Is capital flow management effective? Evidence based on U.S. monetary policy shocks

Jian Wang[†]

The Chinese University of Hong Kong (Shenzhen) and Shenzhen Finance Institute

Jason Wu[‡]

Hong Kong Monetary Authority

Abstract

It is challenging to empirically test if emerging markets employ countercyclical capital flow management to combat the large flows driven by global factors, and whether such policy is effective in containing capital flows. The first challenge is that a good gauge of the cyclical dynamics of capital flow management measures is hard to obtain. In addition, the causal effects of capital flow management on capital flows are difficult to establish as such policies are usually endogenous responses to capital flows. We address these issues by using U.S. monetary policy shocks as instruments for a recently developed measure of capital flow management that captures both extensive and intensive margins of policy actions. We find that for a panel of 15 emerging market economies, U.S. monetary policy shocks at quarter $t-1$ lead to adjustments to the capital flow management in these countries at t, which then affect capital flows at $t+1$. In particular, inflow tightening actions increase after dovish U.S. monetary policy shocks and they materially dampen future net portfolio liability inflows, while no evidence is found for outflow policy actions or hawkish U.S. monetary policy shocks.

Keywords: Capital flow management, capital flows, global financial cycles
JEL Classifications: F3, F4, E5

[*]This paper was previously circulated under the title "The Dilemma and International Macroprudential Policy: Is Capital Flow Management Effective?" We thank Yi Huang for many discussions and data assistance. We also thank Nadav Ben Zeev, Menzie Chinn, Charles Engel, Nicolas Magud, Jonathan Ostry, Alessandro Rebucci, Eli Remonola, Kim Ruhl, Ilhyock Shim, Martine Uribe, Frank Warnock, Jing Zhou and seminar/conference participants at the University of Wisconsin-Madison, Southern Methodist University, the University of Texas at Dallas, the 2018 Tsinghua Workshop of International Finance, Hong Kong Institute for Monetary Research (HKIMR), and the Bank for International Settlements for helpful comments. Part of the paper was written when Jason Wu was on a leave from the Federal Reserve Board to visit the HKIMR, whose hospitality is gratefully acknowledged. Wang thanks the National Natural Science Foundation of China (71661137005) for financial support. Xiaomin Guo and Xiaosheng Guo provided excellent research assistance. All views are those of the authors and do not necessarily reflect the views of HKMA.

[†]Email: jianwang@cuhk.edu.cn.
[‡]Email: jkmwu@hkma.gov.hk.

1 Introduction

Following the 2008 global financial crisis, countercyclical capital flow management policy has been recommended, especially for emerging economies, as a way to defend against financial instability and to preserve monetary autonomy. Rey (2013) shows that over the global financial cycles, shocks emanating from "center economies" such as the U.S. induce large and volatile international capital flows and prevent the conduct of independent monetary policy for countries with open capital markets, even if they have flexible exchange rate arrangements.[1] IMF (2011) argues that volatile capital flows may carry macroeconomic and financial stability risks to receiving countries, and measures to manage capital flows can help mitigate these risks.[2] Several theoretical studies find that countercyclical capital flow management and other macroprudential policies help to stabilize domestic financial markets and maintain monetary policy autonomy. For instance, Jeanne and Korinek (2019), Jeanne (2013), Korinek (2011), Korinek (2018) and Farhi and Werning (2014) theoretically examine the welfare improvements of countercyclical capital flow management. Davis and Presno (2017) show in a small open economy model with nominal rigidity and credit frictions that capital controls allow greater monetary policy autonomy in a country with a flexible exchange rate. Benigno et al. (2016) propose prudential capital flow management in tranquil times as part of the optimal policy mix when exchange rate policy is costly.

As a practical matter, however, it is not clear if countries follow this policy recommendation and if capital flow management policies can effectively shield an economy from volatile international capital inflows and outflows. For instance, Fernandez et al. (2016) find that capital controls in 78

[1] Giovanni et al. (2017) find that the global financial cycles account for a substantial fraction (over 40%) of observed domestic corporate credit growth in Turkey. Several studies that precede Rey (2013) provide empirical support for her arguments in various ways. For instance, Frankel et al. (2004) document that a flexible exchange rate does not help to insulate countries from a full transmission of international interest rates in the long run. Tong and Wei (2010) find that capital flow management provided countries more cushioning during the 2008 financial crisis than flexible exchange rate regimes.

[2] These arguments echoed early voices in the 1990s that capital control policies should be adopted in the countries for which currencies were still pegged to the U.S. dollar or whose domestic financial markets remained underdeveloped.

countries are acyclical over the period 1995-2011. The empirical support for the effectiveness of capital flow management policy is also at best mixed.[3] For instance, Edison and Reinhart (2001) find that capital controls failed to stop hot money in two out of three emerging markets during the crises of the 1990s. More recently, Forbes et al. (2015) show that most capital flow management measures do not significantly affect capital flows and other key targets in an expansive but short panel of countries.[4] In contrast, Ostry et al. (2012) and Zeev (2017), among others, document empirical evidence in favor of capital flow management policies, especially for emerging markets. For instance, Zeev (2017) shows in a panel of 33 emerging market economies that capital inflow controls significantly shield the economies from global credit supply shocks.

In this paper, we contribute to the literature by providing empirical evidence that emerging market economies (EMEs) tend to adopt countercyclical capital flow management in response to U.S. monetary shocks. Using these shocks as exogenous instruments, we further show that the actions to manage capital flows are indeed effective in altering portfolio flows, which helps justify their use.

Two important deviations from the literature account for the differences between our results and previous empirical findings. First, we focus on the *quarterly changes* in the number of capital flow management policies for a group of EMEs, using the novel dataset of Pasricha et al. (2018). Whereas most previous studies focus on the *presence* of capital controls, as measured for example by an annual capital control index, changes in the number of capital flow management policies measure the time-varying intensity of capital flow management, and are therefore a good gauge of the cyclical dynamics of these policies. The commonly used capital control indexes largely result in two broad groups: advanced economies with no capital controls, and EMEs that have controls. Within each group, the indexes usually have little time and cross-country variations. Although these indexes are good indicators of whether or not capital controls exist, they are not suitable for

[3]See Magud et al. (2018) and Erten et al. (forthcoming) for surveys on the topic.

[4]Other recent examples of negative or mixed findings include Klein (2012) and Forbes et al. (2016).

studying whether capital controls respond to shocks.

Second, we use a very powerful and arguably exogenous "push" factor — U.S. monetary policy shocks — to explain the imposition of capital flow management policies and identify their effectiveness. Using these shocks as exogenous instruments helps us resolve a classic simultaneity problem: it is hard to identify the causal effect of capital controls on capital flows when countries with more volatile flows are also more likely to impose controls. Our instrumental variable approach overcomes this simultaneity by applying the key insight of works such as Rey (2013) and Miranda-Agrippino and Rey (forthcoming) that global factors, for instance U.S. monetary policy shocks, bring about global financial cycles that lead to excessive surges and retrenchments in capital flows in "periphery" countries, which in turn necessitates the use of capital flow management. Indeed, we show empirically that EMEs take capital flow management actions in response to unanticipated U.S. monetary shocks in the prior quarter; in turn, capital flow management actions propagated by these shocks alter portfolio flows in the intended direction in the following quarter. This timeline in our empirical study and our choice of monetary policy measures help to minimize the possibility that monetary policy shocks affect capital flows through channels other than the shocks' effects on capital flows management.

We measure U.S. monetary policy shocks as the changes to the two-year on-the-run Treasury yield over a short time window that surrounds FOMC announcements.[5] For a panel of 15 EMEs, we first regress the number of capital flow management actions in quarter t on these shocks in quarter $t-1$ and other pre-determined variables. We show that for the average EME, a "dovish" ("hawkish") U.S. monetary policy shock of one percentage point results in a 1.7 standard deviation increase (decline) in the "net-net" number of capital inflow reducing actions in the following quarter.[6] We then include U.S. monetary policy shocks as instruments in a panel generalized method

[5] In a robustness check, we also include the shocks extracted from 10-year Treasury yields to capture monetary policy shocks to long-term interest rates.

[6] Aizenman and Pasricha (2013) find that EMEs modify capital controls in response to capital inflow pressures. Pasricha (2017) documents that the capital control policies in 21 EMEs react to both the currency appreciation pressures against their trade competitors and the domestic macroprudential motivations. However, these studies do not

of moments (GMM) framework where the dependent variable measures portfolio flows into and out of the 15 EMEs in quarter $t + 1$. The estimated causal effect in our baseline specification suggests that a one standard deviation increase in the "net-net" number of inflow reducing actions in quarter t, which is in response to a dovish U.S. monetary policy shock in quarter $t - 1$, causes a two-fifths of a standard deviation decline in "net-net" portfolio inflows in the next quarter $(t + 1)$. This estimate is robust to various alternative specifications.

In uncovering this causal effect, we rely on the exclusion restriction that U.S. monetary policy shocks cannot influence capital flows outside of their impact on capital flow management. While one might be concerned that investors could react to U.S. monetary shocks by altering their flows to EMEs regardless of capital flow management, we alleviate this concern in our identification scheme by using U.S. monetary policy shocks in quarter $t - 1$ to instrument capital flow management at t, with the goal of estimating the response of capital flows in quarter $t + 1$. Since the monetary policy shocks we use are unexpected changes to yields within a short (30-minute) window around FOMC announcements, we view it as unlikely that such shocks have direct impact (i.e., not through their effects on capital flow management) on capital flows as far ahead as two quarters later. And while it is well-known that exclusion restrictions cannot be directly tested, we nonetheless find some empirical support for this assumption in data.[7] In any case, a failure of this exclusion restriction actually *strengthens* our result—the fact that we detect a *decrease* in net-net capital inflows following a tightening of capital flow management in spite of a supposed boost to inflows due to an easing monetary policy shock suggests that if anything, we may have *underestimated* the causal effect of interest. In other words, even if our exclusion restriction does not hold, it is likely the case that our results cannot be overturned qualitatively.

Delving into the drivers behind our results of net-net capital inflows, we document a couple of

connect the capital controls directly to U.S. monetary shocks.

[7]We find that our main results are not driven by monetary shocks' effect on capital flows through alternative channels such as the interest rate, equity returns and home prices. The empirical support we found are consistent with the finding in Fratzscher et al. (2009), Fratzscher et al. (2016), Chari et al. (forthcoming), and other papers that the impact of U.S. monetary policy shocks on capital flows lasts for only one quarter following the shocks.

interesting asymmetries. In these exercises, capital inflows and outflows are examined separately in response to different U.S. monetary shocks (dovish versus hawkish shocks) since inflows and outflows are of different types. The first asymmetry is that our key result of net-net capital inflows is driven by the effectiveness of net inflow tightening actions applied on *non-residents* in altering net portfolio inflows from abroad, whereas we could not find evidence that net outflow easing actions applied on *residents* react to U.S. monetary policy shocks.[8] Focusing on the role of net inflow tightening actions applied on non-residents, a second asymmetry we find resonates with the "2.5-lemma" paradigm of Han and Wei (2018) — EMEs tend to take actions to stem inflows when the U.S. eases monetary policy and these actions are indeed effective in stemming inflows, whereas there is no statistically significant evidence that actions are taken when the U.S. tightens monetary policy. This finding suggests that capital flow management policies may be preemptive: if the policy succeeds fending off the capital inflows driven by the U.S. easing policy, EMEs that adopt the policy may face less pressure to stabilize their financial markets when the U.S. reverses its monetary policy. For instance, Ostry et al. (2012) find that during the global financial crisis, economies with stronger pre-crisis capital controls or foreign exchange-related prudential measures were in general more resilient.

It is important to clarify the issues that this paper does not address. Although we provide empirical evidence that capital flow management in EMEs react to U.S. monetary policy shocks and that the actions alter portfolio flows, our empirical results do not say anything about which types of capital controls are optimal under what circumstances, nor anything about the practical implementation challenges associated with using capital flows management—such as complexity, credibility, and coordination with other policies, as stipulated by Mendoza (2018) in the broader context of macroprudential policies.[9] A number of recent studies is helpful in this regard: Coimbra

[8]In a related study, Zeev (2017) finds that capital inflow controls help to stabilize a country's output—rather than capital flows—in response to global credit supply shocks, while no such evidence exists for capital outflow controls.

[9]See, for instance, Bianchi and Mendoza (2018) for a detailed treatment of the problem of time inconsistency for macroprudential policies.

and Rey (2017) and Coimbra and Rey (2018) provide early warning indicators to policymakers and help facilitate more optimal deployment of capital controls, while Wei and Zhou (2018) find that institution qualities such as public governance are key to the effectiveness of capital flow management.

Our study does not assess the costs of capital controls, such as a loss in financial market efficiency and an increase in risks related to say shadow banking activities.[10] Finally, our empirical framework does not directly test if the use of capital controls improves a country's monetary policy autonomy, which is the subject of Han and Wei (2018) and Aizenman et al. (2020).

The remainder of the paper is arranged as follows. Section 2 introduces the data. Our econometric strategy is outlined in section 3. Key results and robustness checks are presented in section 4, followed by an exploration of the drivers behind the key results in section 5. Section 6 concludes.

2 Data

Our dataset contains the following 15 EMEs: Argentina, Brazil, China, Colombia, India, Indonesia, Malaysia, Mexico, Peru, Philippines, Russia, South Africa, South Korea, Thailand, and Turkey. Pasricha et al. (2018) collected capital control actions taken by these EMEs, which are suitable for our study since they have largely floating exchange rate regimes.[11] The capital controls data is then merged with information on portfolio flows, macroeconomic indicators, and U.S. monetary policy shocks.

The dataset of Pasricha et al. (2018) includes some macroprudential policy changes that are not conventional capital control policies, which may accentuate the countercyclicality of actions in

[10]For instance, Alfaro et al. (2017) and Forbes (2007) find that capital controls increase financial constraints and reduce real investment for small and mid-sized firms.

[11]The dataset of Pasricha et al. (2018) contains 18 countries. Chile, Egypt, and Morocco are excluded in our regression analysis because the data for these countries showed that they took very few capital control actions, although we include these countries in certain charts for comparison purposes. In Table A.1 of the online appendix, we show that our results are robust to excluding China from the sample, whose currency is managed against the U.S. dollar to varying degrees throughout our sample.

their dataset. We address this concern in one of our robustness checks.

2.1 Changes in capital control policies

To capture capital controls, we use the data of Pasricha et al. (2018), who collected the capital control *actions* between January 2001 and December 2018.[12] This dataset departs in several important respects from other available measures of capital controls. First, other datasets on capital controls are usually indices on extensive margins (i.e., how many types of transactions are regulated), while the data of Pasricha et al. (2018) include both extensive and intensive margins — the data captures the number of control *actions* taken over time, thus providing information about the intensity of capital controls. Using similar data that provides information about intensive margin of capital controls, Aizenman and Pasricha (2013) and Pasricha (2017) find that the changes in capital controls are countercyclical, in contrast to the acyclical finding in studies that focus purely on extensive margins, such as that of Fernandez et al. (2015). In contrast, Acosta-Henao et al. (2020) find that capital controls do not change frequently in 21 emerging markets, even after they consider both intensive and extensive margins of the policy. The major difference between their data and the one in Pasricha et al. (2018) is that they measure the intensity of controls by constructing the de jure tax rate of controls. As a result, Acosta-Henao et al. (2020) have to focus on two specific controls: unremunerated reserve requirements and taxes on inflows/outflows, while Pasricha et al. (2018) include all capital control measures on the Balance of Payment. This difference may explain why Acosta-Henao et al. (2020)'s capital control measure displays less time variations than that of Pasricha et al. (2018).[13]

Second, the *quarterly* dataset of Pasricha et al. (2018) provides more time series variations

[12] The data was downloaded from `http://www.nber.org/papers/w20822`.

