

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

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Abstract

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

Keywords: Capital flow management, capital flows, global financial cycles

JEL Classifications: F3, F4, E5

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1 Introduction

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

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

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

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

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

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

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

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

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

studying whether capital controls respond to shocks.

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

We measure U.S. monetary policy shocks as the changes to the two-year on-the-run Treasury yield over a short time window that surrounds FOMC announcements.⁵ For a panel of 15 EMEs, we first regress the number of capital flow management actions in quarter t on these shocks in quarter $t - 1$ and other pre-determined variables. We show that for the average EME, a “dovish” (“hawkish”) U.S. monetary policy shock of one percentage point results in 0.5 standard deviations increase (decline) in tightening actions on non-resident inflows and 1.6 standard deviations increase (decline) in easing actions on resident outflows, leading to a 1.7 standard deviation increase (decline) in the “net-net” number of capital inflow reducing actions in the following quarter.⁶

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

⁶[Aizenman and Pasricha \(2013\)](#) find that EMEs modify capital controls in response to capital inflow pressures.

We then 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 out of the 15 EMEs in quarter $t+1$. In these exercises, we examine capital inflows and outflows separately in response to different U.S. monetary shocks (dovish versus hawkish shocks) and document a couple of interesting asymmetries. The first asymmetry is that capital flow management actions in quarter t affect capital inflows in quarter $t+1$ through net inflow tightening actions applied on *non-residents*, which alter net portfolio inflows from abroad, whereas we could not find evidence that net outflow easing actions applied on *residents* significantly influence net portfolio outflows.⁷ 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. Such a policy reaction is consistent with the issue of “fear of appreciation” as discussed in [Levy-Yeyati et al. \(2013\)](#)—EMEs have recently aimed at limiting currency appreciations to protect their domestic industries, which is motivated by the neo-mercantilism. Our finding suggests that capital flow management policies may be preemptive: if the policy succeeds fending off the capital inflows driven by the U.S. easing policy, EMEs that adopt the policy may face less pressure to stabilize their financial markets when the U.S. reverses its monetary policy. For instance, [Ostry et al. \(2012\)](#) find that during the global financial crisis, economies with stronger pre-crisis capital controls or foreign exchange-related prudential measures were in general more resilient.

In uncovering the above causal effects, we rely on the exclusion restriction that U.S. monetary [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 U.S. monetary shocks.

⁷In a related study, [Ben-Zeev \(2017\)](#) finds that capital inflow controls help to stabilize a country’s output—rather than capital flows—in response to global credit supply shocks, while no such evidence exists for capital outflow controls.

policy shocks cannot influence capital flows outside of their impact on capital flow management. While one might be concerned that investors could react to U.S. monetary shocks by altering their flows to EMEs regardless of capital flow management, we alleviate this concern in our identification scheme by using U.S. monetary policy shocks in quarter $t - 1$ to instrument capital flow management at t , with the goal of estimating the response of capital flows in quarter $t + 1$. Since the monetary policy shocks we use are unexpected changes to yields within a short (30-minute) window around FOMC announcements, we view it as unlikely that such shocks have direct impact (i.e., not through their effects on capital flow management) on capital flows as far ahead as two quarters later. And while it is well-known that exclusion restrictions cannot be directly tested, we nonetheless find some empirical support for this assumption in data.⁸ In any case, a failure of this exclusion restriction actually *strengthens* our result—the fact that we detect a *decrease* in net-net capital inflows following a tightening of capital flow management in spite of a supposed boost to inflows due to an easing monetary policy shock suggests that if anything, we may have *underestimated* the causal effect of interest. In other words, even if our exclusion restriction does not hold, it is likely the case that our results cannot be overturned qualitatively.

It is important to clarify the issues that this paper does not address. Although we provide empirical evidence that capital flow management in EMEs react to U.S. monetary policy shocks and that the actions alter portfolio flows, our empirical results do not say anything about which types of capital controls are optimal under what circumstances, nor anything about the practical implementation challenges associated with using capital flows management—such as complexity, credibility, and coordination with other policies, as stipulated by [Mendoza \(2016\)](#) in the broader context of macroprudential policies.⁹ A number of recent studies is helpful in this regard: [Coimbra](#)

⁸We find that our main results are not driven by monetary shocks' effect on capital flows through alternative channels such as the interest rate, equity returns and home prices. The empirical support we found are consistent with the finding in [Fratzscher et al. \(2009\)](#), [Fratzscher et al. \(2016\)](#), [Chari et al. \(forthcoming\)](#), and other papers that the impact of U.S. monetary policy shocks on capital flows lasts for only one quarter following the shocks.

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

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

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

The remainder of the paper is arranged as follows. Section 2 introduces the data. Our econometric strategy is outlined in section 3. Key results and robustness checks are presented in section 4. Section 5 concludes.

