HONG KONG INSTITUTE FOR MONETARY RESEARCH

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HKIMR Working Paper No.05/2019

March 2019

Hong Kong Institute for Monetary Research
香港金融研究中心
(a company incorporated with limited liability)

The Dilemma and International Macroprudential Policy: Is Capital Flow Management Effective? *

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Abstract

This paper provides empirical evidence that emerging market economies adjust capital flow management in response to U.S. monetary policy shocks. Using these shocks as exogenous instruments, we find that such adjustments cause changes to portfolio capital flows — in partic-ular, a one standard deviation increase in the net number of inflow reducing measures reduces net portfolio inflows by two-fifths of a standard deviation. These findings provide support to the “Dilemma” literature, which recommends emerging market economies use capital con-trols and other macroprudential policies to shield their financial markets and monetary policy autonomy from large and volatile flows brought about by global financial cycles.

Keywords: Capital control, capital flows, global financial cycles
JEL classification: F3, F4, E5

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We thank Yi Huang for many discussions and data assistance. We would also like to thank seminar/conference participants at the University of Wisconsin-Madison, the University of Texas at Dallas, the 2018 Tsinghua Workshop of International Finance, Hong Kong Institute for Monetary Research (HKIMR) and The Chinese University of Hong Kong, Shenzhen for helpful comments. Part of the paper was written when Jason Wu was visiting 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. The views expressed in this paper are those of the authors, and do not necessarily reflect those of the Hong Kong Monetary Authority, Hong Kong Institute for Monetary Research, its Council of Advisers, or the Board of Directors.

1 Introduction

The Mundell-Fleming "Trilemma" has long been the centerpiece of international macroeconomics: a country cannot have a fixed exchange rate, an independent monetary policy and free international capital flows all at the same time.[1] Rey (2013) went a step further and argued that it is a "Dilemma" rather than a Trilemma: a country can have either an independent monetary policy or free international capital flows, but not both, due to the existence of global financial cycles. The rationale is that over these 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. Studies that precede Rey (2013), such as Frankel et al. (2004) and Tong and Wei (2010), among others, provide empirical support for the Dilemma paradigm in various ways.[2]

The key policy recommendation that emerged from this literature is that countercyclical capital controls may be deployed to defend financial stability and to preserve monetary autonomy. IMF (2011) and Jeanne (2013) are among the proponents of macroprudential capital flow management policies and international policy coordinations. Jeanne and Korinek (forthcoming), Korinek (2011), Korinek (2018) and Farhi and Werning (2014) theoretically examine the welfare improvements of countercyclical capital controls. 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 controls in tranquil times as part of the optimal policy mix when exchange rate policy is costly.

A major presumption behind this policy recommendation is that capital controls can effectively shield an economy from global financial cycles by preventing volatile international capital flows

[1] See, for example, Obstfeld et al. (2005).

[2] 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 controls provided countries more cushioning during the 2008 financial crisis than flexible exchange rate regimes.

into and out of the economy. However, empirical support for this presumption is 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) find that most capital control measures do not significantly affect capital flows and other key targets in an expansive but short panel of countries. Other recent examples of negative or mixed findings include Klein (2012), Forbes et al. (2016) and Chamon and Garcia (2016). In contrast, 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. Ben Zeev (2017) documents 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, in line with the Dilemma literature. Using these shocks as exogenous instruments, we further show that the actions of managing capital flows are indeed effective in altering portfolio flows in the future, which justifies 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 dataset created by Pasricha et al. (2018). 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. Most previous studies focus on the *presence* of capital controls, as measured for example by an annual capital control index. 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. (2011) for a survey on the topic.

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 the Dilemma literature — global factors, such as U.S. monetary policy shocks, necessitate the use of capital flow management. Rey (2013) documents that U.S. monetary policy is an important determinant of the global financial cycles that lead to excessive surges and retrenchments in capital flows in "periphery" countries. Indeed, we show empirically that EMEs take capital flow management actions in response to unanticipated U.S. monetary shocks; in turn, capital flow management actions propagated by these shocks alter portfolio flows in the intended direction, affirming the policy recommendations in Rey (2013) and related Dilemma studies.