[13] Separately, Zhou (2017) collects changes in capital controls around financial crises and demonstrates that capital controls tighten during times of financial crisis. Her measure of capital control changes seems to have substantially more time variations, especially for those aimed at slowing down inflows, than other capital control measures such as those in Quinn et al. (2011) and Fernandez et al. (2016).

needed in an analysis of the cyclical behaviors of capital flow management policies and capital flows, a marked improvement over the annual capital control indices commonly used in the literature. Last but not least, the data of Pasricha et al. (2018) improves the comparability of policy actions over time and across countries by determining and eliminating policy actions that are insignificant; in addition, they also provide weighted versions of measures that reflect the importance of asset classes involved — that is, the measure of the stance of capital controls is not purely based on a count of the number of actions taken, but rather recognizes the economic impact they leave.

Each policy action is categorized by Pasricha et al. (2018) into one of four categories: inflow easing, inflow tightening, outflow easing, and outflow tightening. The following variables are available for each country c and quarter t:

- $IE_{c,t}$ is the number of actions taken to ease capital inflow controls on non-residents;
- $IT_{c,t}$ is the number of actions taken to tighten capital inflow controls on non-residents;
- $OE_{c,t}$ is the number of actions taken to ease capital outflow controls on residents;
- $OT_{c,t}$ is the number of actions taken to tighten capital outflow controls on residents.

Weighted versions of these four variables, $WIE_{c,t}$, $WIT_{c,t}$, $WOE_{c,t}$ and $WOT_{c,t}$, respectively, are constructed by weighting each action by the magnitude of the investment type it influences.[14] This is necessary because unweighted variables may present a biased view of capital controls if the actions taken focus on investments that are not very economically relevant. In our empirical work, we focus on non-FDI investment types that are most relevant for portfolio flows, and use both unweighted and weighted measures.

From the above four variables, Pasricha et al. (2018) further calculate measures of net changes in capital control policies:

[14] The investment types captured are portfolio debt, portfolio equity, foreign direct investment (FDI), financial derivatives, and other investments.

- $NIT_{c,t} \equiv IT_{c,t} - IE_{c,t}$ is the net number of inflow tightening actions applied on non-residents;
- $NOE_{c,t} \equiv OE_{c,t} - OT_{c,t}$ is the net number of outflow easing actions applied on residents;
- $NNKIR_{c,t} \equiv NIT_{c,t} + NOE_{c,t}$ is the "net-net" number of capital inflow reducing actions.

The weighted counterparts of these three variables are $WNIT_{c,t}$, $WNOE_{c,t}$ and $WNNKIR_{c,t}$, respectively.[15] Figure 1 plots, across the 18 countries, how $NNKIR_{c,t}$ has evolved over time. One can observe that some countries, such as India, have used actions more proactively than others, such as Mexico. Over time, it appears that actions are more frequent during and after the financial crisis than before.[16] By definition, a positive value of $NNKIR_{c,t}$ indicates that more capital inflow reduction measures were adopted than capital outflow inducing measures and vice versa. The fact that $NNKIR_{c,t}$ tends to be more positive than negative in our data suggests that countries were more focused on preventing portfolio inflow surges than putting up "gates" to prevent outflows; the exceptions seem to be China and India, which have been proactive in preventing outflows particularly after the Taper Tantrum in 2013.

[*Figure 1 here.*]

2.2 U.S. monetary policy shocks

Our identification strategy posits that capital control actions react to exogenous U.S. monetary policy shocks. These shocks cannot be appropriately measured by quarterly changes in the federal funds rate target range, as monetary policy in the post-crisis period is no longer represented by

[15] Pasricha et al. (2018) also defines $NKIR_{c,t} \equiv IT_{c,t} + OE_{c,t}$, the net number of inflow reducing actions, and $NKII_{c,t} \equiv IE_{c,t} + OT_{c,t}$, the net number of inflow inducing actions. Another way to define $NNKIR_{c,t}$ is therefore $NNKIR_{c,t} \equiv NKIR_{c,t} - NKII_{c,t}$.

[16] Naturally, the pre- and post-crisis paradigm shift raises the question about whether the effects of capital controls on portfolio flows have changed. We show that our estimated causal effects are present both pre- and post-crisis in Table A.3 of the online appendix.

just the funds rate. The stance of policy is now a combination of the target range, forward guidance, and the degree of unconventional policy, namely the rise of quantitative easing programs and their subsequent wind-down.[17] In addition, with far more active communications from the Federal Reserve since the crisis, changes in the funds rate target are now well anticipated by market participants and do not appropriately measure "surprises" in monetary policy communications, such as unanticipated inclusions of certain words in the post-FOMC meeting statement or changes to the Fed's rate projections, which may prompt capital control actions.

A more credible measure of the U.S. monetary policy shocks can be derived from event studies. In Hanson and Stein (2015) and Gilchrist et al. (2015), for example, monetary policy shocks are defined as the changes of the two-year nominal U.S. Treasury yield within a 30-minute window — typically 10 minutes before and 20 minutes after — of FOMC announcements. The underlying assumption is that the FOMC announcements are the only news that drive asset prices that are sensitive to U.S. monetary policy shocks (e.g., U.S. Treasury bonds) in such a short window, and thus changes in the two-year yield capture the magnitude of the market surprise about the FOMC's decisions.

Based on the historical schedule of FOMC meetings, there are at least two monetary policy shocks per quarter; we denote the first shock y_t^1 and the second shock y_t^2.[18] During extraordinary times, however, there may be more policy announcements than those associated with the two regular meetings. For instance, on November 25, 2008, the FOMC announced the first round of large-scale asset purchases after a non-regular meeting as the impact of of Lehman Brothers' collapse reverberated across markets and started to affect economic performance. When they exist, we denote these third and fourth shocks y_t^3 and y_t^4, respectively.

[17] Against this backdrop, the use of "shadow rate" measures such as that of Wu and Xia (2016) has become more popular. We discuss the shadow rate more in section 3.1.

[18] There are eight scheduled FOMC meetings per year; in each quarter, the first meeting typically occurs about one month into the quarter, while the second occurs about half a month before the end of the quarter. A full list of announcements can be found on https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm.

Figure 2 displays U.S. monetary policy shocks identified using the event study methodology, expressed in percentage points changes in the two-year Treasury yield within the 30 minute window. As evident, y_t^3 and y_t^4 — the green and orange bars, respectively — are present, although they only appear during very bad times. While we include these third and fourth shocks in Figure 2 as an illustration of monetary policy decisions, their sparseness means that we cannot include them in regression analyses below.

[*Figure 2 here.*]

Monetary policy shocks can be either "easing shocks" (yield goes down) or "tightening shocks" (yield goes up). An easing (tightening) shock is often referred to as a "dovish" ("hawkish") surprise from the Fed. Throughout our sample period there is a balance of both easing and tightening shocks, which suggests that the Fed delivered unexpected news about monetary policy on both sides. For example, during the thick of the financial crisis, an unscheduled FOMC conference call on March 10, 2008 induced a big rise in yields (the big green bar during the crisis in chart 2) as the FOMC did not deliver on a rate cut when it was revealed to the market that the call took place—rather, the FOMC announced swap lines with other central banks, as well as several liquidity facilities. In contrast, nine months later on December 16, 2008, the FOMC cut rates from 1 percent to the zero lower bound target range of 0 to 0.25 percent, and offered the forward guidance that "[...] economic conditions are likely to warrant exceptionally low levels of the federal funds rate for some time. ", which delivered more accommodation than the market expected and led to a 17 basis points monetary policy easing shock (the big orange bar during the crisis in chart 2). The monetary policy shocks during our sample period of 2000 to 2015 are essentially not serially correlated (correlation between shock and the previous shock is 0.04).

In part reflecting enhanced communications by the Federal Reserve since the financial crisis, shocks have generally become smaller since 2010. That said, the magnitude of y_t^2 has generally become larger than that of y_t^1 over time, which could be due to the fact that since June 2012, the so-called "dots", or the FOMC's projections of the federal funds rate path, are released in conjunction with the post-meeting statement for the second regular meeting of each quarter; the dots generally elicit substantial market attention and asset price reactions.

2.3 Portfolio flows

Like many other studies of capital flow dynamics, we employ portfolio flows from the IMF's International Financial Statistics (IFS). Of the four categories of capital flows available — FDI, portfolio, derivative and "other" — we focus on portfolio flows predicated on two facts. First, portfolio flows, which consist primarily of equity and bond investments, have accounted for much of the recent increase in global capital flows as documented in Evans and Hnatkovska (2014); these flows greatly influence the economic fate of EMEs, as discussed by Forbes and Warnock (2012) and others. Second, portfolio flows are also the main targets of capital control actions, the effectiveness of which is the key interest of this paper. For instance, the effect of removing capital controls on portfolio equity flows is studied in Henry (2000a), Henry (2000b) and Bekaert et al. (2005), among others.[19]

Merging the IFS data with the capital controls data described in section 2.1 results in a quarterly dataset from the first quarter of 2001 through the third quarter of 2015 for 18 EMEs. There are three types of portfolio flows data: **portfolio flows on the liability side** ($P^L_{c,t}$), which are net purchases of domestic assets by non-residents, **portfolio flows on the asset side** ($P^A_{c,t}$), which are net purchases of foreign assets by residents, and **net-net portfolio flows** ($P^N_{c,t}$), the difference of the two. All portfolio flows data are in the U.S. dollars. These flows are likely commensurate with capital control action variables $NIT_{c,t}$, $NOE_{c,t}$, and $NNKIR_{c,t}$, respectively. Figure 3 shows the z-scores of $P^N_{c,t}$, across the 18 EMEs.

[*Figure 3 here.*]

[19]The portfolio flows can be further decomposed into portfolio debt and portfolio equity flows. Our findings hold in both types of portfolio flows and results are reported in Table A.2 of the online appendix.

As can be seen, the quarterly net-net portfolio flows have generally become larger in magnitude over time, reflecting the so-called “risk on” sentiment by investors in advanced economies after the financial crisis. That said, the Taper Tantrum in 2013 seems to have led to substantial net-net outflows in many countries. Nonetheless, the flows across the countries in our panel showed divergence toward the end of the sample period: while countries in Emerging Asia seem sensitive to the episode of renminbi devaluation and the associated capital flight from China in 2015, countries in Latin America saw strong net-net inflows.

In addition to using the z-scores of $P^N_{c,t}$ as our main dependent variable, throughout the paper, we also use the z-scores of portfolio flows as a percentage of trend nominal GDP obtained using a two-sided Hodrick-Prescott filter ($GDP^*_{c,t}$) as an alternative dependent variable, since it is reasonable to posit that flows expressed in dollars get larger as the economy grows.[20]

2.4 Other country fundamentals

Since portfolio flows are influenced by country fundamentals, we merge capital controls and portfolio flows data with the following variables: $\pi_{c,t}$, the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$, the real GDP growth rate calculated as the year-on-year change in real GDP; $CA_{c,t}$, the current account balance in U.S. dollars; $s_{c,t}$, the nominal exchange rate, expressed as the units of the local currency per U.S. dollar. We standardized $CA_{c,t}$ using $GDP^*_{c,t}$.

Table 1 presents the mean and standard deviation of these fundamental variables for each country, together with $NNKIR_{c,t}$ and $\left(\frac{P^N}{GDP^*}\right)_{c,t}$. Some cross-sectional variation can be seen: while some EMEs such as Argentina, Russia and Turkey have had inflation problems, others such as South Korea, Malaysia and Thailand have enjoyed low inflation and stable growth. Countries with high inflation also saw the largest average exchange rate depreciations; perhaps not surprisingly,

[20]The appropriateness of HP-filtering has been debated, see Hamilton (2018) for example. In Table A.6 of the online appendix, we show that the main results are largely unchanged when the procedure of Hamilton (2018) is used instead to estimate $GDP^*_{c,t}$.

Argentina and Russia saw average net portfolio outflows. Currencies appreciated in the countries with high economic growth, current account surplus and net portfolio inflows such as China and Thailand.

[*Table 1 here.*]

3 Methodology

In obtaining estimates of the causal effect of capital flow management on portfolio flows, the key challenge is a classic simultaneity problem: changes in capital controls may quell excessive portfolio flows, but countries with excessive flows are likely to impose more capital controls. This simultaneity means that a simple regression of portfolio flows on capital control actions yields biased estimates of the causal effect of interest. Instead, our strategy is built on the insight of Rey (2013) and Han and Wei (2018) who concluded that in the face of shocks from advanced economies, particularly monetary policy shocks, a flexible exchange rate alone is inadequate in absorbing these shocks and that EMEs necessarily need to impose countercyclical capital controls. In this section we discuss the use of U.S. monetary policy shocks as instruments for capital control actions.

3.1 Monetary policy shocks as instruments for capital controls

The key assumption behind our identification strategy is that EMEs will take capital control actions when they are confronted with U.S. monetary policy shocks. A dovish shock may prompt authorities to take actions to stay ahead of net inflows, which could be due to non-resident investors trying to gain relatively high returns in EMEs and/or domestic residents repatriating money home as U.S. yields become less attractive. In contrast, a hawkish shock may prompt authorities to increase controls on net outflows, as non-resident flows may "stop" while residents flow may "flight", in the parlance of Forbes and Warnock (2012).[21]

We find that this hypothesis receives empirical support in our data. Following the literature, we start with the analysis on net-net capital control actions and their effects on net-net portfolio flows. Net-net portfolio flows drop significantly below their mean and induce the collapse of the credit and asset prices during emerging-market financial crises such as Sudden Stops.[22] Policymakers in emerging markets usually pay close attentions to net-net capital flows and are prompted to impose additional capital controls when there are large net-net flows leaving the country. For instance, Korinek and Sandri (2016) argue that capital flows can increase the aggregate net worth of the economy by reducing net inflows over economic booms, which makes the economy less vulnerable to sudden stops and excessive currency depreciations during recessions.

The results based on net-net capital flows may not reveal enough information for the policy-making purpose as inflows and outflows are of different types and may need different policies. For instance, inflows and outflows are owned by different agents, triggered by different motivations, and responding to different policies. In particular, Broner et al. (2013) emphasized the importance of the behaviors of gross capital flows in understanding the sources of fluctuations in net-net capital flows and the effects of capital control policies. Therefore, in the second set of empirical exercises, we break the net-net capital control actions into the actions on net inflows from non-residents, $NIT_{c,t}$, and the actions on net outflows by residents, $NOE_{c,t}$. Then we examine their effects on non-resident and resident portfolio flows, respectively.

Our empirical results generally suggest that emerging-market economies adjust capital flow management in response to U.S. monetary policy shocks and such policy actions influence future portfolio flows. Specifically, we first regress $NNKIR_{c,t}$, the net-net number of inflow reducing actions, on U.S. monetary policy shocks in the previous quarter and some pre-determined regres-

[21] Examples of early studies on Sudden Stops and capital flights include Faucette et al. (2005) and Mendoza (2010), among others.