2 Data

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

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

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

2.1 Changes in capital control policies

To capture capital controls, we use the data of [Pasricha et al. \(2018\)](#), who collected the capital control *actions* between January 2001 and December 2015.¹² This dataset departs in several important respects from other available measures of capital controls. First, other datasets on capital controls are usually indices on extensive margins (i.e., how many types of transactions are regulated), while the data of [Pasricha et al. \(2018\)](#) include both extensive and intensive margins — the data captures the number of control *actions* taken over time, thus providing information about the intensity of capital controls. Using similar data that provides information about intensive margin of capital controls, [Aizenman and Pasricha \(2013\)](#) and [Pasricha \(2017\)](#) find that the changes in capital controls are countercyclical, in contrast to the acyclical finding in studies that focus purely on extensive margins, such as that of [Fernandez et al. \(2015\)](#). In contrast, [Acosta-Henao et al. \(2020\)](#) find that capital controls do not change frequently in 21 emerging markets, even after they consider both intensive and extensive margins of the policy. The major difference between their data and the one in [Pasricha et al. \(2018\)](#) is that they measure the intensity of controls by constructing the *de jure* tax rate of controls. As a result, [Acosta-Henao et al. \(2020\)](#) have to focus on two specific controls: unremunerated reserve requirements and taxes on inflows/outflows, while [Pasricha et al. \(2018\)](#) include all capital control measures on the Balance of Payment. This difference may explain why [Acosta-Henao et al. \(2020\)](#)'s capital control measure displays less time variations than that of [Pasricha et al. \(2018\)](#).¹³

Second, the *quarterly* dataset of [Pasricha et al. \(2018\)](#) provides more time series variations 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 liter-

¹²The data was downloaded from <http://www.nber.org/papers/w20822>.

¹³Separately, [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. \(2016\)](#).

ature. Last but not least, the data of [Pasricha et al. \(2018\)](#) improves the comparability of policy actions over time and across countries by determining and eliminating policy actions that are insignificant; in addition, they also provide weighted versions of measures that reflect the importance of asset classes involved — that is, the measure of the stance of capital controls is not purely based on a count of the number of actions taken, but rather recognizes the economic impact they leave.

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

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

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

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;

¹⁴The 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.¹⁵

[Figure 1 here.]

Figure 1 displays $NIT_{c,t}$ and $NOE_{c,t}$. 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-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.

Figure 2 plots, across the 15 countries, how $NNKIR_{c,t}$ has evolved over time. One can observe that some countries, such as India, have used actions more proactively than others, such as Mexico. Over time, it appears that actions are more frequent during and after the financial crisis than before.¹⁶ By definition, a positive value of $NNKIR_{c,t}$ indicates that more capital inflow reduction measures were adopted than capital outflow inducing measures and vice versa. The fact that $NNKIR_{c,t}$ tends to be more positive than negative in our data suggests that countries were more focused on preventing portfolio inflow surges than putting up “gates” to prevent outflows; the exceptions seem to be China and India, which have been proactive in preventing outflows particularly after the Taper Tantrum in 2013.

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

¹⁶Naturally, 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 on net portfolio flows are present both pre- and post-crisis in Table A.2 of the online appendix.

[Figure 2 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.¹⁷ In addition, with far more active communications from the Federal Reserve since the crisis, changes in the funds rate target are now well anticipated by market participants and do not appropriately measure “surprises” in monetary policy communications, such as unanticipated inclusions of certain words in the post-FOMC meeting statement or changes to the Fed’s rate projections, which may prompt capital control actions.

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

Based on the historical schedule of FOMC meetings, there are at least two monetary policy shocks per quarter; we denote the first shock y_t^1 and the second shock y_t^2 .¹⁸ During extraordi-

¹⁷Against 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.

¹⁸There 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.

nary 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 3 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 3 as an illustration of monetary policy decisions, their sparseness means that we cannot include them in regression analyses below.

[Figure 3 here.]

Monetary policy shocks can be either “easing shocks” (yield goes down) or “tightening shocks” (yield goes up). An easing (tightening) shock is often referred to as a “dovish” (“hawkish”) surprise from the Fed. Throughout our sample period there is a balance of both easing and tightening shocks, which suggests that the Fed delivered unexpected news about monetary policy on both sides. For example, during the thick of the financial crisis, an unscheduled FOMC conference call on March 10, 2008 induced a big rise in yields (the big green bar during the crisis in chart 3) as the FOMC did not deliver on a rate cut when it was revealed to the market that the call took place—rather, the FOMC announced swap lines with other central banks, as well as several liquidity facilities. In contrast, nine months later on December 16, 2008, the FOMC cut rates from 1 percent to the zero lower bound target range of 0 to 0.25 percent, and offered the forward guidance that “[...] economic conditions are likely to warrant exceptionally low levels of the federal funds rate for some time.”, which delivered more accommodation than the market expected and led

A full list of announcements can be found on <https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm>.

to a 17 basis points monetary policy easing shock (the big orange bar during the crisis in chart 3). The monetary policy shocks during our sample period of 2000 to 2015 are essentially not serially correlated (correlation between shock and the previous shock is 0.04).

