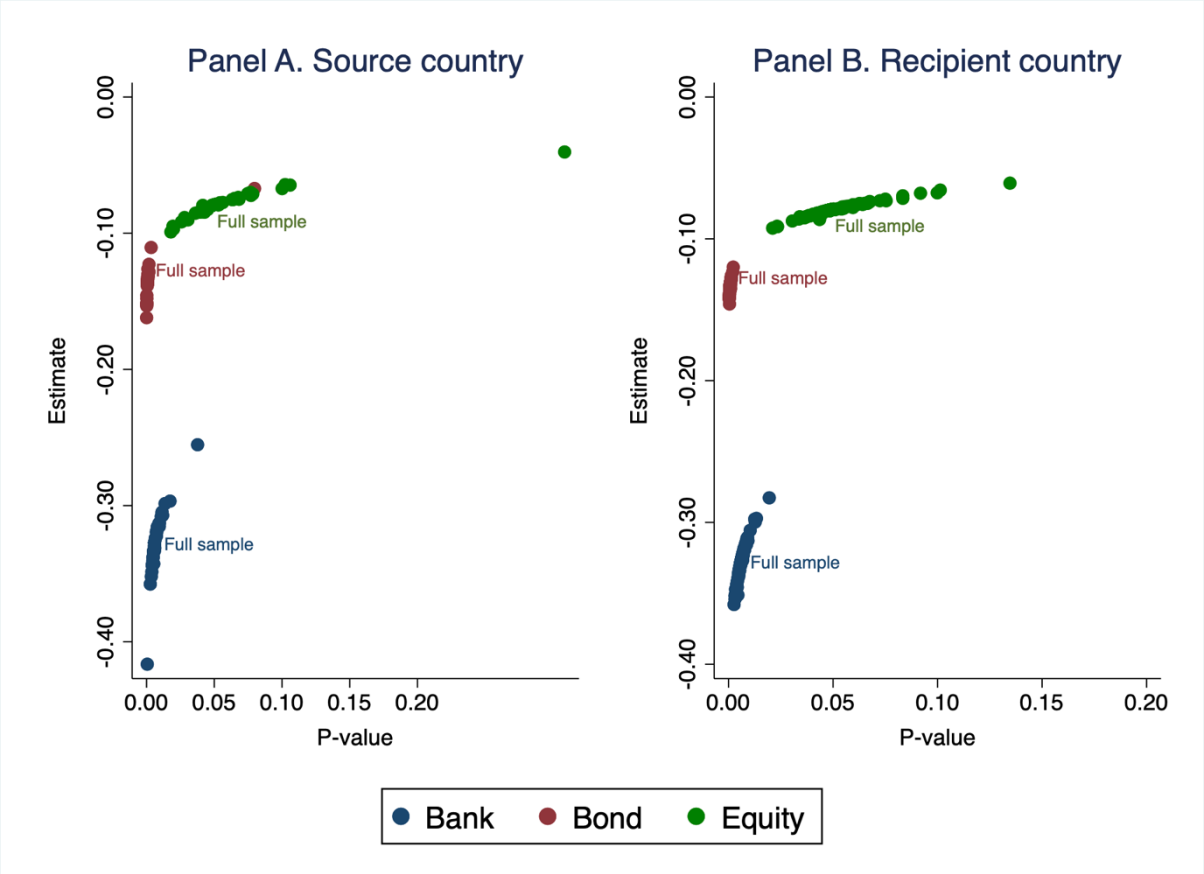
Notes: The specification includes different lags of the dependent variable and country-pair fixed effects and source-by-time fixed effects. For banking flows, the independent variables are lagged by one period. Standard errors are clustered at the destination-time level. *, ** and *** indicate significance at the 90%, 95% and 99% confidence level, respectively.

Table A.10. Robustness Checks Censoring Observations with Small Assets

	(1) Bank baseline	(2) Bank min. assets	(3) Bond baseline	(4) Bond min. assets	(5) Equity baseline	(6) Equity min. assets
WUI	-0.33***	-0.37***	-0.13***	-0.11***	-0.08**	-0.09**
	(0.12)	(0.12)	(0.04)	(0.04)	(0.04)	(0.04)
GDP	0.14***	0.14***	-0.00	0.01	0.01	0.01
	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.83***	-0.72***	-0.14***	0.00	-0.71***	-0.57***
	(0.08)	(0.09)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	138,942	134,408	85,241	71,016	126,553	94,719
R-squared	0.06	0.06	0.76	0.77	0.55	0.56

Notes: The specification includes different lags of the dependent variable and country-pair fixed effects and source-by-time fixed effects. For banking flows, the independent variables are lagged by one period. Standard errors are clustered at the destination-time level. *, ** and *** indicate significance at the 90%, 95% and 99% confidence level, respectively.

Figure A.1. Sample Stability Robustness Check



Notes: The figure reports coefficients estimated by dropping one recipient country (Panel A) and one source country (Panel B) at a time.