[22] For instance, see Mendoza (2010) and Calvo et al. (2006).

sors in the first stage of our methodology:

$$NNKIR_{c,t} = \theta_c + \gamma_1 y^1_{t-1} + \gamma_2 y^2_{t-1} + \Gamma' \mathbf{Z}_{c,t-1} + \xi_{c,t}. \tag{1}$$

In equation (1), θ_c is a country fixed effect; y^1_{t-1} and y^2_{t-1} are the first and second monetary policy shocks in the previous quarter, respectively; and $\mathbf{Z}_{c,t-1}$ is the vector of pre-determined (in a time series sense) country fundamentals discussed in Section 2.4:

$$\mathbf{Z}_{c,t-1} \equiv [\pi_{c,t-1}, g_{c,t-1}, \Delta(CA/GDP^*)_{c,t-1}, \Delta \ln s_{c,t-1}]'.$$

The economic fundamentals in $\mathbf{Z}_{c,t-1}$ are among the widely-believed important drivers of capital controls. For instance, Forbes et al. (2015) argues that countries adjust capital flow management measures in response to changes in variables that capital controls are intended to influence such as exchange rate movements, inflation, portfolio inflows and financial fragilities. We included many other variables in the original regressions, but most of them are not statistically significant and are removed from our final regression. The setup in equation (1) assumes that upon observing fundamentals and monetary policy shocks from quarter $t-1$, authorities in EMEs decide whether to impose additional capital controls in quarter t. For ease of comparisons, all variables in equation (1), except for y^1_{t-1} and y^2_{t-1}, are standardized by country-specific mean and standard deviation (i.e., z-scores are used in these regressions.)[23]

Table 2 shows the results of this first-stage regression for the 15 emerging markets in our sample.[24] Country fundamentals $\mathbf{Z}_{c,t-1}$ being absent (column (1)) or present (column (2)) does not affect that the coefficient on the second U.S. monetary policy shock, y^2_{t-1}, by very much. Changing the dependent variable to the weighted version of capital control actions (column (4))

[23] To validate that this transformation — done at the country-level — is not driving the results, Table A.4 of the online appendix shows the results do not change qualitatively when the variables are not transformed.

[24] As discussed in Section 2, we removed Egypt, Mexico and Morocco because of their very limited number of capital control actions over the sample period.

also does not affect the results. Because y^2_{t-1} is expressed in percentage points, its coefficient in column (2), our preferred specification, suggests that a dovish monetary shock that culminates to a 1 percentage point decline in the two-year Treasury yield results in a 1.7 standard deviation increase in $NNKIR_{c,t}$. Therefore, on average, EMEs impose more inflow reducing measures when there is a perception that monetary policy in the U.S. has eased.[25]

[*Table 2 here.*]

One question that arises from the first-stage regressions in Table 2 is why the second monetary policy shock of the quarter, y^2_{t-1}, is statistically significant, while the first shock y^1_{t-1} is not. There are two possible reasons for this: first, since the second shock is closer to the following quarter t, EMEs could be more sensitive to this shock when deciding $NNKIR_{c,t}$. A second reason could be that as discussed in Section 2.2, since June 2012, the second shock is associated with the meetings when the FOMC releases its projections for the path of interest rates along with the statement, which typically elicited larger market reactions (see Figure 2). So, for about 30 percent of our time series, the second meeting of each quarter has plausibly exerted more influence on EMEs than the first.[26]

To further demonstrate the quality of our instruments, column (3) of Table 2 shows that when these monetary policy shocks are replaced by quarterly changes in the shadow rate of Wu and Xia (2016), a popular measure of the stance of monetary policy during the zero lower bound period, $NNKIR_{c,t}$ is not explained by this alternative measure. This highlights the power of *unanticipated* monetary policy shocks in prompting policy responses from EMEs.

[25] we also ran the first-stage regression using contemporaneous shocks and found a positive association between NNKIR and U.S. monetary policy shocks. This could be because the two variables — now in the same month — are both reacting to news, for instance buoyant economic data in the U.S.

[26] Another possible instrument is the sum of all monetary policy shocks is used as the instrument. For example, if there are two shocks in quarter t, this instrument can be defined as $y^1_t + y^2_t$. Table A.5 of the online appendix contains the result. Not surprisingly, the results are weaker, in part because positive and negative shocks in the same quarter are offset under this method.

3.2 Efficient GMM estimation of the causal effect of controls on flows

Under the instrumental variables setup, the fitted capital control action from equation (1), $\widehat{NNKIR}_{c,t}$, is used as a regressor to explain portfolio flows in the next quarter, $P^N_{c,t+1}$:

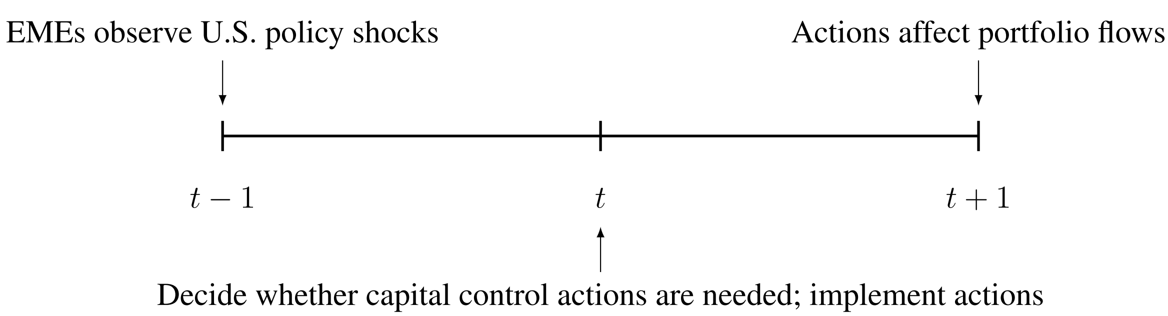
$$P^N_{c,t+1} = \alpha_c + \beta\widehat{NNKIR}_{c,t} + \Psi'\widetilde{\mathbf{Z}}_{c,t} + \sum_{i=0}^{3}\phi_i P^N_{c,t-i} + \varepsilon_{c,t+1}. \tag{2}$$

All variables in equation (2) are expressed in their z-scores and the causal parameter of interest is β. Importantly, equation (2) assumes that capital control actions impact net portfolio flows, but not right away — the impact will be felt in the next quarter as actions take time to implement. This regression also includes pre-determined country fundamentals $\widetilde{\mathbf{Z}}_{c,t}$, defined as:[27]

$$\widetilde{\mathbf{Z}}_{c,t} \equiv \left[\pi_{c,t} - \pi^{U.S.}_{c,t}, g_{c,t} - g^{U.S.}_{c,t}, \Delta(CA/GDP^*)_{c,t}, \Delta \ln s_{c,t}\right]'$$

In particular, the use of $\widetilde{\mathbf{Z}}_{c,t}$ is recognition that while capital control actions may be determined on the basis on a country's own fundamentals, investors will likely look at cross-country differentials in inflation and growth when deciding portfolio allocations. In addition, lags of $P^N_{c,t+1}$ are included in recognition that flows can have momentum, and α_c is the country fixed effect to control for unobserved heterogeneity specific to each country.

The timeline below illustrates the timing of events according to our identification strategy:



[27]Our main results hold when we replace pre-determined country fundamentals with their expected values measured by the IMF's forecasts. Results are available upon request.

Equations (1) and (2) constitute a typical Two Stage Least Squares (TSLS) setup: the key identification assumptions are that the instruments y^1_{t-1} and y^2_{t-1} are not simultaneously determined with $NNKIR_{c,t}$, and that they influence $P^N_{c,t+1}$ only through their effects on $NNKIR_{c,t}$. The former assumption could be tenuous if the FOMC places significant weight on developments abroad when deciding monetary policy, but as we show in Section 4.4, our result still holds when we remove FOMC meeting when developments abroad may have played a role. The latter assumption is the subject of the next section.

Since our model is over-identified — there are more than one instrument in equation (1) — rather than using standard TSLS, we apply efficient generalized method of moments (GMM) to within-transformed variables.[28] With only a moderate number of countries in our panel, rather than clustering our standard errors along the cross-section or time series dimension, we use the spatial correlation consistent standard errors of Driscoll and Kraay (1998) over a window of 12 quarters. As discussed in Cameron and Miller (2015), this standard error is suitable for panels where the number of cross-sectional units is fixed. In all specifications below we report the Sargan-Hansen $J-$statistics, which tests the null of validity of over-identifying restrictions.

4 Empirical findings

In this section, we will show that capital control actions do have a causal effect on net-net portfolio flows. In particular, if more inflow reducing actions are taken, this should reduce net-net inflows, meaning that $\beta < 0$ in equation (2). This section also shows that our key results are robust to various alternative specifications.

[28]Within transformations are used to handle the country fixed effects.

4.1 The key result

Table 3 presents the key results. Column (1) shows the regression in equation (2) without instruments — that is, $NNKIR_{c,t}$ is included as the main regressor instead of the GMM estimation that uses instruments. The coefficient of interest is not statistically significant and has the wrong sign: the positive coefficient estimate suggests that as the net-net number of inflow reducing actions increases, net-net portfolio inflows will *also increase*. This puzzling result may be driven by simultaneity: it could be that higher $NNKIR_{c,t}$ leads to lower $P^N_{c,t+1}$, but at the same time countries with more inflows may impose more inflow reducing measures.[29]

[*Table 3 here.*]

Column (2) is the key result of this paper, which properly identifies the causal effect by using instrumental variable efficient GMM described in Section 3. All variables except the instruments y^1_{t-1} and y^2_{t-1} are converted into z-scores before they enter the regressions. The statistically significant causal coefficient estimate of interest is about -0.4, which suggests that a one standard deviation increase in $NNKIR_{c,t}$ leads to an economically meaningful *decline* of net-net portfolio inflows by more than two-fifths of a standard deviation.[30] When the trend GDP-normalized flows is used as the dependent variable instead (column (3)), the estimated causal impact is little changed. In terms of diagnostic statistics, the Sargan-Hansen $J-$statistics p-value indicates that the null of valid over-identifying restrictions cannot be rejected.

As for the pre-determined economic fundamentals, the signs of the estimated coefficients suggest that a higher inflation differential and depreciating currency reduce net-net inflows, although these relationships are not statistically significant. Higher growth differential and an improving

[29]The fact that capital control actions are measured in time t and flows are measured at time $t+1$ does not absolve this problem, since there is substantial autocorrelation in flows.

[30]We also estimate the *cumulative* net-net portfolio flows—normalized by nominal GDP—in response to an impulse in $NNKIR_{c,t}$, with the latter instrumented by U.S. monetary policy shocks using the methodology of Jorda et al. (2020). The results suggest that the impact of $NNKIR$ on net-net portfolio flows mostly comes through in the first quarter hence, although it is persistent, with no evidence of reversal through six quarters. Details are available upon request.

current account induce net inflows, with the estimate of the former effect statistically significant.

4.2 The exclusion restriction: Are there other channels at play?

Our identification assumption assumes that the monetary policy shocks y^1_{t-1} and y^2_{t-1} influence $P^N_{c,t+1}$ only through their effects on $NNKIR_{c,t}$, commonly known as an exclusion restriction. This could be violated if U.S. monetary policy shocks affect capital flows through other channels besides capital controls. As demonstrated by Angrist and Pischke (2008), such exclusion restrictions cannot be directly tested. Instead, we check whether these shocks might also drive portfolio flows through three alternative channels: an interest rate differential channel and two asset price channels – cross-country differentials in equity returns or home price growth. The intuition for these channels would be that a dovish U.S. monetary policy shock could push up the relative interest rate, equity returns, or home price growth of the EME, and these in turn push capital flows toward it.[31] Our exclusion restriction would therefore be more tenuous if these three channels exist.

To investigate whether any of the three channels are at play, we repeat the first-stage regression, but replace $NNKIR_{c,t}$ with the differential, vis-à-vis the U.S., of the EME's policy interest rate, equity returns and home price growth.[32] The regression results, not reported in the paper but are available upon request, show that U.S. monetary policy shocks affect next quarter's nominal interest rate differential — a dovish (first) shock widens the interest differential as expected, but they do not affect house price growth differential or equity return differential in the following quarter. While prolonged periods of accommodative monetary policy in the U.S. may inflate asset prices in EMEs, the impact of a monetary policy *shock* may not immediately feed through assets in the following quarter.

[31] We thank a referee for recommending us to explore these channels.

[32] Nominal policy interest rates are obtained from the IMF's International Finance Statistics (IFS). Quarterly house price data are from the Bank for International Settlements and the data for equity returns are from Bloomberg and Wind. Like most of the other variables in the paper, all three differential variables were standardized by country-specific mean and standard deviation (i.e., z-scores).

These results suggest that monetary policy shocks may affect portfolio flows through an interest rate channel, other than the capital flow management channel we explore in the paper. Since we have two monetary policy shocks — following the first and second FOMC meetings, respectively, of each quarter — we are able to instrument both $NNKIR_{c,t}$ and nominal interest rate differential to identify the causal effects of these two variables on portfolio flows. The model in column (4) of Table 3 is just-identified, showing estimates of causal effects for both $NNKIR_{c,t}$ and interest rate differential, $i_{c,t} - i_{US,t}$. It is evident that the estimate of the causal effect of capital flow management actions on net-net portfolio flows is qualitatively similar even when nominal rate differential is in the model, which is itself not statistically significant.

We also investigate if EMEs policymakers tighten capital flow restrictions in response to U.S. credit supply shocks — i.e., a different exclusion restriction that credit shocks influence portfolio flows through capital controls — in column (5) of Table 3.[33] Like Ben Zeev (2019), we use the Excess Bond Premium (EBP) of Gilchrist and Zakrajsek (2012) as a measure of credit supply shocks. Monthly data of the EBP is obtained from the Federal Reserve Board's website and is averaged within a quarter to arrive at a quarterly version of EBP. We substitute our instruments in the benchmark model — U.S. monetary policy shocks — with the EBP to instrument for NNKIR. The estimated causal effect in column (3) is that a 1 standard deviation increase in NNKIR reduces net-net portfolio flows by 0.19 standard deviation, which is smaller (and less statistically significant) than the estimates obtained using monetary policy shocks as the instrument. This could be due to the fact that the EBP is a significantly weaker instrument than monetary policy shocks — indeed, in a first stage regression of NNKIR on EBP (and other controls), the *p*-value of the coefficient is 0.099; the R-squared of the first stage regression is also significantly lower than that for monetary policy shocks.

[33] We thank a referee for recommending us this exercise.

4.3 Other types of flows and other measures of capital controls

FDI and "other" flows. One might wonder how the actions captured by $NNKIR$—aimed mostly at financial flows—affect foreign direct investments (FDI). To investigate this, we replace the net-net portfolio flows dependent variable in the key regressions with net FDI flows from the same IMF dataset, $FDI^N_{c,t+1}$, as the dependent variable. Column (2) of Table 4 shows that, contrary our key result using net-net portfolio flows, which is reprinted in column (1), more net-net inflow tightening measures—a larger $NNKIR_{c,t}$—leads to increased FDI flows in the next quarter. This may reflect a substitution effect between FDI and other capital flows as more restrictions imposed on portfolio flows could be an impetus for investors to substitute to FDI inflows. For instance, Wang and Wang (2015) and Alquist et al. (2019) find evidence that FDI is used as vehicle to evade capital controls in emerging markets. This result is also consistent with previous findings that FDI flow is countercyclical, while portfolio flow is procyclical (e.g., Aguiar and Gopinath (2005) and Alquist et al. (2016)).

[*Table 4 here.*]

In addition to portfolio flows, which captures mostly debt and equity flows, "other" flows in the IMF data, which includes bank flows, are also important for EMEs—indeed, for 10 out of the 15 EMEs in our regressions, the standard deviation of quarterly "other" flows is larger than that of portfolio flows when measured in dollar terms. This is also why the dataset of Pasricha et al. (2018) captures prudential control actions.[34] Therefore, we also estimate the causal effect of an increase in $NNKIR$ on *combined* portfolio and "other" flows—$P\&O^N_{c,t+1}$. Column (3) of Table 4 shows that the estimated effect—at 0.34 standard deviations of this combined flows—is only slightly smaller than our key results, shown in column (1). Our hypothesis that more net-net inflow

[34] We thank a referee for pointing this out. The referee also suggested that "derivative" flows might also be relevant, but we omit it from this analysis as data for this type of flow is not available for several countries, and such flows tend to be quite small when compared to portfolio and "other" flows any ways. In the last part of Section 4.4 we parse out these prudential actions from $NNKIR_{c,t}$ so that this key regressor better matches the dependent variable of portfolio flows.

management measure dampens financial inflows.