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

2.3 Portfolio flows

Like many other studies of capital flow dynamics, we employ portfolio flows from the IMF’s International Financial Statistics (IFS). Of the four categories of capital flows available — FDI, portfolio, derivative and “other” — our benchmark results focus on portfolio flows, which consist primarily of equity and bond investments. The category of portfolio flows has 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 \(2012\)](#). In addition, portfolio flows are often main target of capital control actions and, effectiveness of which is key interest of this paper. For instance, the effect of removing capital controls on portfolio equity flows is studied in [Henry \(2000a\)](#), [Henry \(2000b\)](#) and [Bekaert et al. \(2005\)](#), among others.¹⁹ In robustness checks, we also examine the effect of capital controls on FDI and other flows.

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 15 EMEs. There are three types of portfolio flows data: **portfolio flows on the liability side** ($P_{c,t}^L$), which are net

¹⁹The portfolio flows can be further decomposed into portfolio debt and portfolio equity flows. Our findings hold in both types of net portfolio flows and results are reported in Table A.3 of the online appendix.

purchases of domestic assets by non-residents, **portfolio flows on the asset side** ($P_{c,t}^A$), which are net purchases of foreign assets by residents, and **net-net portfolio flows** ($P_{c,t}^N \equiv P_{c,t}^L - P_{c,t}^A$). 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 4, 5 and 6 here.]

Figures 4, 5 and 6 shows the z-scores of $P_{c,t}^L$, $P_{c,t}^A$ and $P_{c,t}^N$, respectively, across the 15 EMEs. The charts show that net-net portfolio flows is large driven by portfolio liabilities. In fact, the time-series variance of portfolio liabilities accounts for 92% of that of net-net portfolio flows on average across countries (correlation between $P_{c,t}^L$ and $P_{c,t}^A$ is just 12% on average). This calls for a focus on the relationship between $P_{c,t}^L$ and $NIT_{c,t}$ and indeed this will be the starting point of our analysis. Also observed is that quarterly net-net portfolio flows became 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 (near the end of our sample) appears to have led to substantial outflows in both liabilities and net-net in many countries. Flows of Emerging Asia countries were also sensitive to the episode of renminbi devaluation and the associated capital flight from China in 2015, while countries in Latin America saw strong inflows over the same period.

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

²⁰The appropriateness of HP-filtering has been debated, see [Hamilton \(2018\)](#) for example. In Table A.4 of the online appendix, we show that the main results on net portfolio flows are largely unchanged when the procedure of [Hamilton \(2018\)](#) is used instead to estimate $GDP_{c,t}^*$.

2.4 Other country fundamentals

Portfolio flows are also influenced by country fundamentals. We merge capital controls and portfolio flows data with the following variables: $\pi_{c,t}$, the CPI inflation rate calculated as the year-on-year change in the CPI index; $g_{c,t}$, the real GDP growth rate calculated as the year-on-year change in real GDP; $CA_{c,t}$, the current account balance in U.S. dollars; $s_{c,t}$ is the nominal exchange rate denoted by 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 $\left(\frac{PN}{GDP^*}\right)_{c,t}$. 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 flow management on portfolio flows, the key challenge is a classic simultaneity problem: changes in capital controls may quell excessive portfolio flows, but countries with excessive flows are likely to impose more capital controls. This simultaneity means that a simple regression of portfolio flows on capital control actions yields biased estimates of the causal effect of interest. Instead, our strategy is built on the insight of [Rey \(2013\)](#) and [Han and Wei \(2018\)](#) who concluded that in the face of shocks from advanced economies, particularly monetary policy shocks, a flexible exchange rate alone is inadequate in

absorbing these shocks and that EMEs necessarily need to impose countercyclical capital controls. In this section we discuss the use of U.S. monetary policy shocks as instruments for capital control actions.

3.1 Monetary policy shocks as instruments for capital controls

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

We find that this hypothesis receives empirical support in our data. As previewed in section 2.3, we start with the analysis on capital control actions targeting non-residents and residents— $NIT_{c,t}$ and $NOE_{c,t}$, respectively—because liabilities and assets flows are driven by different agents, triggered by different motivations, and could respond differently to policy shocks. [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. We then analyze the totality of authorities’ actions— $NNKIR_{c,t}$.

Our empirical results suggest that emerging-market economies adjust capital flow management in response to U.S. monetary policy shocks and such policy actions influence future portfolio flows. Specifically, in the first stage of our methodology, we regress $NIT_{c,t}$, $NOE_{c,t}$ and their sum, $NNKIR_{c,t}$, on U.S. monetary policy shocks in the previous quarter and other pre-determined

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

regressors:

$$NIT_{c,t}, NOE_{c,t} \text{ or } NNKIR_{c,t} = \theta_c + \gamma_1 y_{t-1}^1 + \gamma_2 y_{t-1}^2 + \Gamma' \mathbf{Z}_{c,t-1} + \xi_{c,t}. \quad (1)$$

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

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

The economic fundamentals in $\mathbf{Z}_{c,t-1}$ are among the widely-believed important drivers of capital controls. For instance, [Forbes et al. \(2015\)](#) argues that countries adjust capital flow management measures in response to changes in variables that capital controls are intended to influence such as exchange rate movements, inflation, portfolio inflows and financial fragilities.²² The setup in equation (1) assumes that upon observing fundamentals and monetary policy shocks from quarter $t - 1$, authorities in EMEs decide whether to impose additional capital controls in quarter t . For ease of comparisons, all variables in equation (1), except for y_{t-1}^1 and y_{t-1}^2 , are standardized by country-specific mean and standard deviation (i.e., z-scores are used in these regressions.)²³