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.[4] For a panel of 15 EMEs, we first regress the number of capital flow management actions on these shocks and other predetermined 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.[5]

Next, we include U.S. monetary policy shocks as instruments in a panel generalized method of moments (GMM) framework where the dependent variable measures portfolio flows into and

[4] 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.

[5] 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 connect the capital controls directly to the U.S. monetary shocks.

out of the 15 EMEs. The estimated causal effect in our baseline specification suggests that a one standard deviation increase in the "net-net" number of inflow reducing actions causes a two-fifths of a standard deviation decline in "net-net" portfolio inflows in the next quarter. This estimate is robust to various alternative specifications.

Delving into the drivers behind our results, we document a couple of interesting asymmetries. The first is that our key result 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.[6] 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.

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. In other words, this study does not address the possibility that policymakers have over- or under-responded to the U.S. monetary policy shocks. Studies like Coimbra and Rey (2017) and Coimbra and Rey (2018) are promising in this regard, as they provide early warning indicators to policymakers and help facilitate more optimal deployment of capital controls. Relatedly, our work does not address how capital flows interact with institution qualities; an example of such studies is Wei and Zhou (2017), who find that weak public governance tends to lead to over-borrowing in foreign currency-denominated short-term debt.

[6] In a related study, Ben Zeev (2017) finds that capital inflow controls help to stabilize a country's output in response to global credit supply shocks, while no such evidence exists for capital outflow controls. However, he didn't examine the effect of capital controls on capital flows.

Our study is also silent on the costs of capital controls, such as a loss in financial market efficiency and an increase in risks related to say shadow banking activities. For instance, see Alfaro et al. (2017) and Forbes (2007). Wei and Zhang (2007) document that capital controls can also substantially increase the cost of international trade, through more stringent reporting requirements on exporters and importers targeted at reducing evasive maneuvers such as misinvoicing.

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. (2017). As well, we do not consider the cross-country spillover effects of capital controls, which is studied by Forbes et al. (2016) and Pasricha et al. (2018), among others.

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

The dataset we use contains the following 18 EMEs: Argentina, Brazil, Chile, China, Colombia, Egypt, India, Indonesia, Malaysia, Mexico, Morocco, 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.[7] The capital controls data is then merged with information on portfolio flows, macroeconomic indicators, and U.S. monetary policy shocks. In our regression analysis, Egypt, Mexico and Morocco are excluded from the sample, since the data for these countries showed that they took very few capital control actions. Conditional on active capital control actions, we investigate if the actions are driven by U.S. monetary policy shocks and if they are effective in influencing future

[7] 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.

capital flows.

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 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* of 18 EMEs between January 2001 and December 2018.[8] 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).[9]

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

[8] In the paper, Pasricha et al. (2018) described 17 economies, namely Argentina, Brazil, Chile, China, Colombia, India, Indonesia, South Korea, Malaysia, Mexico, Morocco, Peru, Philippines, Russia, South Africa, Thailand, and Turkey. In the dataset made available online by the same authors, Egypt is also included. The data was downloaded from `http://www.nber.org/papers/w20822`.

[9] 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).

significant; 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.[10] 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:

- $NIT_{c,t} \equiv IT_{c,t} - IE_{c,t}$ 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;

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

- $NNKIR_{c,t} \equiv NIT_{c,t} + NOE_{c,t}$ 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.[11] 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.[12] 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 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.[13] In addition, with far more active communications from the Federal

[11] 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 $NNKIR_{c,t} \equiv NKIR_{c,t} - NKII_{c,t}$.

[12] 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.

[13] 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.

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.[14] 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.

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

[14]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`.