The importance of intensive margins when measuring capital controls. An alternative dataset for capital flow management often used in the literature is that of Fernandez et al. (2015), which indicates whether capital controls *exist* but does not contain information about the intensive margins of the controls. To demonstrate the importance of capturing intensive margins when assessing capital flow management policies, we repeat the regression using this a measure constructed from Fernandez et al. (2015), and compare the results with our key result. Fernandez et al. (2015) contains indicators — by asset types e.g., equity, bonds — whether restrictions to purchases locally or issuances abroad exist for residents and nonresidents. This definition does not directly map to the data of Pasricha et al. (2018), and therefore we create a measure using the data of Fernandez et al. (2015) that proxies — to the best of our ability — the net-net capital inflow tightening measure in our paper ($NNKIR$). Then we repeat our benchmark regressions by replacing $NNKIR$ with the above proxy in level and in first difference. We cannot find any statistical significance in the regression results, which highlights the importance of including intensive margins in capital control measures.[35]

4.4 Robustness checks

Removing FOMC meetings where there seemed to be concerns about economies abroad. As discussed in Section 3.2, one of the assumptions behind our identification strategy is that the FOMC's decisions on monetary policy and its communications are exogenous to the developments from EMEs. Since the FOMC takes all sorts of information into account when deciding monetary policy, it is difficult to decisively show this exogeneity. However, we can glean from the post-meeting statement the gravity of concerns from abroad to the FOMC's decision at a particular meeting. To

[35]Details about these regressions and their results are available upon request.

this end, we check whether our key result still holds when we remove FOMC meetings for which the post-meeting statement includes the following words: "foreign", "abroad", and "international".[36] Table 5 shows the results of this robustness check.

[*Table 5 here.*]

Column (2) of the table shows that the statistical significance of the causal effect is still present when FOMC meetings for which the development abroad likely played a role were removed from the sample. That said, when compared to our key result, which is reprinted in column (1), the estimated causal effect is smaller, as the meetings that were removed were indeed ones involving significant global issues, such as the large oil price decline in 2014. Normalizing flows by trend GDP does not materially change the estimate of the causal effect, as shown in column (3).

Using the weighted version of $NNKIR_{c,t}$. Pasricha et al. (2018) created a weighted version of $NNKIR_{c,t}$—$WNNKIR_{c,t}$—to better measure the intended impact of capital control actions by recognizing the sizes of the investment types affected (see Section 2.1). Table 6 examines whether the causal effect of capital controls on flows is still valid when capital control actions are measured by $WNNKIR_{c,t}$ instead.

[*Table 6 here.*]

Column (2) of the table shows that when $WNNKIR_{c,t}$ is used as the main regressor, the estimated causal effect actually increases slightly when compared to the key result, which is reprinted in column (1). Normalizing flows by trend GDP does not affect this outcome, as shown in column (3).

Monetary policy shocks measured using longer-term yields. Many monetary policy announcements in the sample period, particularly after the financial crisis, are associated with Fed asset

[36] This method is likely quite conservative, since it encompasses not just EME references, but global developments including Japan and the euro area. For example, there were no meetings in our sample where "emerging economies" were explicitly mentioned in the post-meeting statement.

purchases or *quantitative easing* programs. These unconventional monetary policy programs usually aim to influence longer-term interest rates (e.g., 10-year Treasury yields) and may have a significant impact on international capital flows. For instance, Chari et al. (forthcoming) identify U.S. monetary policy shocks by extracting the unexpected components from the daily changes in five-year Treasury futures on the date of FOMC announcements. The identified shocks are found to exhibit sizable effects on U.S. holdings of emerging market assets. Our monetary policy shocks identified from the two-year Treasury yield may not be able to sufficiently capture shocks to longer-term yields.

In order to take into account the effects of unconventional monetary policy on long-term yields, we follow procedure similar to Gilchrist et al. (2015): we regress the changes to the 10-year Treasury yield within the 30-minute window of the first and second FOMC announcements of the quarter on y^1_{t-1} and y^2_{t-1}, respectively, and use the residuals of these regressions, e^1_{t-1} and e^2_{t-1} as additional instruments. These two additional instruments capture the monetary policy shocks expressed through longer-term interest rates that are *not already* captured by changes in the 2-year yield.

[*Table 7 here.*]

Column (1) of Table 7 shows the first stage regression. As can be seen, e^2_{t-1} in particular explains $NNKIR_{c,t}$, although y^2_{t-1} is more important. As can be seen in columns (2) and (3), our key results do not change qualitatively when e^1_{t-1} and e^2_{t-1} are included as instruments in a subsample that includes both the financial crisis as well as the post-crisis period where QE was abundantly used.

Parsing out prudential policy changes not targeting at portfolio flows. Although difficult to know for sure, it is possible that the dataset of Pasricha et al. (2018) includes changes to certain prudential policy instruments that are not targeted at portfolio flows, such as regulations on the amount of credit risk banks can take. If that is the case, the effects of capital flow management on portfolio flows we identified may be co-mingled with those of countercyclical prudential policies.

Our strategy to alleviate this concern is to show that changes in prudential policies do not significantly influence portfolio flows. To do that, we first obtain changes in prudential policies for our sample of economies from Cerutti et al. (2017), who construct a dataset that captures the intensity of usage of nine common types of prudential tools.[37] We compute a "prudential tightening" variable $PT_{c,t}$ by summing up all positive values across the nine types; a "prudential loosening" variable $PL_{c,t}$ is computed similarly by summing up all negative values. Table 8 shows that $PT_{c,t}$ and $PL_{c,t}$ have only small correlations with the four basic variables in Pasricha et al. (2018), $IT_{c,t}, OT_{c,t}, IE_{c,t}$ and $OE_{c,t}$, indicating that these two data sets are indeed capturing different policy actions.

[*Table 8 here.*]

Table 9 more formally shows that changes in prudential policies are not driving portfolio flows. We begin by constructing a *net* prudential tightening measure akin to $NNKIR_{c,t}$, $NPT_{c,t} \equiv PT_{c,t} - PL_{c,t}$. Column (2) shows that when $NPT_{c,t}$ is used instead of $NNKIR_{c,t}$ as the explanatory variable of interest, it does not significantly reduce portfolio flows at $t+1$.[38] In an even more stringent test, we subtract $NPT_{c,t}$ from $NNKIR_{c,t}$ and use that as the key regressor. The goal of this exercise is to parse out prudential policies from capital control policies in the most conservative way, since the capital control actions in Pasricha et al. (2018) are likely to include only a small fraction of the prudential policies documented in Cerutti et al. (2017), if at all (see Table 8). This variable, $NNKIR_{c,t}^{noprud}$, is the explanatory variable of interest in columns (3) and (4). As can be seen, the effects of the prudential policy-free net-net number of inflow reducing actions

[37] Cerutti et al. (2017) constructs this data for a significantly larger panel of 64 countries.

[38] That said, we found that $NPT_{c,t}$ is indeed countercyclical, in that it increases when there are easing U.S. monetary policy shocks at $t-1$.

on portfolio flows is actually a bit stronger: a one standard deviation increase in this variable reduces net-net portfolio inflows by 0.524 standard deviations (column 3) and trend GDP-normalized net-net portfolio inflows by 0.463 standard deviations (column 4).

[*Table 9 here.*]

5 Drivers of empirical findings

We have shown in Section 4 that an increase in the number of "net-net" inflow reducing actions indeed reduces "net-net" inflows, and this result is robust to a number of alternative specifications. The policy implication of this result is that EMEs could increase $NNKIR_{c,t}$ to temper inflows if needed. But can the policy message be made more precise? The section provides insights into the relative roles of capital control actions taken on non-residents and residents, respectively.

5.1 Breaking down $\mathbf{NNKIR}_{c,t}$ into $\mathbf{NIT}_{c,t}$ and $\mathbf{NOE}_{c,t}$

Recall from Section 2.1 that there are two components to $NNKIR_{c,t}$: the net number of actions taken to tighten net inflows from non-residents, $NIT_{c,t}$, and the net number of actions taken to ease outflows by residents, $NOE_{c,t}$. These two components are displayed in Figure 4.

[*Figure 4 here.*]

As can be seen, in some cases $NIT_{c,t}$ and $NOE_{c,t}$ reinforced each other, for example at the outset of the crisis in Thailand and over the course of the recession in Peru. In other cases, actions are deployed in opposite directions. Pasricha et al. (2018) also document this conflicting nature of capital control policies in EMEs, from the point of view of managing net capital inflows. This could be because actions are taken by different authorities, or they target different types of investments. We also observe that there is a great deal of heterogeneity across countries: whereas India preferred to use $NIT_{c,t}$, Malaysia seems to have used $NOE_{c,t}$ more proactively.

5.2 Asymmetric monetary policy shocks

Since $NIT_{c,t}$ and $NOE_{c,t}$ are deployed in different ways across countries and across time, the natural next question is how these two components of $NNKIR_{c,t}$ react to monetary policy shocks. To explore this case, we inspect the regressions of $NIT_{c,t}$ and $NOE_{c,t}$ on monetary policy shocks, but with one important modification: since one would expect inflow tightening and outflow easing actions to be introduced when there is a dovish shock (and vice versa in the event of a hawkish shock) we decompose the instruments y^1_{t-1} and y^2_{t-1} into these two types of shocks:

$$y^{i-}_{t-1} \equiv y^i_{t-1}\mathbf{1}(y^i_{t-1} \leq 0) \text{ for } i = 1, 2, \text{“dovish” shock} \tag{3}$$

$$y^{i+}_{t-1} \equiv y^i_{t-1}\mathbf{1}(y^i_{t-1} > 0) \text{ for } i = 1, 2, \text{“hawkish” shock.} \tag{4}$$

The usefulness of these asymmetric monetary policy shock instruments are displayed in Table 10.

[*Table 10 here.*]

Column (2) in the table shows the regression of $NNKIR_{c,t}$ on the asymmetric shocks. Compared to the baseline first-stage regression, which is reprinted in column (1), the explanatory power of y^2_{t-1} comes from its dovish part, y^{2-}_{t-1}, and not its hawkish part, y^{2+}_{t-1}. This finding can be viewed as supportive of the concept of a “2.5-lemma” a là Han and Wei (2018) — while a floating exchange rate and other adjustments could insulate a country from the monetary tightening in “center economies”, capital controls need to be imposed when the center economies have a monetary easing.

When $NNKIR_{c,t}$ is decomposed into $NIT_{c,t}$ and $NOE_{c,t}$, in columns (3) and (4), respectively, we observe that while $NIT_{c,t}$ is statistically explained by the dovish shock y^{2-}_{t-1}, $NOE_{c,t}$ is not. This means that upon a dovish shock from the Fed, the average EME tends to take action by increasing the net number of inflow tightening measures applied to non-residents, probably because non-residents would find EMEs more attractive when Fed policy is perceived to have eased.

Column (3) also suggests that net inflow tightening actions are taken on non-resident flows when inflation is low and growth is strong, and when the nominal exchange rate appreciates. In contrast, there is no significant evidence that EMEs adjust net outflow controls on residents in response to U.S. monetary policy shocks. This may be due to the fact that net capital flows in many EMEs are mostly driven by flows of non-resident investors rather than residents. Therefore, it would be more effective to change restrictions on net capital inflows by non-residents to temper large net capital flows.

5.3 Does $\mathbf{NIT_{c,t}}$ affect non-resident portfolio flows?

Having found that monetary policy shocks drive $NNKIR_{c,t}$ because $NIT_{c,t}$ changes during monetary easing episodes, we next turn to the component of $P^N_{c,t+1}$ that responds to $NIT_{c,t}$. Since the capital control actions summarized by $NIT_{c,t}$ are ones that target non-residents, we estimate the impact of $NIT_{c,t}$ on *portfolio liability flows*, $P^L_{c,t+1}$. Recall that these flows represent changes in investments by non-residents. Table 11 shows the key result, along with several robustness checks.

[*Table 11 here.*]

The key estimated causal effect of $NIT_{c,t}$ on $P^L_{c,t+1}$ is presented in column (1). The estimated coefficient suggests that a one standard deviation increase in the net number of inflow tightening actions on non-residents leads to almost nine-tenths of a standard deviation decline in net portfolio flows from non-residents. This result is found to be robust when "concerns abroad" FOMC meetings are removed (column (2)), when the weighted version of $NIT_{c,t}$ is used (column (3)), and when $P^L_{c,t+1}$ is expressed as a percent of trend GDP (column (4)).[39]

To summarize, we found in this section that EMEs increase the net number of inflow tightening actions applied to non-residents when dovish U.S. monetary policy shocks materialize. In contrast, there is no statistically significant evidence that inflow easing actions are taken when tightening

[39]See Section 4.4 for more details on these robustness checks.

shocks arrive. Using this asymmetric relationship, we show that our key result in Section 4.1 is driven by the causal effect that net inflow tightening actions on non-residents reduce their portfolio flows. In contrast, we do not find strong evidence that EMEs change capital controls on residents in response to U.S. monetary policy shocks. However, resident lending and nonresident capital flight become increasingly important for capital flows in many emerging markets, which policymakers should be vigilant about in the future.

6 Conclusions

We find evidence that EMEs adjust their capital flow management in a countercyclical manner in response to the U.S. monetary policy shocks — EMEs increase the "net-net" number of inflow reducing actions when a dovish Fed policy shock materializes. Using these monetary policy shocks as exogenous instruments, we identified the causal effect of capital controls on portfolio flows, showing that a one standard deviation increase in the "net-net" number of inflow reducing actions reduces "net-net" portfolio flows in the following quarter by two-fifths of a standard deviation, using a panel of 15 EMEs. We exploit the cross-country and over-time variations of capital control *actions* using the dataset of Pasricha et al. (2018) to obtain our results. In doing so, we contribute to the literature by providing more definitive evidence that capital flow management actions affect capital flows, and also show that actions tend to be used more intensely when monetary policy eases. The findings of this paper provide empirical support to a policy recommendation that re-emerged after the financial crisis: under appropriate circumstances, countercyclical capital flow management should be used to ameliorate the impact of external shocks. Our results may be used to argue that such capital flow management should be adopted because they are effective in tempering large and volatile global capital flows, particularly restrictions applied to non-residents which is found to affect portfolio liability flows. We also found evidence that capital flow management is used to restriction inflows from non-residents when U.S. monetary policy eases unexpectedly.

This study does not represent a normative assessment of capital controls, as it only shows that capital controls are effective in altering portfolio flows and does not address the potential *costs* associated with capital controls. In addition, our estimates are for the causal effect of an increased use of controls on a given type of flow, and does not differentiate the various forms of controls that are in policymakers' toolkits, for example an outright ban on a type of transaction versus a tax imposed. In this regard, our results are muted on the optimal form or timing of controls; studies providing policymakers with an early warning system to help "time" capital controls may be a promising direction for future research.

References

Acosta-Henao, Miguel, Laura Alfaro, and Andres Fernandez Martin, "Sticky Capital Controls," *NBER Working Papers No. 26997*, 2020.

Aguiar, Mark and Gita Gopinath, "Fire-Sale Foreign Direct Investment and Liquidity Crises," *The Review of Economics and Statistics*, 2005, *87* (3), 439–452.

Aizenman, J. and G. K. Pasricha, "Why do emerging markets liberalize capital outflow controls? Fiscal versus net capital flow concerns," *Journal of International Money and Finance*, 2013, *39*, 28–64.

_ , M. Chinn, and H. Ito, "Financial spillovers and macroprudential policies," *Open Economies Review*, 2020, *31*, 529–563.

Alfaro, L., A. Chari, and F. Kanczuk, "The real effects of capital controls: Firm-level evidence from a policy experiment," *Journal of International Economics*, 2017, *108*, 191–210.

Alquist, Ron, Nicolas Berman, Rahul Mukherjee, and Linda Tesar, "Financial constraints, institutions, and foreign ownership," *Journal of International Economics*, May 2019, *118*, 63–83.

_ , Rahul Mukherjee, and Linda Tesar, "Fire-sale FDI or business as usual?," *Journal of International Economics*, 2016, *98* (C), 93–113.