Table 2 shows the results of this first-stage regression for the 15 emerging markets in our sample. Odd-numbered columns are ones that used U.S. monetary policy shocks y_{t-1}^1 and y_{t-1}^2 as regressors. As y_{t-1}^2 is expressed in percentage points, estimated coefficients in columns (1) and (3) indicate that a dovish monetary shock that culminates to a 1 percentage point decline in the two-year Treasury yield results in a 0.5 and 1.6 standard deviations increase in $NIT_{c,t}$ and $NOE_{c,t}$, respectively, meaning that the average EME imposed more tightening actions on non-

²²We included many other variables in the original regressions, but most of them are not statistically significant and are removed from our final regression.

²³To validate that this transformation — done at the country-level — is not driving the results, Table A.5 of the online appendix shows the results on net portfolio flows do not change qualitatively when the variables are not transformed.

resident inflows and more easing actions on resident outflows when monetary policy in the U.S. was perceived to have eased. Column (5) documents that net-net inflow reducing measure—the sum of $NIT_{c,t}$ and $NOE_{c,t}$ —increases by 1.7 standard deviations in response to a 1 percentage point increase in y_{t-1}^2 .²⁴

[Table 2 here.]

The first-stage regressions in Table 2 indicate the second monetary policy shock of the quarter, y_{t-1}^2 , is statistically significant, while the first shock y_{t-1}^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 capital controls in quarter 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 3). 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.²⁵

To further demonstrate the quality of our instruments, the even-numbered columns of Table 2 show that when the 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, neither $NIT_{c,t}$, $NOE_{c,t}$ nor $NNKIR_{c,t}$ are explained by this alternative measure. This highlights the power of *unanticipated* monetary policy shocks in prompting responses from EMEs.

²⁴we also ran the first-stage regression using contemporaneous shocks and found a positive association between these capital control action variables and U.S. monetary policy shocks. This could be because these variables—now in the same month—are both reacting to news, for instance buoyant economic data in the U.S.

²⁵Another 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 $y_t^1 + y_t^2$. Table A.6 of the online appendix contains the result for $NNKIR_{c,t}$. 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 measures from equation (1), $\widehat{NIT}_{c,t}$, $\widehat{NOE}_{c,t}$ and $\widehat{NNKIR}_{c,t}$, are used as regressors to explain portfolio flows in the next quarter. We match flow measures to the capital action measures: $P_{c,t+1}^L$ matches with $\widehat{NIT}_{c,t}$ (non-resident flows and net inflow tightening measures on non-residents), $P_{c,t+1}^A$ with $\widehat{NOE}_{c,t}$ (resident flows and net outflow easing measure on residents), and $P_{c,t}^N$ with $\widehat{NNKIR}_{c,t}$ (net-net flows and net-net inflow reducing measures).

Our second-stage regressions take the form of:

$$P_{c,t+1}^j = \alpha_c + \beta \widehat{N^j}_{c,t} + \Psi' \tilde{\mathbf{Z}}_{c,t} + \sum_{i=0}^3 \phi_i P_{c,t-i}^{NL} + \varepsilon_{c,t+1}, \quad (2)$$

where

$$N^j = \begin{cases} NIT & \text{if } j = L \\ NOE & \text{if } j = A \\ NNKIR & \text{if } j = N \end{cases} \quad (3)$$

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 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 $\tilde{\mathbf{Z}}_{c,t}$, defined as:²⁶

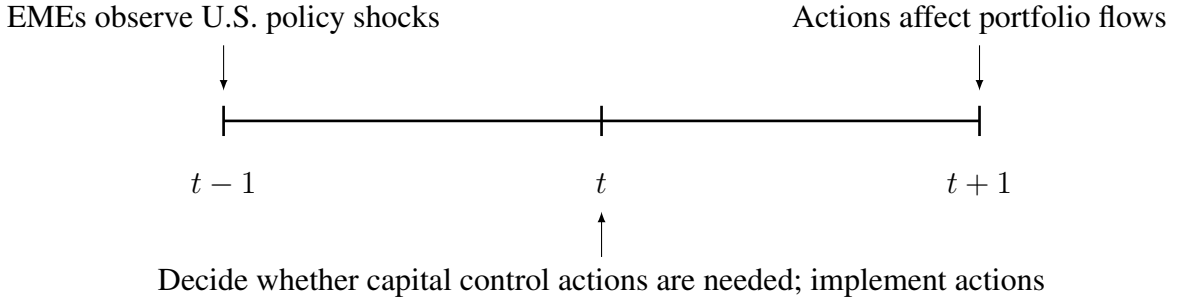
$$\tilde{\mathbf{Z}}_{c,t} \equiv [\pi_{c,t} - \pi_{c,t}^{U.S.}, g_{c,t} - g_{c,t}^{U.S.}, \Delta(CA/GDP^*)_{c,t}, \Delta \ln s_{c,t}]'$$

In particular, the use of $\tilde{\mathbf{Z}}_{c,t}$ is recognition that while capital control actions may be determined on

²⁶Our main results hold when we replace pre-determined country fundamentals with their expected values measured by the IMF's forecasts. Results are available upon request.