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); throughout our sample period there is a balance of both easing and tightening shocks. An easing (tightening) shock is often referred to as a "dovish" ("hawkish") surprise from the Fed. 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 others — 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.[15]

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

[15]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.

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.*]

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.[16]

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

[16] 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 $GDP^*_{c,t}$.

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, 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 controls 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).[17]

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.[18] 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. Recently, 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

[17]Examples of early studies on Sudden Stops and capital flights include Calvo (1998), Mendoaz (2010) and Faucette et al. (2005), among others.

[18]For instance, see Mendoaz (2010) and Calvo et al. (2006).

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 regressors 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:

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

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), expect 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.)[19]

Table 2 shows the results of this first-stage regression for the 15 emerging markets in our sample.[20] Country fundamentals $\mathbf{Z}_{c,t-1}$ being absent (column (1)) or present (column (2)) does

[19]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.

[20]As discussed in section 2, we removed Egypt, Mexico and Morocco because of their very limited number of

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) 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.

[*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.[21]

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.

capital control actions over the sample period.

[21] 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, $P^N_{c,t+1}$:

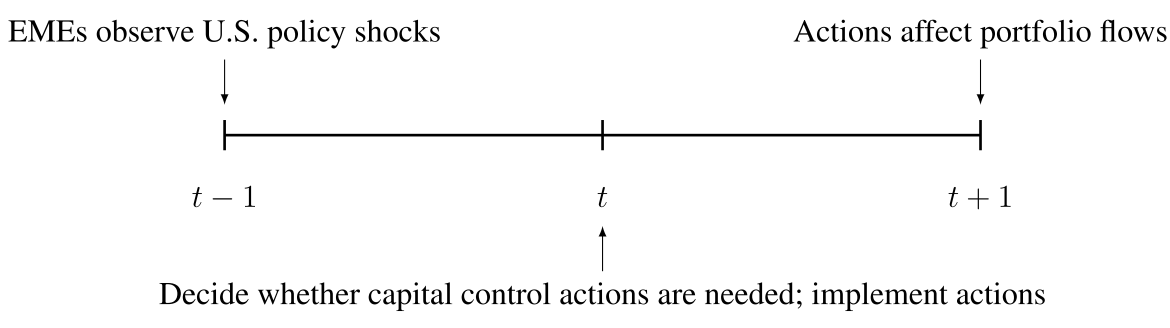
$$P^N_{c,t+1} = \alpha_c + \beta \widehat{NNKIR}_{c,t} + \Psi' \widetilde{\mathbf{Z}}_{c,t} + \sum_{i=0}^{3} \phi_i P^N_{c,t-i} + \varepsilon_{c,t+1}. \tag{2}$$

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:

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

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:



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, while the latter assumption could be violated if, for instance, investors take into account monetary policy shocks directly when deciding their allocations to EMEs, i.e., shocks are omitted variables in the right hand side of equation (2).

In regard to the first assumption, as we will show in section 4.2, our result still holds when we remove FOMC meeting when developments abroad may have played a role. For the second assumption, our research design–where the monetary policy shocks instruments are observed at $t-1$ whereas the portfolio flows are measure *two* quarters later at $t+1$–ameliorates the likelihood that the instruments affect the dependent variable outside of their impact on the key regressor. That is because investors in EMEs may not be that sensitive to U.S. monetary policy news that occurred two quarters ago. In all specifications below we report the Sargan-Hansen $J-$statistics, which tests the null of validity of over-identifying restrictions.

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.[22] 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.

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

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.

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.[23]

[*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. When the trend GDP-normalized flows is used as the dependent variable instead (column (3)), the estimated causal impact is little changed.

[23]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.

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

4.2 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 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".[24] Table 4 shows the results of this robustness check.

[*Table 4 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

[24] 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.