Angrist, J. D. and J. Pischke, *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton University Press, 2008.

Bekaert, G., C. R. Harvey, and C. Lundblad, "Does financial liberalization spur growth?," *Journal of Financial Economics*, 2005, *77*, 3–55.

Benigno, G., H. Chen, C. Otrok, A. Rebucci, and E. R. Young, "Optimal capital controls and real exchange rate policies: A pecuniary externality perspective," *Journal of Monetary Economics*, 2016, *84*, 147–165.

Bianchi, J. and E. G. Mendoza, "Optimal time-consistent macroprudential policy," *Journal of Political Economy*, 2018, *126*, 588–634.

Broner, F., T. Didier, A. Erce, and S. L. Schmukler, "Cross capital flows: Dynamics and crises," *Journal of Monetary Economics*, 2013, *60*, 113–133.

Calvo, G., A. Izquierdo, and E. Talvi, "Sudden stops and phoenix miracles in emerging markets," *American Economic Review Papers and Proceedings*, 2006, *96*, 405–410.

Cameron, A. C. and D. L. Miller, "A practitioner's guide to cluster-robust inference," *The Journal of Human Resources*, 2015, *50*, 317–372.

Cerutti, E., R. Correa, E. Fiorentino, and E. Segalla, "Changes in prudential policy instruments—A new cross-country database," *International Journal of Central Banking*, 2017, *13*, 477–503.

Chari, A., K. Stedman, and C. Lundblad, "Taper tantrums: QE, its aftermath and emerging market capital flows," *Review of Financial Studies*, forthcoming.

Coimbra, N. and H. Rey, "Financial cycles with heterogeneous intermediaries," *NBER Working Paper No. 23245*, 2017.

_ **and** _ , "Financial cycles and credit growth across countries," *AEA Papers and Proceedings*, 2018, *108*, 509–12.

Davis, S. J. and I. Presno, "Capital controls and monetary policy autonomy in a small open economy," *Journal of Monetary Economics*, 2017, *85*, 114–130.

Driscoll, J. C. and A. C. Kraay, "Consistent covariance matrix estimation with spatially dependent panel data," *Review of Economics and Statistics*, 1998, *80*, 549–560.

Edison, H. and C. Reinhart, "Stopping hot money," *Journal of Development Economics*, 2001, *66*, 533–553.

Erten, B., A. Korinek, and J. A. Ocampo, "Capital controls: Theory and evidence," *Journal of Economic Literature*, forthcoming.

Evans, M. D. D. and V. Hnatkovska, "International capital flows, returns and world financial integration," *Journal of International Economics*, 2014, *92*, 14–33.

Farhi, E. and I. Werning, "Dilemma not trilemma? Capital controls and exchange rates with volatile capital flows," *IMF Economic Review*, 2014, *62*, 569–605.

Faucette, J., A. Rothenberg, and F. Warnock, "Outflows-induced sudden stops," *Journal of Policy Reform*, 2005, *8*, 119–129.

Fernandez, A., A. Rebucci, and M. Uribe, "Are capital controls countercyclical?," *Journal of Monetary Economics*, 2015, *76*, 1–14.

_ , M. W. Klein, A. Rebucci, M. Schindler, and M. Uribe, "Capital control measures: A new dataset," *IMF Economic Review*, 2016, *64*, 548–574.

Forbes, K., "One cost of the Chilean capital controls: Increased financial constraints for smaller traded firms," *Journal of International Economics*, 2007, *71*, 294–323.

_ and F. E. Warnock, "Capital flow waves: Surges, stops, flight, and retrenchment," *Journal of International Economics*, 2012, *88*, 235–251.

_ , M. Fratzscher, and R. Straub, "Capital-flow management measures: What are they good for?," *Journal of International Economics*, 2015, *96*, S76–S97.

—, —, T. Kostka, and R. Straub, “Bubble thy neighbour: Portfolio effects and externalities from capital controls,” *Journal of International Economics*, 2016, *99*, 85–104.

Frankel, J., S. Schmukler, and L. Serven, “Global transmission of interest rates: Monetary independence and currency regime,” *Journal of International Money and Finance*, 2004, *23*, 701–733.

Fratzscher, M., C Saborowski, and R. Straub, “Monetary policy shocks and portfolio choice,” *ECB Working Paper*, 2009.

—, M. Duca, and R. Straub, “On the international spillovers of US quantitative easing,” *Economic Journal*, 2016, *128*, 330–377.

Gilchrist, S., D. Lopez-Salido, and E. Zakrajsek, “Monetary policy and real borrowing costs at the zero lower bound,” *American Economic Journal: Macroeconomics*, 2015, *7(1)*, 77–109.

Gilchrist, Simon and Egon Zakrajsek, “Credit Spreads and Business Cycle Fluctuations,” *American Economic Review*, June 2012, *102* (4), 1692–1720.

Giovanni, J., S. Kalemli-Ozcan, M. Ulu, and Y. Baskaya, “International Spillovers and Local Credit Cycles,” *NBER Working Paper No. 23149*, 2017.

Hamilton, J. D., “Why You Should Never Use the Hodrick-Prescott Filter,” *Review of Economists and Statistics*, 2018, *100(5)*, 831–843.

Han, X. and S. Wei, “International transmission of monetary shocks: Between a trilemma and dilemma,” *Journal of International Economics*, 2018, *110*, 205–219.

Hanson, S. G. and J. C. Stein, “Monetary policy and long-term real rates,” *Journal of Financial Economics*, 2015, *115(3)*, 429–448.

Henry, P. B., “Do stock market liberalizations cause investment booms?,” *Journal of Financial Economics*, 2000, *58*, 301–334.

_ , “Stock market liberalization, economic reform, and emerging market equity prices,” *Journal of Finance*, 2000, *55*, 529–564.

IMF, “Recent experiences in managing capital inflows: Cross-cutting themes and possible framework,” *IMF Policy Paper*, 2011.

Jeanne, O., “Macroprudential policies in a global perspective,” *Paper Prepared for 2013 Asia Economic Policy Conference, Federal Reserve Bank of San Francisco*, 2013, *November.*

_ **and A. Korinek**, “Managing credit booms and busts: a Pigouvian taxation approach,” *Journal of Monetary Economics*, 2019, *107*, 2–17.

Jorda, Oscar, Moritz Schularick, and Alan M. Taylor, “The effects of quasi-random monetary experiments,” *Journal of Monetary Economics*, 2020, *112* (C), 22–40.

Klein, M., “Capital controls: Gates versus walls,” *Brookings Papers on Economic Activity*, 2012, *Fall*, 317–355.

Korinek, A., “Capital controls and currency wars,” *mimeo*, 2011.

_ , “Regulating capital flows to emerging markets: An externality view,” *Journal of International Economics*, 2018, *111*, 61–80.

_ **and D. Sandri**, “Capital controls or macroprudential regulation?,” *Journal of International Economics*, 2016, *99*, S27–S42.

Magud, N., C. Reinhart, and K. Rogoff, “Capital controls: Myth and reality–A portfolio balance approach,” *Annals of Economics and Finance*, 2018, *19*, 1–47.

Mendoza, E. G., "Sudden stops, financial crises, and leverage," *American Economic Review*, 2010, *100*, 1941–1966.

_ , "Macroprudential Policy: Promise and Challenges," in Enrique G. Mendoza, Ernesto Pastn, and Diego Saravia, eds., *Monetary Policy and Global Spillovers: Mechanisms, Effects and Policy Measures*, Vol. 25 of *Central Banking, Analysis, and Economic Policies Book Series*, Central Bank of Chile, November 2018, chapter 7, pp. 225–277.

Miranda-Agrippino, S. and H. Rey, "US monetary policy and the global financial cycle," *Review of Economic Studies*, forthcoming.

Ostry, J. D., A. R. Ghosh, M. Chamon, and M. S. Qureshi, "Tools for managing financial stability risks from capital inflows," *Journal of International Economics*, 2012, *88(2)*, 407–421.

Pasricha, G. K., "Policy rules for Capital Controls," *Bank of Canada Staff Working Papers No. 2017-42*, 2017.

_ , M. Falagiarda, M. Bijsterbosch, and J. Aizenman, "Domestic and multilateral effects of capital controls in emerging markets," *Journal of International Economics*, 2018, *115*, 48–58.

Quinn, D., M. Schindler, and A. M. Toyoda, "Assessing measures of financial openness and integration," *IMF Economic Review*, 2011, *59(3)*, 488–522.

Rey, H., "Dilemma not trilemma: the global financial cycle and monetary policy independence," *Jackson Hole Symposium on Economic Policy*, 2013, pp. 284–333.

Tong, H. and S. Wei, "The composition matters: Capital inflows and liquidity crunch during global economic crisis," *Review of Financial Studies*, 2010, *24(6)*, 2023–2052.

Wang, Jian and Xiao Wang, "Benefits of foreign ownership: Evidence from foreign direct investment in China," *Journal of International Economics*, 2015, *97* (2), 325–338.

Wei, S. and J. Zhou, “Quality of public governance and structure of nations and firms,” *NBER Working Papers No. 24184*, 2018.

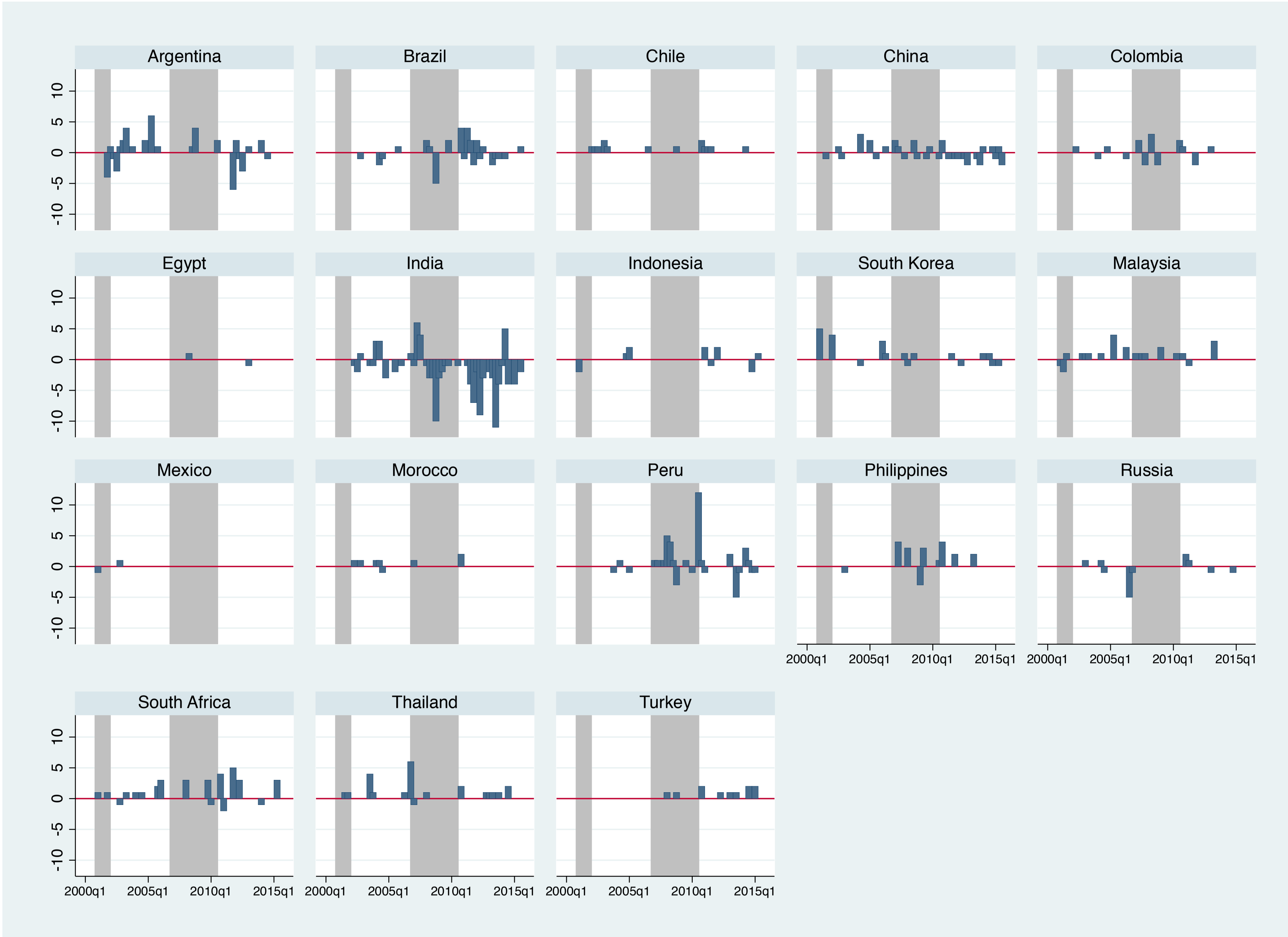
Wu, J. C. and F. D. Xia, “Measuring the macroeconomic impact of monetary policy at the zero lower bound,” *Journal of Money, Credit, and Banking*, 2016, *48(2)*, 253–291.

Zeev, N. Ben, “Capital controls as shock absorbers,” *Journal of International Economics*, 2017, *109*, 43–67.

Zeev, Nadav Ben, “Global credit supply shocks and exchange rate regimes,” *Journal of International Economics*, 2019, *116* (C), 1–32.

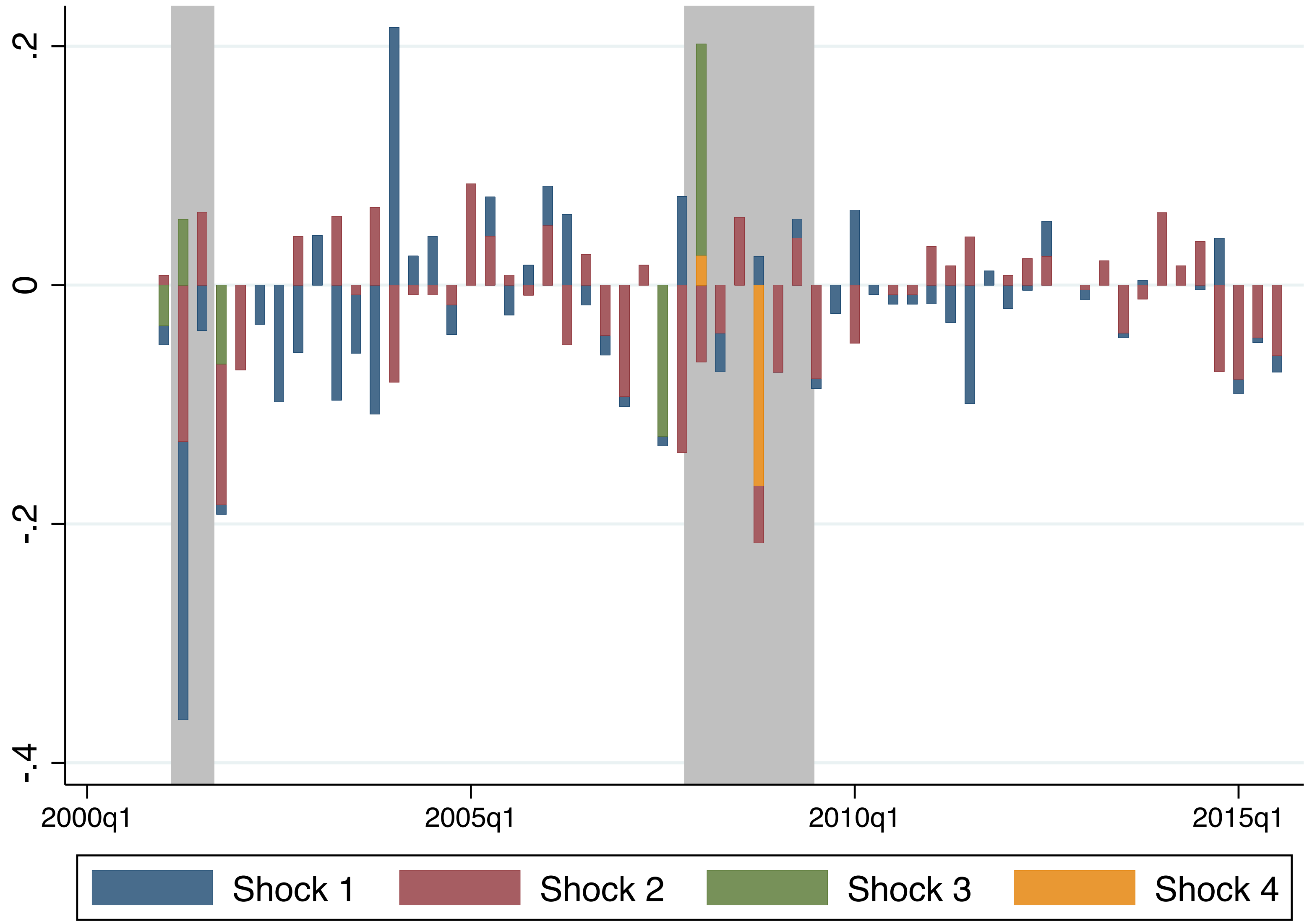
Zhou, J., “Financial crises, debt maturity, and capital controls,” *mimeo*, 2017.