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 $P_{c,t+1}^j$ 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_{t-1}^1 and y_{t-1}^2 are not simultaneously determined with $N_{c,t}^j$, and that they influence $P_{c,t+1}^j$ through effects on $N_{c,t}^j$. The former assumption becomes tenuous if the FOMC places significant weight on developments abroad when deciding monetary policy, but as we show in section 4.2, our result still holds when we remove FOMC meeting when developments abroad may have played a role. The latter assumption is the subject of the next section.

Since our model is over-identified — there are more than one instrument in equation (1) — rather than using standard TSLS, we apply efficient generalized method of moments (GMM) to within-transformed variables.²⁷ 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

²⁷Within transformations are used to handle the country fixed effects.

number of cross-sectional units is fixed. In all specifications below we report the Sargan-Hansen J -statistics, which tests the null of validity of over-identifying restrictions.

4 Empirical findings

Subsection 3.1 demonstrated that U.S. monetary policy shocks are highly relevant instruments for capital control measures $NIT_{c,t}$ and $NOE_{c,t}$. We now estimate the key regressions in equation (2), first by showing that net-net inflow reducing actions have a causal effect on net-net portfolio flows. We then show that this result is due to the effect of inflow tightening measures in reducing non-resident portfolio flows and this effect is robust to various alternative specifications. Finally, we put the results on net-net portfolio flows through a battery of robustness tests.

We are interested in net-net portfolio flows for two reasons. First, 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. In particular, 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.²⁸ 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. In addition, net-net portfolio flows may better capture the effect of capital controls than net portfolio liability and asset flows.²⁹ Although capital inflows (gross liabilities) and outflows (gross assets) are traditionally driven by non-residents and residents respectively, there are increasing shares of residents participating in lending to the country and in non-residents fleeing a country.³⁰ Such activities loosen the mapping

²⁸For instance, see [Mendoza \(2010\)](#) and [Calvo et al. \(2006\)](#).

²⁹Of course, the net-net flows cannot reveal the underlying drivers of net flows, which is also an important concern of policymakers.

³⁰We thank a referee for pointing this out for us.

between $NIT_{c,t}/NOE_{c,t}$ and net portfolio liability/asset flows, which may disguise the effect of capital controls on flows in the data.

4.1 Key results

Table 3 presents estimation of regressions in equations 2. All variables except the instruments y_{t-1}^1 and y_{t-1}^2 are converted into z-scores before they enter the regressions. Column (1) shows that a one standard deviation increase in inflow tightening measures on non-residents reduces portfolio liability flows by 0.8 standard deviations. Column (2) on the other hand shows that outflow easing measures on residents have no causal effects on portfolio asset flows and the coefficient on $NOE_{c,t}$ —expected to be positive as easing outflows should increase residents’ portfolio assets abroad—has a negative sign. This finding may not be so surprising: when a country faces surge in capital inflows (e.g., with expectations of currency appreciation or rising asset prices), easing capital outflow measures may not induce much capital outflows as these outflows would be moving against fundamentals. This result is consistent with previous findings that inflow controls are usually more effective than the outflow ones. For instance, [Magud et al. \(2018\)](#) review over 40 empirical studies and find that capital inflow controls tend to be more effective than outflow controls in altering the composition of capital flows toward longer-term flows.

[Table 3 here.]

Due to the strong effects of $NIT_{c,t}$ on $P_{c,t}^L$ —recall from Figures 4 to 6 and section 2.3 that liability flows is the key driver of net flows—column (3) shows that a one standard deviation increase in net-net portfolio inflow reducing measures reduces net portfolio inflows by an economically meaningful 0.4 standard deviations.³¹ As for the pre-determined economic fundamentals, the sign-

³¹We also estimate the *cumulative* net-net portfolio flows—normalized by nominal GDP—in response to an impulse in $NNKIR_{c,t}$, with the latter instrumented by U.S. monetary policy shocks using the methodology of [Jorda et al. \(2020\)](#). The results suggest that the impact of $NNKIR$ on net-net portfolio flows mostly comes through in the first quarter hence, although it is persistent, with no evidence of reversal through six quarters. Details are available upon request.

s of estimated coefficients suggest that a higher inflation differential and depreciating currency reduce net portfolio 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.

For the rest of this section, we will focus on $P_{c,t}^L$ and $P_{c,t}^N$. Table 4 presents more results for $P_{c,t}^L$. Column (1) of Table 4 shows the importance of the instrument variable approach: when $NIT_{c,t}$ is included in equation (2) as the main regressor without using instruments in Ordinary Least Squares regression, the coefficient of interest is not statistically significant and has the wrong sign (a positive coefficient suggests that as the net number of inflow tightening actions increases, portfolio liabilities *increases*). This puzzling result is likely driven by simultaneity: higher $NIT_{c,t}$ lowers $P_{c,t+1}^L$ but at the same time countries with more non-resident inflows may impose more inflow tightening measures.³²

[Table 4 here.]