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 5 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 5 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 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. (2018) 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 6 here.*]

Column (1) of Table 6 shows the first stage regression. As can be seen, e^2_{t-1} in particular explains $NNKIR_{c,t+1}$, 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 targeted at capital 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 counter-cyclicality of capital flow management and its effect on portfolio flows we uncovered could be driven by these 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.[25] 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 7 shows that $PT_{c,t}$ and $PL_{c,t}$ have only small correlations with the four basic variables in Pasricha et al. (2018),

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

$IT_{c,t}, OT_{c,t}, IE_{c,t}$ and $OE_{c,t}$, indicating that these two data sets are indeed capturing different policy actions.

[*Table 7 here.*]

Table 8 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 $t+1$.[26] 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 7). 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 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 8 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

[26] 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 $t-1$.

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 NNKIR$_{c,t}$ into NIT$_{c,t}$ and 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 9.

[*Table 9 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 10 shows the key result, along with several robustness checks.

[*Table 10 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)).[27]

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 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 reduces their portfolio flows. In contrast, we do not find strong evidence that EMEs change capital controls on residents in response to the U.S. monetary policy shocks.

[27] See section 4.2 for more details on these robustness checks.

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.

The findings of this paper provide empirical support to the main policy implications of the Dilemma literature: even for countries with flexible exchange rate regimes, macroprudential capital controls are actively used in response to U.S. monetary policy shocks; such capital controls are adopted because they are effective in tempering large and volatile global capital flows.

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.