Figure 1: Z-scores of $NNKIR_{c,t}$ across countries and time



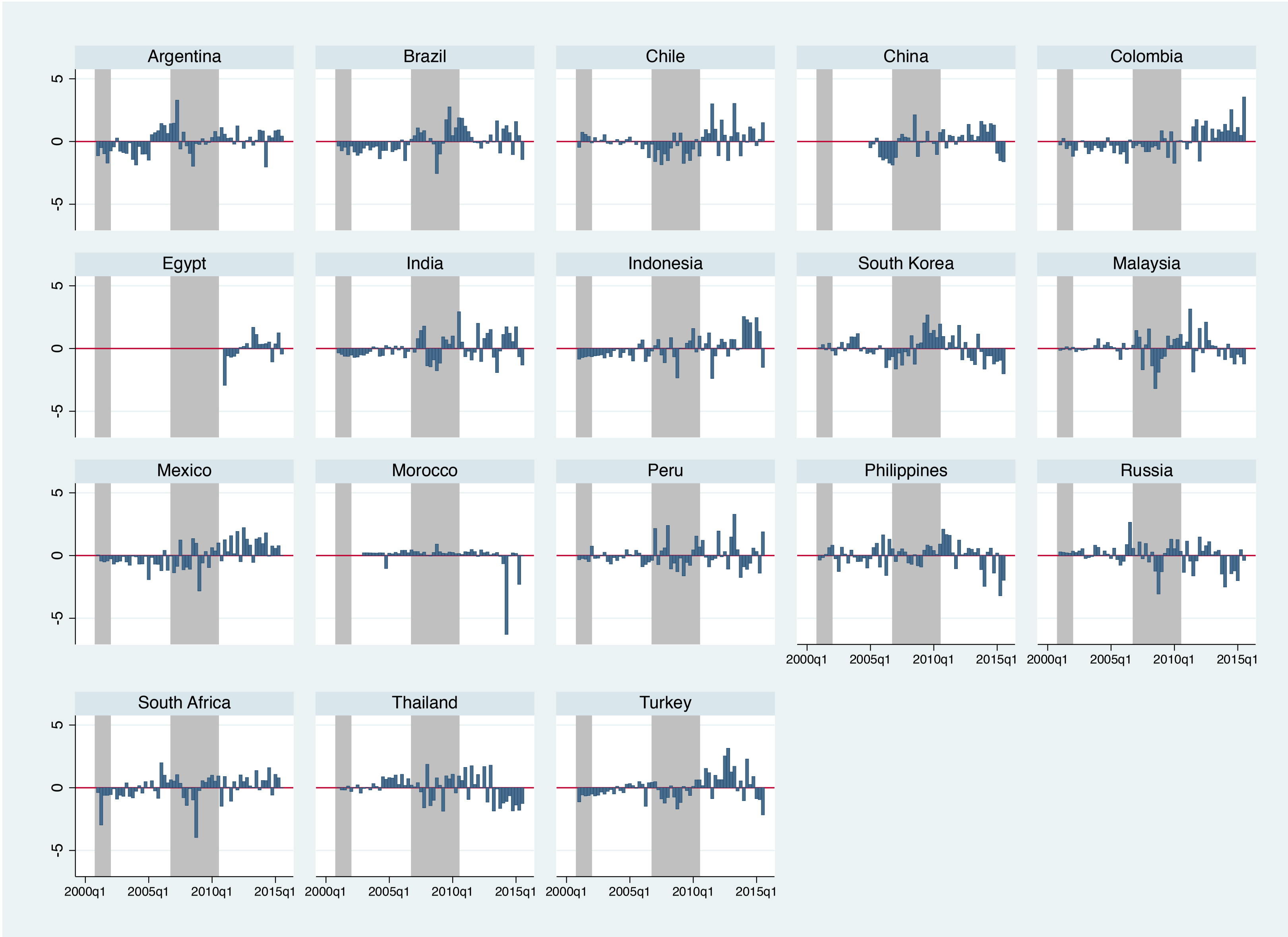
Note: $NNKIR_{c,t}$ is the number of net-net capital inflow reducing actions calculated according to the description in section 2.1, using the data of Pasricha et al. (2018). NBER recessions are indicated by the shaded grey time periods.

Figure 2: y_t^1, y_t^2, y_t^3 and y_t^4 across time



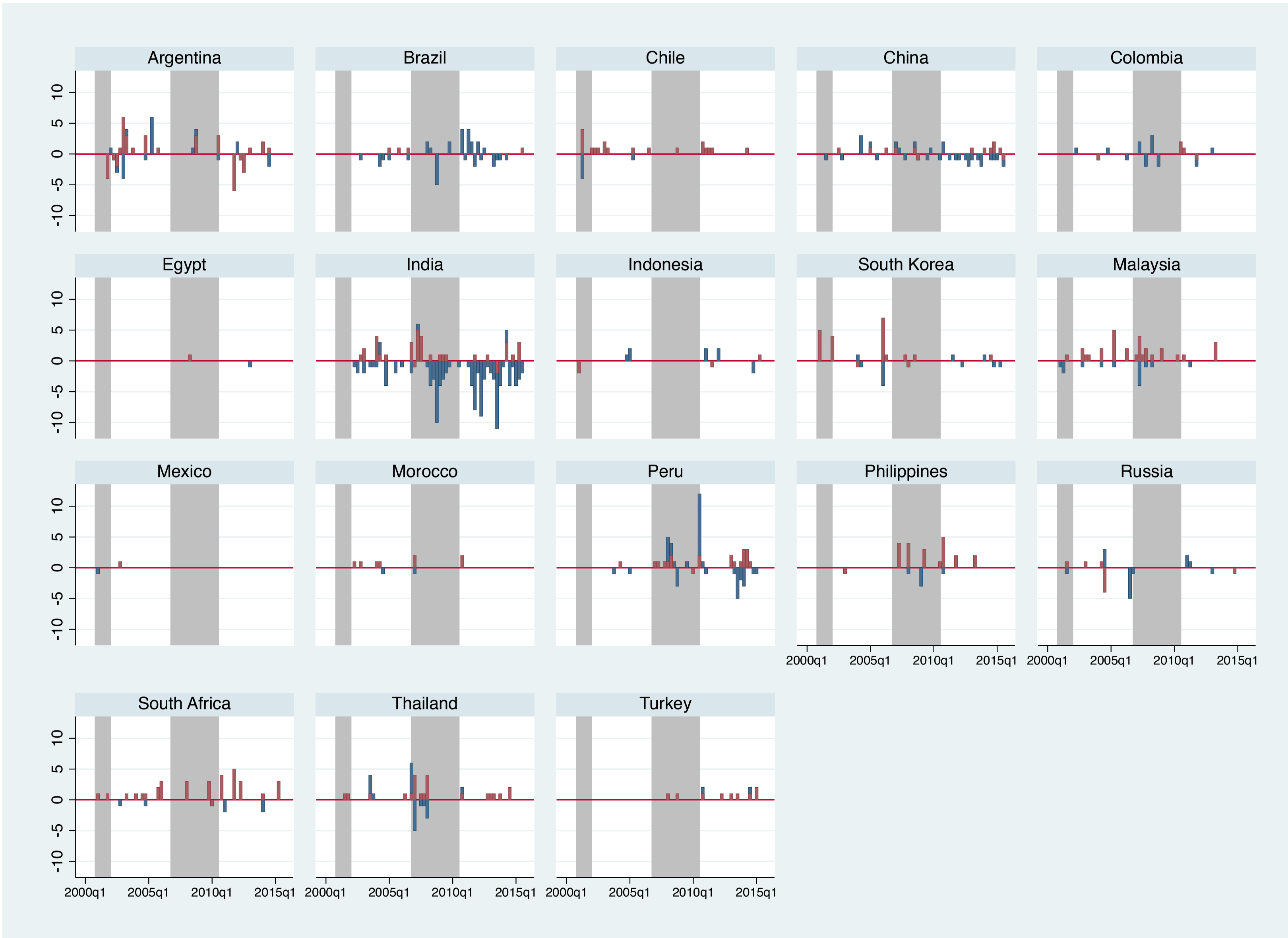
Note: y_t^1, y_t^2, y_t^3 and y_t^4 are calculated as the change in the two-year Treasury yield 10 minutes before and 20 minutes after the first, second, third and fourth FOMC announcements, respectively. These changes are recorded as percentage point changes. NBER recessions are indicated by the shaded grey time periods.

Figure 3: Z-scores of $P^N_{c,t}$ across countries and time



Note: $P^N_{c,t}$ is the net-net portfolio flows data from IFS, as discussed in section 2.3. Z-score is calculated as $P^N_{c,t}$ minus the country-specific sample mean and then divided by country-specific sample standard deviation. NBER recessions are indicated by the shaded grey time periods.

Figure 4: Z-scores of $NIT_{c,t}$ and $NOE_{c,t}$ across countries and time



Note: $NIT_{c,t}$ (in ▬) and $NOE_{c,t}$ (in ▬) are the net number of inflow tightening actions imposed on non-residents and the net number of outflow easing actions imposed on residents, respectively, calculated according to the description in section 2.1, using the data of Pasricha et al. (2018). NBER recessions are indicated by the shaded grey time periods.

Table 1: Summary statistics

	$\pi_{c,t}$		$g_{c,t}$		$\left(\frac{CA}{GDP^*}\right)_{c,t}$		$\Delta \ln s_{c,t}$		$NNKIR_{c,t}$		$\left(\frac{P^N}{GDP^*}\right)_{c,t}$	
	Mean	S.d.	Mean	S.d.	Mean	S.d.	Mean	S.d.	Mean	S.d.	Mean	S.d.
Argentina	17.65%	23.40%	2.99%	7.10%	0.96%	0.79%	3.85%	14.81%	0.19	1.69	-0.22%	0.76%
Brazil	6.64%	2.70%	3.01%	2.98%	0.17%	0.55%	1.38%	9.35%	0.03	1.29	0.28%	0.49%
Chile	3.00%	1.36%	4.18%	2.44%	1.31%	1.44%	0.43%	6.21%	0.24	0.50	-0.58%	1.37%
China	2.40%	2.18%	10.51%	4.24%	1.45%	0.80%	-0.45%	1.03%	-0.02	0.99	0.03%	0.28%
Colombia	4.79%	1.89%	4.20%	2.05%	-0.30%	0.39%	0.77%	6.88%	0.05	0.78	0.17%	0.63%
Egypt	8.72%	4.39%	4.98%	3.66%	-3.26%	2.18%	1.22%	3.64%	0.00	0.19	-0.24%	0.65%
India	6.98%	3.07%	7.37%	1.92%	-0.95%	0.57%	0.65%	3.80%	-1.20	2.98	0.26%	0.34%
Indonesia	7.72%	3.49%	5.34%	1.00%	0.74%	0.62%	0.80%	5.64%	0.05	0.63	0.29%	0.38%
South Korea	2.79%	1.15%	3.98%	2.09%	0.77%	0.63%	-0.02%	4.82%	0.22	1.00	0.06%	0.74%
Malaysia	2.28%	1.48%	4.88%	2.78%	4.00%	1.22%	0.30%	3.22%	0.29	0.87	0.09%	2.11%
Mexico	4.36%	0.98%	2.20%	2.72%	-0.41%	0.21%	1.01%	5.20%	0.00	0.19	0.35%	0.79%
Morocco	1.62%	1.22%	4.55%	2.06%	-2.54%	1.07%	-0.09%	4.28%	0.10	0.40	-0.10%	0.45%
Peru	2.67%	1.53%	5.31%	3.02%	0.52%	0.94%	-0.13%	2.71%	0.32	2.04	0.22%	0.82%
Philippines	4.24%	1.90%	5.13%	1.88%	-1.74%	0.79%	-0.04%	2.93%	0.25	1.06	0.15%	0.72%
Russia	11.25%	4.42%	3.50%	5.28%	2.18%	0.70%	1.47%	7.40%	-0.07	0.78	-0.10%	0.44%
South Africa	5.84%	2.71%	3.09%	1.88%	0.00%	0.52%	1.02%	8.60%	0.44	1.25	0.46%	1.32%
Thailand	2.47%	2.01%	3.92%	3.65%	1.11%	0.98%	-0.29%	3.16%	0.37	1.03	0.02%	0.77%
Turkey	15.45%	15.52%	5.16%	5.62%	-0.85%	0.79%	2.72%	9.57%	0.19	0.51	0.29%	0.61%

Note: Means and standard deviations are calculated using 59 quarterly observations (2001q1-2015q3) for each country in the table, except in the case of $\left(\frac{P^N}{GDP^*}\right)_{c,t}$ for China, where a later sample start date means that there are 43 quarterly observations. $\pi_{c,t}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; $\left(\frac{CA}{GDP^*}\right)_{c,t}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\Delta \ln s_{c,t}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar; $NNKIR_{c,t}$ is the net-net number of inflow restricting measures from Pasricha et al. (2018), as described in section 2.1; $\left(\frac{P^N}{GDP^*}\right)_{c,t}$ is the net portfolio flows in U.S. dollars (as described in section 2.3) as a percentage of the HP-filtered trend nominal GDP.

Table 2: First-stage regressions

	Dependent variable			
	$NNKIR_{c,t}$			$WNNKIR_{c,t}$
	(1)	(2)	(3)	(4)
y^1_{t-1}	0.239	-0.274		-0.006
	(0.335)	(0.307)		(0.308)
y^2_{t-1}	-1.429*	-1.713**		-1.701***
	(0.834)	(0.762)		(0.594)
Δr^{shadow}_{t-1}			-0.052	
			(0.037)	
$\pi_{c,t-1}$		-0.019	-0.025	-0.042**
		(0.021)	(0.022)	(0.018)
$g_{c,t-1}$		0.077***	0.071***	0.081***
		(0.023)	(0.024)	(0.018)
$\Delta(CA/GDP^*)_{c,t-1}$		0.028	0.034	0.026
		(0.035)	(0.034)	(0.031)
$\Delta \ln s_{c,t-1}$		-0.176***	-0.172***	-0.167***
		(0.033)	(0.033)	(0.034)
Observations	870	841	841	841
Countries	15	15	15	15
R^2	0.006	0.046	0.039	0.046
Standard error type	Driscoll and Kraay (1998) (12 quarters)			

Note: The regressions shown in this table take the general form of equation 1. $NNKIR_{c,t}$ and $WNNKIR_{c,t}$ are the net-net change in inflow reducing measures and its weighted counterpart, respectively, from Pasricha et al. (2018); see section 2.1. y^1_{t-1} is the first monetary policy shock in quarter $t-1$ measured as the change in the two-year Treasury yield within a 30-minute window of the first FOMC announcement of the quarter, y^2_{t-1} is the second. $\Delta r^{shadow}_{c,t-1}$ is the quarterly changes in the shadow real rate of Wu and Xia (2016). $\pi_{c,t-1}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t-1}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; $(CA/GDP^*)_{c,t-1}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln s_{c,t-1}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. All variables with the exception of y^1_{t-1}, y^2_{t-1} and Δr^{shadow}_{t-1} are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. R^2s are overall R-squareds.