Columns (3) to (6) of Table 4 show that our key results hold up well in alternative setups.³³ When the trend GDP-normalized flows is used as the dependent variable instead (column (3)), the estimated causal impact is little changed compared to the key result, reproduced in column (2). [Pasricha et al. \(2018\)](#) created a weighted version of $NIT_{c,t}$ — $WNIT_{c,t}$ —to better measure the intended impact of capital control actions by recognizing the sizes of the investment types affected (see Section 2.1). Column (4) shows that when $WNNKIR_{c,t}$ is used as the main regressor, the estimated causal effect is almost the same as that in column (2).

Column (5) of Table 4 shows that our key results are robust to removing FOMC meetings where there seems to be concerns about economies abroad. One of the assumptions behind our identification strategy is that the FOMC’s decisions on monetary policy and its communications

³²The 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.

³³In all of these cases, the Sargan-Hansen J —statistics p-value indicates that the null of valid over-identifying restrictions cannot be rejected.

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. That said, post-meeting statements provide a gauge for the gravity of concerns from abroad to the FOMC's decisions. 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”.³⁴ Column (5) 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 although 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.

Investors may also focus on the real effective exchange rate (REER) as a “pull factor” instead of relative inflation and nominal exchange rate, as REER better captures competitors’ (i.e., other countries attracting capital flows) exchange rate fluctuations.³⁵ Column (6) demonstrates that when $\Delta \ln REER_{c,t}$ is included in the regression instead of the nominal exchange rate and relative inflation rates, the causal effect of interest continues to be significant and in fact becomes larger in magnitude.³⁶

We find that our results on $NIT_{c,t}$ and $NNKIR_{c,t}$ are mainly driven by net inflows tightening following dovish U.S. monetary policy shocks. Instruments y_{t-1}^1 and y_{t-1}^2 can be decomposed into these two types of shocks:

$$y_{t-1}^{i-} \equiv y_{t-1}^i \mathbf{1}(y_{t-1}^i \leq 0) \text{ for } i = 1, 2, \text{ “dovish” shock} \quad (4)$$

$$y_{t-1}^{i+} \equiv y_{t-1}^i \mathbf{1}(y_{t-1}^i > 0) \text{ for } i = 1, 2, \text{ “hawkish” shock.} \quad (5)$$

³⁴This 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.

³⁵We thank an anonymous referee for making this suggestion.

³⁶REER data is from the IMF.

The usefulness of these asymmetric monetary policy shock instruments are displayed in Table 5.

[Table 5 here.]

Columns (1) and (3) of the table show the regression of $NIT_{c,t}$ and $NNKIR_{c,t}$, respectively, on the asymmetric shocks. Compared to the baseline first-stage regression, the explanatory power of y_{t-1}^2 for both $NIT_{c,t}$ and $NNKIR_{c,t}$ comes from its dovish part, y_{t-1}^{2-} , and not its hawkish part, y_{t-1}^{2+} . Columns (2) and (4) show that capital control actions following a dovish U.S. monetary policy shock can reduce portfolio liability flows and net portfolio flows, respectively, in the following quarter and these effects are similar in magnitude to the ones documented in Table 4. These findings can be viewed as supportive of the concept of a “2.5-lemma” à la [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 are pursuing monetary easing.

Our findings suggest 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 (2) 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. These results are consistent with studies on “fear of appreciation.” [Levy-Yeyati et al. \(2013\)](#) point out that most exchange rate interventions after 2000 are aimed at limiting appreciations rather than sudden and large depreciations as documented in the literature of “fear of floating”, and that this type of actions addressing “fear of appreciation” is particularly popular among emerging markets after the Fed adopted zero interest rate and quantitative easing policies following the 2008 global financial crisis.

4.2 Further robustness checks

Our results of net-net portfolio flows are also robust to various alternative settings. Table 6 contains the same regressions as in table 4 except the dependent variable is the net-net portfolio flow, $P_{c,t+1}^N$ and the key regressor is the net-net inflow reducing actions, $NNKIR_{c,t}$. The table shows that when the key regression in column (2) is modified—using GDP-weight portfolio flows (column (3)), using weighted version of $NNKIR_{c,t}$ (column (4)), removing FOMC meetings where the post-meeting statements expressed concerns about the economy abroad (column (5)), or replacing relative inflation and nominal exchange rate changes with log changes in $REER_{c,t}$ (column (6))—capital flow management action remains a key causal drive of portfolio flows.

[Table 6 here.]

The rest of this section contain other robustness checks.

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

measures.³⁷

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. \(forthcoming\)](#) identify U.S. monetary policy shocks by extracting the unexpected components from the daily changes in five-year Treasury futures on the date of FOMC announcements. The identified shocks are found to exhibit sizable effects on U.S. holdings of emerging market assets. Our monetary policy shocks identified from the two-year Treasury yield may not be able to sufficiently capture shocks to longer-term yields.