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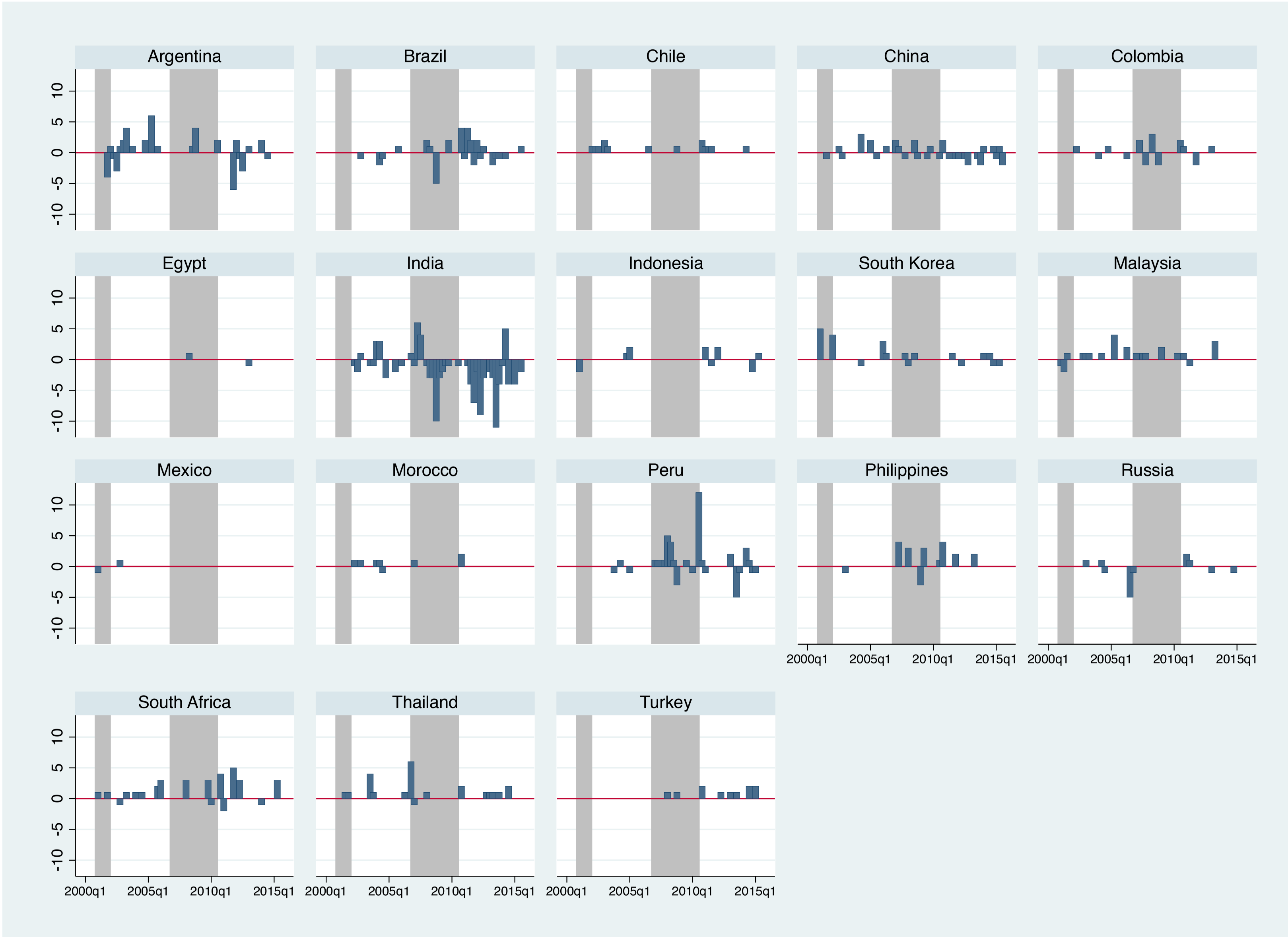
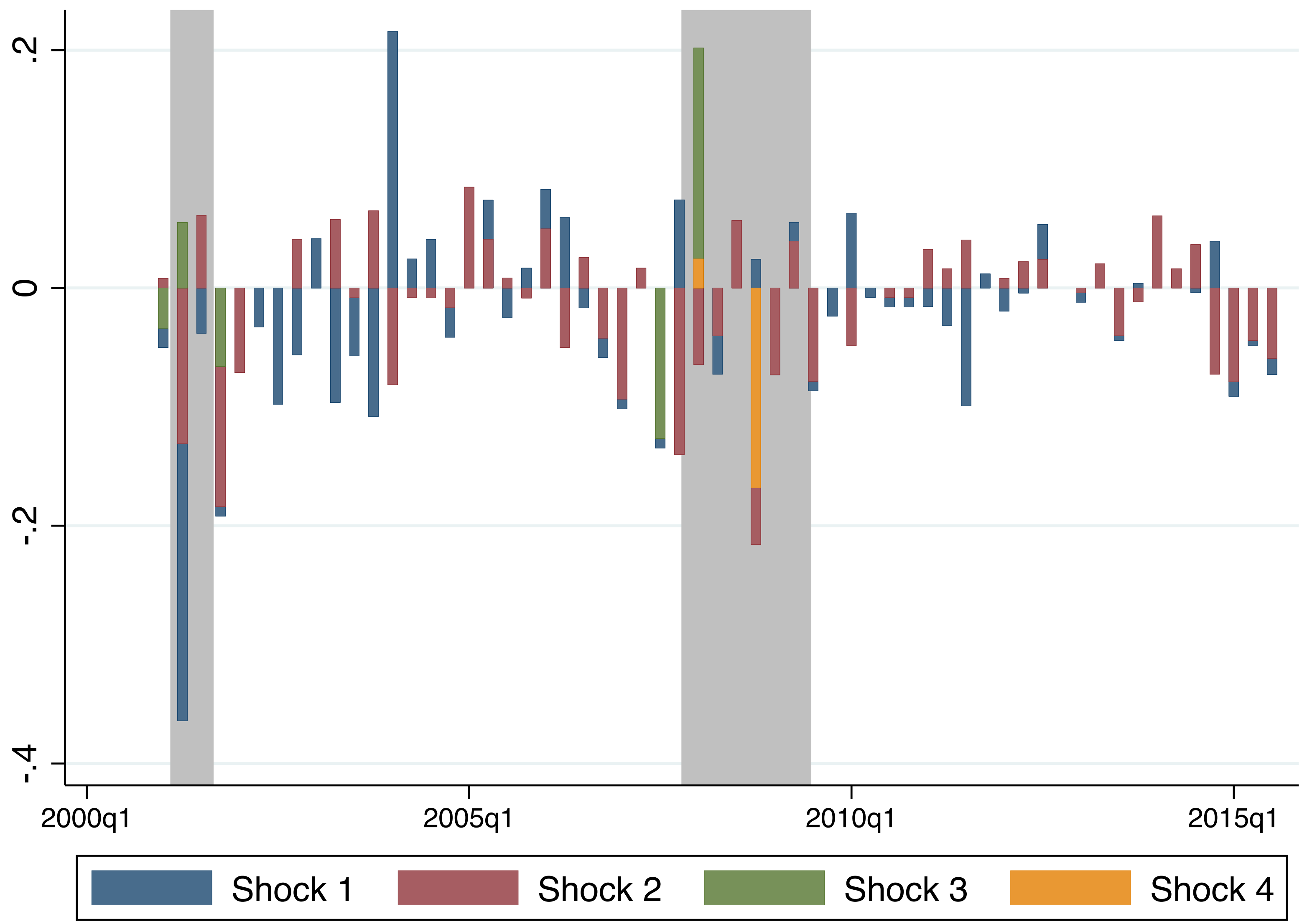
Figure 1: Z-scores of $NNKIR_{c,t}$ across countries and time