Table 3: Causal effect of $NNKIR_{c,t}$ on portfolio flows

	Dependent variable				
	$P^N_{c,t+1}$		$\left(\frac{P^N}{GDP^*}\right)_{c,t+1}$	$P^N_{c,t+1}$	
	No instruments	Key result: GMM-FE	Key result: GMM-FE	Just-identified: GMM-FE	EBP as instrument GMM-FE
	(1)	(2)	(3)	(4)	(5)
$NNKIR_{c,t}$	0.011	-0.403***	-0.354***	-0.496***	-0.185*
	(0.026)	(0.108)	(0.111)	(0.125)	(0.108)
$i_{c,t} - i_{US,t}$				-0.171	
				(0.204)	
$\pi_{c,t} - \pi^{U.S.}_{c,t}$	0.035	-0.008	-0.008	0.065	0.005
	(0.036)	(0.029)	(0.033)	(0.032)	(0.090)
$g_{c,t} - g^{U.S.}_{c,t}$	0.042	0.079***	0.068**	0.044	0.082**
	(0.045)	(0.031)	(0.037)	(0.053)	(0.031)
$\Delta\left(CA/GDP^*\right)_{c,t}$	0.006	0.002	0.002	-0.001	0.022
	(0.040)	(0.034)	(0.026)	(0.037)	(0.034)
$\Delta \ln s_{c,t}$	-0.061	-0.038	-0.054	-0.029	-0.026
	(0.057)	(0.045)	(0.039)	(0.037)	(0.042)
	four lagged dependent variables are included				
Observations	795	795	795	795	795
Countries	15	15	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)				
S-H $J-$statistics p-value	n/a	0.675	0.593	0.487	0.708

Note: The regressions shown in this table are fixed effects (within transformation) regressions that take the general form of equations (1) and (2), estimated with efficient GMM. $P^N_{c,t+1}$ is the net-net portfolio flow detailed in section 2.3. $NNKIR_{c,t}$ is the net-net change in inflow reducing measures, from Pasricha et al. (2018); see section 2.1. $\pi_{c,t}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; when these variables have the superscript "U.S.", they are inflation and growth rates for the U.S., respectively; $(CA/GDP^*)_{c,t}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln s_{c,t}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar; $i_{c,t-1} - i_{US,t-1}$ is the nominal policy rate relative to the U.S. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). In column (5), the Excess Bond Premium (EBP) of Gilchrist and Zakrajsek (2012) is used as the instrumental varaible. Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. "S-H $J-$ statistics" is the Sargan-Hansen test of the null that the over-identifying restrictions are valid.

Table 4: Robustness check—FDI and "other" flows

	Dependent variable		
	$P^N_{c,t+1}$	$FDI^N_{c,t+1}$	$P\&O^N_{c,t+1}$
	Key result	FDI flows	Portfolio and other flows
	(1)	(2)	(3)
$NNKIR_{c,t}$	-0.403***	0.399**	-0.344***
	(0.108)	(0.104)	(0.097)
$\pi_{c,t} - \pi^{U.S.}_{c,t}$	-0.008	-0.029	-0.019
	(0.029)	(0.027)	(0.025)
$g_{c,t} - g^{U.S.}_{c,t}$	0.079***	0.050***	0.065**
	(0.031)	(0.019)	(0.028)
$\Delta\left(CA/GDP^*\right)_{c,t}$	0.002	0.057	-0.064*
	(0.034)	(0.017)	(0.039)
$\Delta \ln s_{c,t}$	-0.038	0.010	-0.175***
	(0.045)	(0.020)	(0.048)
	four lags of dependent variable are included		
Observations	795	795	772
Countries	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)		
S-H $J-$statistics p-value	0.675	0.577	0.664

Note: The regressions shown in this table are fixed effects (within transformation) regressions that take the general form of equations (1) and (2), estimated with efficient GMM. $P^N_{c,t+1}$ is the net-net portfolio flow detailed in section 2.3, while $FDI^N_{c,t+1}$ and $P\&O^N_{c,t+1}$ are the net FDI flow and net-net portfolio plus other flow, respectively, as defined in section 4.3. $NNKIR_{c,t}$ is the net-net change in inflow reducing measures, from Pasricha et al. (2018); see section 2.1. $\pi_{c,t}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; when these variables have the superscript "U.S.", they are inflation and growth rates for the U.S., respectively; $\left(CA/GDP^*\right)_{c,t}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln s_{c,t}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. "S-H $J-$statistics" is the Sargan-Hansen test of the null that the over-identifying restrictions are valid.

Table 5: Robustness check—"concerns abroad" FOMC meetings removed

	Dependent variable		
	$P^N_{c,t+1}$		$\left(\frac{P^N}{GDP^*}\right)_{c,t+1}$
	Key result	"concerns abroad" FOMC meetings removed	"concerns abroad" FOMC meetings removed
	(1)	(2)	(3)
$NNKIR_{c,t}$	-0.403***	-0.259**	-0.236**
	(0.108)	(0.116)	(0.110)
$\pi_{c,t} - \pi^{U.S.}_{c,t}$	-0.008	-0.009	-0.013
	(0.029)	(0.028)	(0.027)
$g_{c,t} - g^{U.S.}_{c,t}$	0.079***	0.066**	0.060**
	(0.031)	(0.029)	(0.029)
$\Delta\left(CA/GDP^*\right)_{c,t}$	0.002	0.019	0.021
	(0.034)	(0.034)	(0.028)
$\Delta \ln s_{c,t}$	-0.038	-0.014	-0.024
	(0.045)	(0.043)	(0.041)
	four lags of dependent variable are included		
Observations	795	753	753
Countries	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)		
S-H $J-$statistics p-value	0.675	0.742	0.737

Note: The regressions shown in this table are fixed effects (within transformation) regressions that take the general form of equations (1) and (2), estimated with efficient GMM. $P^N_{c,t+1}$ is the net-net portfolio flow detailed in section 2.3. $NNKIR_{c,t}$ is the net-net change in inflow reducing measures, from Pasricha et al. (2018); see section 2.1. $\pi_{c,t}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; when these variables have the superscript "U.S.", they are inflation and growth rates for the U.S., respectively; $\left(CA/GDP^*\right)_{c,t}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln s_{c,t}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. "S-H $J-$ statistics" is the Sargan-Hansen test of the null that the over-identifying restrictions are valid.

Table 6: Robustness check: Using $WNNKIR_{c,t}$ as the causal variable

	Dependent variable		
	$P^N_{c,t+1}$		$\left(\frac{P^N}{GDP^*}\right)_{c,t+1}$
	Key result (1)	$WNNKIR_{c,t}$ as causal variable (2)	$WNNKIR_{c,t}$ as causal variable (3)
$NNKIR_{c,t}$	-0.403***		
	(0.108)		
$WNNKIR_{c,t}$		-0.443***	-0.377***
		(0.118)	(0.118)
$\pi_{c,t} - \pi^{U.S.}_{c,t}$	-0.008	-0.022	-0.017
	(0.029)	(0.030)	(0.033)
$g_{c,t} - g^{U.S.}_{c,t}$	0.079***	0.088***	0.073**
	(0.031)	(0.030)	(0.031)
$\Delta\left(CA/GDP^*\right)_{c,t+1}$	0.002	0.011	0.006
	(0.034)	(0.033)	(0.026)
$\Delta \ln s_{c,t}$	-0.038	-0.033	-0.048
	(0.045)	(0.043)	(0.039)
	four lags of dependent variable are included		
Observations	795	795	795
Countries	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)		
S-H $J-$statistics p-value	0.675	0.705	0.608

Note: The regressions shown in this table are fixed effects (within transformation) regressions that take the general form of equations (1) and (2), estimated with efficient GMM. $P^N_{c,t+1}$ is the net-net portfolio flow detailed in section 2.3. $NNKIR_{c,t}$ is the net-net change in inflow reducing measures and $WNNKIR_{c,t}$ is its weighted counterpart, from Pasricha et al. (2018); see section 2.1. $\pi_{c,t}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; when these variables have the superscript "U.S.", they are inflation and growth rates for the U.S., respectively; $\left(CA/GDP^*\right)_{c,t}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln s_{c,t}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. "S-H $J-$ statistics" is the Sargan-Hansen test of the null that the over-identifying restrictions are valid.

Table 7: Robustness check: Longer-term monetary policy shocks

	Dependent variable		
	$NNKIR_{c,t+1}$	$P^N_{c,t+1}$	$\left(\frac{P^N}{GDP^*}\right)_{c,t+1}$
	First stage	GMM-FE	GMM-FE
	(1)	(2)	(3)
y^1_{t-1}	-0.569		
	(1.148)		
y^2_{t-1}	-3.232***		
	(0.587)		
e^1_{t-1}	-1.693		
	(1.547)		
e^2_{t-1}	-0.521***		
	(0.140)		
$\pi_{c,t-1}$	0.007		
	(0.027)		
$g_{c,t-1}$	0.089**		
	(0.035)		
$\Delta\left(CA/GDP^*\right)_{c,t-1}$	-0.010		
	(0.044)		
$\Delta \ln s_{c,t-1}$	-0.234***		
	(0.028)		
$NNKIR_{c,t}$		-0.320***	-0.200**
		(0.107)	(0.081)
$\pi_{c,t} - \pi^{U.S.}_{c,t}$		0.062***	0.050***
		(0.017)	(0.013)
$g_{c,t} - g^{U.S.}_{c,t}$		0.034	0.040
		(0.029)	(0.026)
$\Delta\left(CA/GDP^*\right)_{c,t}$		-0.098***	-0.092***
		(0.029)	(0.026)
$\Delta \ln s_{c,t}$		-0.175***	-0.166***
		(0.034)	(0.031)
	four lags of dependent variable are included		
Observations	511	511	511
Countries	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)		
S-H $J-$statistics p-value		0.864	0.871

Note: The regressions shown in this table are fixed effects (within transformation) regressions that take the general form of equations (1) and (2). y^1_{t-1} is the first monetary policy shock in quarter $t-1$ measured as the change in the two-year Treasury yield within a 30-minute window of the first FOMC announcement of the quarter, y^2_{t-1} is the second. e^1_{t-1} and e^2_{t-1} are "term premium shocks", defined as the residual of the first and second 30-minute change in the 10-year Treasury yield regressed on y^1_{t-1} and y^2_{t-1}, respectively. $P^N_{c,t+1}$ is the net-net portfolio flow detailed in section 2.3. $NNKIR_{c,t}$ is the net-net change in inflow reducing measures, from Pasricha et al. (2018); see section 2.1. $\pi_{c,t}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; when these variables have the superscript "U.S.", they are inflation and growth rates for the U.S., respectively; $(CA/GDP^*)_{c,t}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln s_{c,t}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. "S-H $J-$ statistics" is the Sargan-Hansen test of the null that the over-identifying restrictions are valid.

Table 8: Correlations between changes in capital controls and changes in prudential policies

	$PT_{c,t}$	$IT_{c,t}$	$OT_{c,t}$		$PL_{c,t}$	$IE_{c,t}$	$OE_{c,t}$
$PT_{c,t}$	1			$PL_{c,t}$	1		
$IT_{c,t}$	0.201	1		$IE_{c,t}$	-0.244	1	
$OT_{c,t}$	0.015	0.049	1	$OE_{c,t}$	-0.102	0.249	1

Note: Correlations shown are pooled (across countries and time) correlations between capital control actions in Pasricha et al. (2018) and changes in prudential policies in Cerutti et al. (2017). $PT_{c,t}$ is the prudential tightening variable, constructed using the data from Cerutti et al. (2017) by summing up all the positive values across the nine categories, while $PL_{c,t}$ is the prudential loosening variable, constructed by summing up all the negative values. $IT_{c,t}, IE_{c,t}, OT_{c,t}$ and $OE_{c,t}$ variables from Pasricha et al. (2018), described in section 2.1.

Table 9: Robustness check: Parsing out prudential policies

	Dependent variable			
	$P^N_{c,t+1}$			$(\frac{P^N}{GDP^*})_{c,t+1}$
	Key result	Prudential Tightening	Prudential policy-free $NNKIR_{c,t}$	Prudential policy-free $NNKIR_{c,t}$
	(1)	(2)	(3)	(4)
$NNKIR_{c,t}$	-0.403***			
	(0.108)			]
$NPT_{c,t}$		-0.242		
		(0.160)		
$NNKIR^{noprud}_{c,t}$			-0.524***	-0.463**
			(0.177)	(0.181)
$\pi_{c,t} - \pi^{U.S.}_{c,t}$	-0.008	0.019	0.025	0.017
	(0.029)	(0.031)	(0.022)	(0.025)
$g_{c,t} - g^{U.S.}_{c,t}$	0.079***	0.067**	0.065**	0.051*
	(0.031)	(0.031)	(0.034)	(0.030)
$\Delta(CA/GDP^*)_{c,t}$	0.002	-0.003	-0.015	-0.015
	(0.034)	(0.027)	(0.039)	(0.031)
$\Delta \ln s_{c,t}$	-0.038	-0.047	-0.072*	-0.069*
	(0.045)	(0.054)	(0.037)	(0.039)
	four lags of dependent variable are included			
Observations	795	714	714	714
Countries	15	14	14	14
Standard error type	Driscoll and Kraay (1998) (12 quarters)			
S-H J-statistics p-value	0.675	0.618	0.697	0.650

Note: The regressions shown in this table are fixed effects (within transformation) regressions that take the general form of e-quations (1) and (2), estimated with efficient GMM. $P^N_{c,t+1}$ is the net-net portfolio flow detailed in section 2.3. $NNKIR_{c,t}$ is the net-net change in inflow reducing measures, from Pasricha et al. (2018); see section 2.1. $NPT_{c,t}$ is the number of net prudential policy tightening measured obtained from Cerutti et al. (2017). $NNKIR^{noprud}_{c,t} \equiv NNKIR_{c,t} - NPT_{c,t}$ is the parsed, or "prudential policy-free" version of $NNKIR_{c,t}$. $\pi_{c,t}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; when these variables have the superscript "U.S.", they are inflation and growth rates for the U.S., respectively; $(CA/GDP^*)_{c,t}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln s_{c,t}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. "S-H $J-$ statistics" is the Sargan-Hansen test of the null that the over-identifying restrictions are valid.