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

[Table 7 here.]

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

³⁷Details about these regressions and their results are available upon request.

used.

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

Our strategy to alleviate this concern is to show that changes in prudential policies do not significantly influence portfolio flows. To do that, we first obtain changes in prudential policies for our sample of economies from [Cerutti et al. \(2017\)](#), who construct a dataset that captures the intensity of usage of nine common types of prudential tools.³⁸ We compute a “prudential tightening” variable $PT_{c,t}$ by summing up all positive values across the nine types; a “prudential loosening” variable $PL_{c,t}$ is computed similarly by summing up all negative values. Table 8 shows that $PT_{c,t}$ and $PL_{c,t}$ have only small correlations with the four basic variables in [Pasricha et al. \(2018\)](#), $IT_{c,t}$, $OT_{c,t}$, $IE_{c,t}$ and $OE_{c,t}$, indicating that these two data sets are indeed capturing different policy actions.

[Table 8 here.]

Table 9 more formally shows that changes in prudential policies are not driving portfolio flows. We begin by constructing a *net* prudential tightening measure akin to $NNKIR_{c,t}$, $NPT_{c,t} \equiv PT_{c,t} - PL_{c,t}$. Column (2) shows that when $NPT_{c,t}$ is used instead of $NNKIR_{c,t}$ as the explanatory variable of interest, it does not significantly reduce portfolio flows at $t + 1$.³⁹ 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

³⁸[Cerutti et al. \(2017\)](#) constructs this data for a significantly larger panel of 64 countries.

³⁹That said, we found that $NPT_{c,t}$ is indeed countercyclical, in that it increases when there are easing U.S. monetary policy shocks at $t - 1$.

way, since the capital control actions in [Pasricha et al. \(2018\)](#) are likely to include only a small fraction of the prudential policies documented in [Cerutti et al. \(2017\)](#), if at all (see Table 8). This variable, $NNKIR_{c,t}^{noprud}$, is the explanatory variable of interest in columns (3) and (4). As can be seen, the effects of the prudential policy-free net-net number of inflow reducing actions on portfolio flows is actually a bit stronger: a one standard deviation increase in this variable reduces net-net portfolio inflows by 0.524 standard deviations (column 3) and trend GDP-normalized net-net portfolio inflows by 0.463 standard deviations (column 4).

[Table 9 here.]

4.3 Other types of flows

How the actions captured by NIT and $NNIKIR$ —aimed mostly at financial flows—affect foreign direct investments (FDI)? To investigate this, we apply our instrumental variable approach on FDI flows—both non-resident (i.e., liability) and net-net FDI from the same IMF dataset, $FDI_{c,t+1}^L$ and $FDI_{c,t+1}^N$, respectively. Column (2) of Table 10 shows that, contrary our key result concerning portfolio flows, which is reprinted in column (1), a larger $NIT_{c,t}$ leads to increased FDI flows in the next quarter. This may reflect a substitution effect between FDI and other capital flows as more restrictions imposed on portfolio flows could be an impetus for non-residents to substitute to FDI inflows. For instance, [Wang and Wang \(2015\)](#) and [Alquist et al. \(2019\)](#) find evidence that FDI is used as vehicle to evade capital controls in emerging markets. Column (5) shows that the same substitution results hold also for net-net FDI flows, presumably because liability FDI flows is a big part of net-net FDI flows. These results are also consistent with previous findings that FDI flow is countercyclical, while portfolio flow is procyclical (e.g., [Aguiar and Gopinath \(2005\)](#) and [Alquist et al. \(2016\)](#)).

[Table 10 here.]

In addition to portfolio flows, which captures mostly debt and equity flows, “other” flows in the IMF data, which includes bank flows and other types of cross-border finance such as trade credit, are also important for EMEs—indeed, for 10 out of the 15 EMEs in our regressions, the standard deviation of quarterly “other” flows is larger than that of portfolio flows when measured in dollar terms. This is also why the dataset of [Pasricha et al. \(2018\)](#) captures prudential control actions.⁴⁰ Therefore, we also estimate the causal effect of an increase in $NNKIR$ on “other” liability flows and “other” net-net flows— $O_{c,t}^L$ and $O_{c,t+1}^N$, respectively. Columns (3) and (6) of Table 10 suggest that there may be a similar substitution effect between other investment flows and portfolio flows. An increase in $NIT_{c,t}$ leads to more other flows in the next quarter, while it reduces portfolio flows. [Lin and Ye \(2017\)](#) documents that multinational firms provide more trade credits to local firms through their subsidies following a favorable global liquidity shock. Our results complement their findings by showing that the increase in other capital flows such as trade credit may be a result of capital control tightening for portfolio flows.