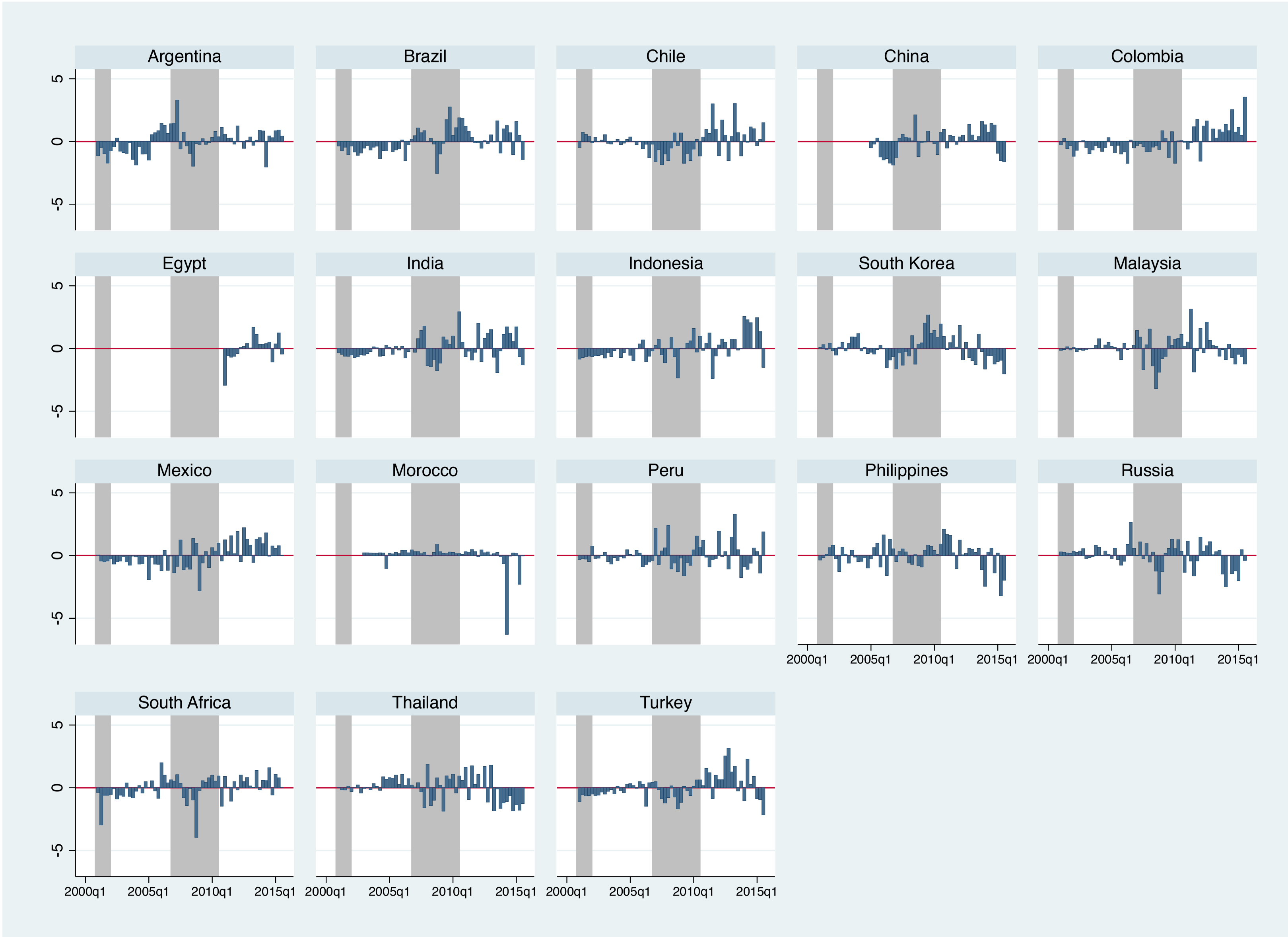
Note: $NNKIR_{c,t}$ is the number of net-net capital inflow reducing actions calculated according to the description in section 2.1, using the data of Pasricha et al. (2018). NBER recessions are indicated by the shaded grey time periods.