Table 10: First-stage regressions for $NIT_{c,t}$ and $NOE_{c,t}$

	Dependent variable			
	$NNKIR_{c,t}$		$NIT_{c,t}$	$NOE_{c,t}$
	(1)	(2)	(3)	(4)
y^1_{t-1}	-0.274			
	(0.307)			
y^2_{t-1}	-1.713**			
	(0.762)			
y^{1-}_{t-1}		0.392	0.065	0.563
		(0.514)	(0.548)	(0.787)
y^{1+}_{t-1}		-1.162	-0.829	-0.754
		(0.982)	(0.722)	(0.758)
y^{2-}_{t-1}		-2.436**	-0.862*	-2.018
		(0.956)	(0.453)	(1.449)
y^{2+}_{t-1}		-0.794	0.492	-1.366
		(2.178)	(1.958)	(1.322)
$\pi_{c,t-1}$	-0.019	-0.019	-0.062**	0.016
	(0.021)	(0.021)	(0.029)	(0.036)
$g_{c,t-1}$	0.077***	0.084***	0.054**	0.025
	(0.023)	(0.023)	(0.026)	(0.031)
$\Delta(CA/GDP^*)_{c,t-1}$	0.028	0.029	-0.019	0.019
	(0.035)	(0.036)	(0.039)	(0.020)
$\Delta \ln s_{c,t-1}$	-0.176***	-0.176***	-0.085**	-0.143***
	(0.033)	(0.034)	(0.035)	(0.033)
Observations	841	841	841	841
Countries	15	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)			
R^2	0.046	0.047	0.016	0.028

Note: The regressions shown in this table take the general form of equation (1). $NNKIR_{c,t}$ is the net-net change in inflow reducing actions while $NIT_{c,t}$ and $NOE_{c,t}$ are net inflow tightening actions and net outflow easing actions, respectively, from Pasricha et al. (2018); see section 2.1. y^1_t is the first monetary policy shock in quarter $t+1$ measured as the change in the two-year Treasury yield within a 30-minute window of the first FOMC announcement of the quarter, y^2_t is the second; variables with superscripts "-" and "+" are the negative and positive parts of the shocks, respectively, as defined in equation (4). $\pi_{c,t-1}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t-1}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; $(CA/GDP^*)_{c,t-1}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln s_{c,t-1}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. All variables with the exception of y^1_{t-1}, y^2_{t-1}, y^{1-}_{t-1}, y^{1+}_{t-1}, y^{2-}_{t-1} and y^{2+}_{t-1} are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. R^2s are overall R-squareds.

Table 11: Causal effects of $NIT_{c,t}$ on non-resident portfolio flows

	Dependent variable			
	$P^L_{c,t+1}$			$\left(\frac{P^L}{GDP^*}\right)_{c,t+1}$
	Key result	"concerns abroad" FOMC meetings removed	$WNIT_{c,t}$ as causal variable	Key result
	(1)	(2)	(3)	(4)
$NIT_{c,t}$	-0.861***	-0.612***		-0.755***
	(0.247)	(0.227)		(0.251)
$WNIT_{c,t}$			-0.865***	
			(0.242)	
$\pi_{c,t} - \pi^{U.S.}_{c,t}$	-0.061	-0.052	-0.093*	-0.077*
	(0.053)	(0.043)	(0.055)	(0.045)
$g_{c,t} - g^{U.S.}_{c,t}$	0.069	0.025	0.064	0.066
	(0.048)	(0.033)	(0.044)	(0.048)
$\Delta\,(CA/GDP^*)_{c,t+1}$	0.038	0.049**	0.037	0.037
	(0.026)	(0.021)	(0.025)	(0.027)
$\Delta \ln s_{c,t}$	-0.073*	-0.049	-0.061	-0.094**
	(0.044)	(0.037)	(0.041)	(0.043)
lagged dependent variable	four lags included			
Observations	795	753	795	795
countries	15	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)			
S-H $J-$statistics p-value	0.812	0.828	0.807	0.829

Note: The regressions shown in this table are fixed effects (within transformation) regressions that take the general form of equations (1) and (2), but instead of instruments y^1_{t-1} and y^2_{t-1}, the positive and negative parts of these variables as defined in equation (4) are used as instruments. The model is estimated with efficient GMM. $P^L_{c,t+1}$ is the net portfolio liability flow detailed in section 2.3. $NIT_{c,t}$ is the number of net inflow tightening actions, from Pasricha et al. (2018); see section 2.1. $\pi_{c,t}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; when these variables have the superscript "U.S.", they are inflation and growth rates for the U.S., respectively; $(CA/GDP^*)_{c,t}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln \Delta s_{c,t}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. "S-H $J-$ statistics" is the Sargan-Hansen test of the null that the over-identifying restrictions are valid.

Online Appendix (not for publication)

Table A.1: Robustness check: Excluding China

	Dependent variable		
	$P^N_{c,t+1}$		$(\frac{P^N}{GDP^*})_{c,t+1}$
	Key result (1)	China excluded (2)	China excluded (3)
$NNKIR_{c,t}$	-0.403***	-0.429***	-0.400***
	(0.108)	(0.129)	(0.131)
$\pi_{c,t} - \pi^{U.S.}_{c,t}$	-0.008	-0.020	-0.028
	(0.029)	(0.028)	(0.028)
$g_{c,t} - g^{U.S.}_{c,t}$	0.079***	0.073**	0.061*
	(0.031)	(0.033)	(0.034)
$\Delta(CA/GDP^*)_{c,t}$	0.002	0.002	0.000
	(0.034)	(0.037)	(0.029)
$\Delta lns_{c,t}$	-0.038	-0.038	-0.062
	(0.045)	(0.047)	(0.040)
lagged dependent variable	four lags included		
Observations	795	756	756
Countries	15	14	14
Standard error type	Driscoll and Kraay (1998) (12 quarters)		
S-H J-statistics p-value	0.675	0.661	0.570

The regressions shown in this table are fixed effects (within transformation) regressions that take the general form of equations (1) and (2), estimated with efficient GMM. $P^N_{c,t+1}$ is the net-net portfolio flow detailed in section 2.3. $NNKIR_{c,t}$ is the net-net change in inflow reducing measures, from Pasricha et al. (2018); see section 2.1. $\pi_{c,t}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; when these variables have the superscript "U.S.", they are inflation and growth rates for the U.S., respectively; $(CA/GDP^*)_{c,t}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln s_{c,t}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. "S-H $J-$ statistics" is the Sargan-Hansen test of the null that the over-identifying restrictions are valid.

Table A.2: Robustness check: Portfolio debt flows and portfolio equity flows

Regressor	Dependent variable				
	$P^{N}_{c,t+1}$	$P^{ND}_{c,t+1}$	$P^{NE}_{c,t+1}$	$(\frac{P^{ND}}{GDP^*})_{c,t+1}$	$(\frac{P^{NE}}{GDP^*})_{c,t+1}$
	Key result	Net debt flows	Net equity flows	Net debt flows	Net equity flows
	(1)	(2)	(3)	(4)	(5)
$NNKIR_{c,t}$	-0.429***	-0.436***	-0.390***	-0.730***	-0.306***
	(0.129)	(0.152)	(0.100)	(0.201)	(0.074)
$\pi_{c,t} - \pi^{U.S.}_{c,t}$	-0.020	-0.009	0.239***	-0.018	0.175***
	(0.028)	(0.017)	(0.039)	(0.022)	(0.032)
$g_{c,t} - g^{U.S.}_{c,t}$	0.073**	0.111**	0.065*	0.155**	0.032
	(0.033)	(0.048)	(0.038)	(0.071)	(0.033)
$\Delta(CA/GDP^*)_{c,t}$	0.002	0.020	0.064*	0.020	0.044*
	(0.037)	(0.029)	(0.037)	(0.040)	(0.026)
$\Delta \ln s_{c,t}$	-0.038	0.058***	0.005	0.054*	0.005
	(0.047)	(0.017)	(0.023)	(0.029)	(0.019)
lag of dependent variable	four lags included				
Observations	756	308	285	308	285
Countries	14	13	13	13	13
Standard error type	Driscoll and Kraay(1998)(12 quarters)				
S-H J-statistics p-value	0.661	0.882	0.937	0.854	0.970

Note: The regressions shown in this table are fixed effects (within transformation) regressions that take the general form of equations (1) and (2), estimated with efficient GMM. $P^{N}_{c,t+1}$ is the net-net portfolio flow detailed in section 2.3. $NNKIR_{c,t}$ is the net-net change in inflow reducing measures, from Pasricha et al. (2018); see section 2.1. $\pi_{c,t}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; when these variables have the superscript "U.S.", they are inflation and growth rates for the U.S., respectively; $(CA/GDP^*)_{c,t}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln s_{c,t}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. "S-H $J-$ statistics" is the Sargan-Hansen test of the null that the over-identifying restrictions are valid.
Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively.

Table A.3: Robustness check: Subsamples

Regressor	Dependent variable				
	$P^N_{c,t+1}$			$(\frac{P^N}{GDP^*})_{c,t+1}$	
	Key result	Subsample 1	Subsample 2	Subsample 1	Subsample 2
	(1)	(2)	(3)	(4)	(5)
$NNKIR_{c,t}$	-0.403***	-0.396***	-0.369**	-0.645***	-0.217
	(0.108)	(0.110)	(0.153)	(0.107)	(0.136)
$\pi_{c,t} - \pi^{U.S.}_{c,t}$	-0.008	-0.018**	0.066***	-0.029**	0.056***
	(0.029)	(0.009)	(0.025)	(0.012)	(0.019)
$g_{c,t} - g^{U.S.}_{c,t}$	0.079***	0.032	0.042	0.033	0.052
	(0.031)	(0.045)	(0.035)	(0.049)	(0.032)
$\Delta(CA/GDP^*)_{c,t}$	0.002	0.066***	-0.098***	0.084***	-0.087***
	(0.034)	(0.019)	(0.034)	(0.027)	(0.032)
$\Delta \ln s_{c,t}$	-0.038	0.043***	-0.178***	0.045***	-0.160***
	(0.045)	(0.009)	(0.039)	(0.013)	(0.040)
lag of dependent variable	four lags included				
Observations	795	284	511	284	511
Countries	15	15	15	15	15
Standard error type	Driscoll and Kraay(1998)(12 quarters)				
S-H J-statistics p-value	0.675	0.828	0.710	0.820	0.748

Note: The regressions shown in this table are fixed effects (within transformation) regressions that take the general form of equations (1) and (2), estimated with efficient GMM. $P^N_{c,t+1}$ is the net-net portfolio flow detailed in section 2.3. $NNKIR_{c,t}$ is the net-net change in inflow reducing measures, from Pasricha et al. (2018); see section 2.1. $\pi_{c,t}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; when these variables have the superscript "U.S.", they are inflation and growth rates for the U.S., respectively; $(CA/GDP^*)_{c,t}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln s_{c,t}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. "S-H $J-$ statistics" is the Sargan-Hansen test of the null that the over-identifying restrictions are valid. Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively.
Subsample 1 uses the data up until 2006Q4 and Subsample 2 uses the data from 2007Q1.

Table A.4: Robustness check: Using untransformed variables

	Dependent variable		
	$P^N_{c,t+1}$	$\left(\frac{P^N}{GDP^*}\right)_{c,t+1}$	
	Key result	Key result	No z-scores
	(1)	(2)	(3)
$NNKIR_{c,t}$	-0.403***	-0.354***	-0.003***
	(0.108)	(0.111)	(0.001)
$\pi_{c,t} - \pi^{U.S.}_{c,t}$	-0.008	-0.008	-0.005**
	(0.029)	(0.032)	(0.002)
$g_{c,t} - g^{U.S.}_{c,t}$	0.079***	0.068**	0.015
	(0.031)	(0.031)	(0.009)
$\Delta\left(CA/GDP^*\right)_{c,t}$	0.002	0.002	-0.059
	(0.034)	(0.026)	(0.070)
$\Delta \ln s_{c,t}$	-0.038	-0.054	-0.001
	(0.045)	(0.039)	(0.005)
lagged dependent variable	four lags included		
Observations	795	795	795
Countries	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)		
S-H $J-$statistics p-value	0.675	0.593	0.762

Note: The regressions shown in this table are fixed effects (within transformation) regressions that take the general form of equations (1) and (2), estimated with efficient GMM. $P^N_{c,t+1}$ is the net-net portfolio flow detailed in section 2.3. $NNKIR_{c,t}$ is the net-net change in inflow reducing measures, from Pasricha et al. (2018); see section 2.1. $\pi_{c,t}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; when these variables have the superscript "U.S.", they are inflation and growth rates for the U.S., respectively; $\left(CA/GDP^*\right)_{c,t}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln s_{c,t}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions), except in column (3), where no transformations were applied. Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. "S-H $J-$statistics" is the Sargan-Hansen test of the null that the over-identifying restrictions are valid.

Table A.5: Robustness check: Intra-quarter monetary policy shocks added together

	Dependent variable		
	$P^N_{c,t+1}$		$\left(\frac{P^N}{GDP^*}\right)_{c,t+1}$
		summed shocks	summed shocks
	(1)	(2)	(3)
$NNKIR_{c,t}$	-0.403***	-0.233*	-0.157
	(0.108)	(0.120)	(0.109)
$\pi_{c,t} - \pi^{U.S.}_{c,t}$	-0.008	0.008	0.014
	(0.029)	(0.032)	(0.033)
$g_{c,t} - g^{U.S.}_{c,t}$	0.079***	0.082**	0.068**
	(0.031)	(0.038)	(0.037)
$\Delta\left(CA/GDP^*\right)_{c,t}$	0.002	0.002	0.003
	(0.034)	(0.029)	(0.022)
$\Delta \ln s_{c,t}$	-0.038	-0.029	-0.041
	(0.045)	(0.044)	(0.039)
lag of dependent variable	four lags included		
Observations	795	759	759
Countries	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)		
S-H $J-$statistics p-value	0.675	0.554	0.493

Note: The regressions shown in this table are fixed effects (within transformation) regressions that take the general form of equations (1) and (2), estimated with efficient GMM. Instead of y^1_t and y^2_t, the sum of all monetary policy shocks within quarter t is used as the instrument. $P^N_{c,t+1}$ is the net-net portfolio flow detailed in section 2.3. $NNKIR_{c,t}$ is the net-net change in inflow reducing measures, from Pasricha et al. (2018); see section 2.1. $\pi_{c,t}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; when these variables have the superscript "U.S.", they are inflation and growth rates for the U.S., respectively; $\left(CA/GDP^*\right)_{c,t}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln s_{c,t}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. "S-H $J-$ statistics" is the Sargan-Hansen test of the null that the over-identifying restrictions are valid.

Table A.6: Robustness check: Using Hamilton trend GDP to normalize variables

	Dependent variable		
	$P^N_{c,t+1}$	$\left(\frac{P^N}{GDP^*}\right)_{c,t+1}$	
	Key result	Key result	Hamilton (2018) trend
	(1)	(2)	(3)
$NNKIR_{c,t}$	-0.403***	-0.354***	-0.371***
	(0.108)	(0.111)	(0.112)
$\pi_{c,t} - \pi^{U.S.}_{c,t}$	-0.008	-0.008	-0.018
	(0.029)	(0.032)	(0.034)
$g_{c,t} - g^{U.S.}_{c,t}$	0.079***	0.068**	0.073**
	(0.031)	(0.031)	(0.030)
$\Delta\,(CA/GDP^*)_{c,t}$	0.002	0.002	0.006
	(0.034)	(0.026)	(0.023)
$\Delta \ln s_{c,t}$	-0.038	-0.054	-0.065*
	(0.045)	(0.039)	(0.038)
lagged dependent variable	four lags included		
Observations	795	795	795
Countries	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)		
S-H $J-$statistics p-value	0.675	0.593	0.588

Note: The regressions shown in this table are fixed effects (within transformation) regressions that take the general form of equations (1) and (2), estimated with efficient GMM. $P^N_{c,t+1}$ is the net-net portfolio flow detailed in section 2.3. $NNKIR_{c,t}$ is the net-net change in inflow reducing measures, from Pasricha et al. (2018); see section 2.1. $\pi_{c,t}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; when these variables have the superscript "U.S.", they are inflation and growth rates for the U.S., respectively; $(CA/GDP^*)_{c,t}$ is the current account in U.S. dollars as a percentage of the HP-filtered trend nominal GDP, also in U.S. dollars; $\ln s_{c,t}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. In column (3), instead of normalizing by HP-filtered trend GDP, the procedure of Hamilton (2018) is used to normalize $P^N_{c,t}$ and $CA_{c,t}$. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). Superscripts *, ** and *** represent statistical significance at the ten, five and one percent level, respectively. "S-H $J-$ statistics" is the Sargan-Hansen test of the null that the over-identifying restrictions are valid.