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



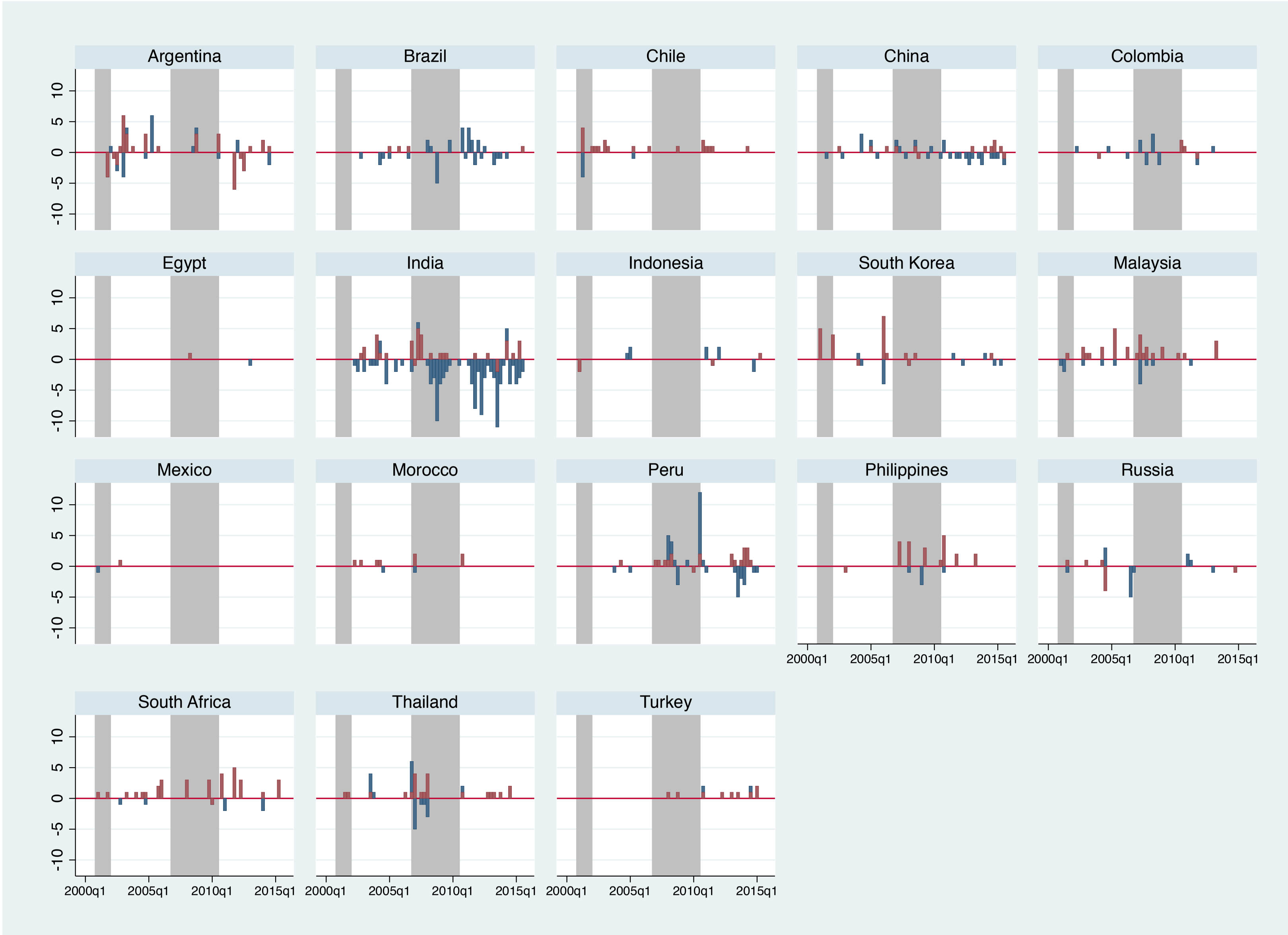
Note: y_t^1, y_t^2, y_t^3 and y_t^4 are calculated as the change in the two-year Treasury yield 10 minutes before and 20 minutes after the first, second, third and fourth FOMC announcements, respectively. These changes are recorded as percentage point changes. NBER recessions are indicated by the shaded 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
Standard error type	Driscoll and Kraay (1998) (12 quarters)			
R^2	0.006	0.046	0.039	0.046

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		
	$P^N_{c,t+1}$		$\left(\frac{P^N}{GDP^*}\right)_{c,t+1}$
	No instruments	Key result: GMM-FE	Key result: GMM-FE
	(1)	(2)	(3)
$NNKIR_{c,t}$	0.011	-0.403***	-0.354***
	(0.026)	(0.108)	(0.111)
$\pi_{c,t} - \pi^{U.S.}_{c,t}$	0.035	-0.008	-0.008
	(0.036)	(0.029)	(0.032)
$g_{c,t} - g^{U.S.}_{c,t}$	0.042	0.079***	0.068**
	(0.045)	(0.031)	(0.031)
$\Delta\left(CA/GDP^*\right)_{c,t}$	0.006	0.002	0.002
	(0.040)	(0.034)	(0.026)
$\Delta \ln s_{c,t}$	-0.061	-0.038	-0.054
	(0.057)	(0.045)	(0.039)
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	n/a	0.675	0.593

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.

Table 4: 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)
lag of dependent variable	four lags 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; $(CA/GDP^*)_{c,t}$ 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 5: 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)
lag of 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	0.705	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 6: 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)
lagged dependent variable	four lags 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; $\left(CA/GDP^*\right)_{c,t}$ 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: 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 8: 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)
lagged dependent variable	four lags 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 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. $NPT_{c,t}$ 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 9: 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 10: 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)
$\Delta\left(CA/GDP^*\right)_{c,t+1}$	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	China excluded	China excluded
	(1)	(2)	(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 (1)	Key result (2)	No z-scores (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)
$\Delta\,(CA/GDP^*)_{c,t}$	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; $(CA/GDP^*)_{c,t}$ 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.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 (1)	Key result (2)	Hamilton (2018) trend (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.