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

Our identification assumption is an exclusion restriction where the monetary policy shocks y_{t-1}^1 and y_{t-1}^2 influence portfolio flows only through their effects on capital control actions. This could be violated if U.S. monetary policy shocks affect capital flows through other channels besides capital controls. As demonstrated by [Angrist and Pischke \(2008\)](#), such exclusion restrictions cannot be directly tested. Instead, we check whether these shocks might also drive portfolio flows through three alternative channels: an interest rate differential channel and two asset price channels—cross-

⁴⁰We thank a referee for pointing this out. The referee also suggested that “derivative” flows might also be relevant, but we omit it from this analysis as data for this type of flow is not available for several countries, and such flows tend to be quite small when compared to portfolio and “other” flows any ways. In the last part of Section 4.2 we parse out these prudential actions from $NNKIR_{c,t}$ so that this key regressor better matches the dependent variable of portfolio flows.

country differentials in equity returns or home price growth. The intuition for these channels would be that a dovish U.S. monetary policy shock could push up the relative interest rate, equity returns, or home price growth of the EME, and these in turn push capital flows toward it.⁴¹ Our exclusion restriction would therefore be more tenuous if these three channels exist.

To investigate whether any of the three channels are at play, we repeat the first-stage regression, but replace $NIT_{c,t}$ or $NNKIR_{c,t}$ with the differential, vis-à-vis the U.S., of the EME’s policy interest rate, equity returns and home price growth.⁴² The regression results, reported in table 11, show that U.S. monetary policy shocks affect next quarter’s nominal interest rate differential (column (1)) — a dovish (first) shock widens the interest differential as expected, but they do not affect equity return differential (column (2)) and house price growth differential (column (3)) in the following quarter. These results suggest that while prolonged periods of accommodative monetary policy in the U.S. may inflate asset prices in EMEs, the impact of a monetary policy *shock* may not immediately feed through assets in the following quarter.

[Table 11 here.]

These results suggest that monetary policy shocks may affect portfolio flows through an interest rate channel, other than the capital flow management channel we explore in the paper. Since we have two monetary policy shocks — following the first and second FOMC meetings, respectively, of each quarter — we can instrument both capital control actions and nominal interest rate differential to identify the causal effects of these two variables on portfolio flows. The model in columns (1) and (3) of Table 12 is just-identified, showing estimates for causal effects of $NIT_{c,t}$ and $NNKIR_{c,t}$, respectively, along with the interest rate differential, $i_{c,t} - i_{US,t}$. The estimate of the causal effect of capital flow management actions on net-net portfolio flows is qualitatively sim-

⁴¹We thank a referee for recommending us to explore these channels.

⁴²Nominal policy interest rates are obtained from the IMF’s International Finance Statistics (IFS). Quarterly house price data are from the Bank for International Settlements and the data for equity returns are from Bloomberg and Wind. Like most of the other variables in the paper, all three differential variables were standardized by country-specific mean and standard deviation (i.e., z-scores).

ilar even when nominal rate differential is in the model, which is itself not statistically significant.

[Table 12 here.]

EMEs policymakers could also take capital flow management actions in response to U.S. credit supply shocks, a different exclusion restriction that credit shocks influence portfolio flows through capital controls. Columns (2) and (4) of Table 12 show the results when capital flow management actions are instrumented using the Excess Bond Premium (EBP) of [Gilchrist and Zakrajsek \(2012\)](#), a common measure of credit supply shocks, instead of U.S. monetary policy shocks.⁴³ The estimated causal effects are that a 1 standard deviation increase in $NIT_{c,t}$ and $NNKIR_{c,t}$ reduce net liability flows and net-net portfolio flows by 0.80 and 0.19 standard deviation, respectively, both smaller than the estimates obtained using monetary policy shocks as the instrument. This could be due to the fact that the EBP is a significantly weaker instrument than monetary policy shocks — indeed, in a first stage regressions of $NIT_{c,t}$ and $NNKIR_{c,t}$ on EBP (and other controls), the p -values of the coefficients are significantly lower than those in regression that use monetary policy shocks.

5 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 tighten capital inflow controls on non-residents and ease capital outflow controls on residents, resulting an 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 the tightening of inflow controls on non-residents reduces portfolio liability flows. Because of this effect, a one standard deviation increase in the “net-net” number

⁴³We thank a referee for recommending us this exercise. Many recent papers including [Ben-Zeev \(2019\)](#) uses the EBP as a measure of credit supply shocks. Monthly data of the EBP is obtained from the Federal Reserve Board’s website and is averaged within a quarter to arrive at a quarterly version of EBP.

of inflow reducing actions reduces “net-net” portfolio flows in the following quarter by two-fifths of a standard deviation, using a panel of 15 EMEs. We exploit the cross-country and over-time variations of capital control *actions* using the dataset of [Pasricha et al. \(2018\)](#) to obtain our results. In doing so, we contribute to the literature by providing more definitive evidence that capital flow management actions affect capital flows, and also show that actions tend to be used more intensely when monetary policy eases.

The findings of this paper provide empirical support to a policy recommendation that re-emerged after the financial crisis: under appropriate circumstances, countercyclical capital flow management should be used to ameliorate the impact of external shocks. Our results may be used to argue that such capital flow management—particularly those applied to portfolio liability flows—should be adopted because they are effective in tempering large and volatile global capital flows, particularly restrictions applied to non-residents which is found to affect portfolio liability flows.

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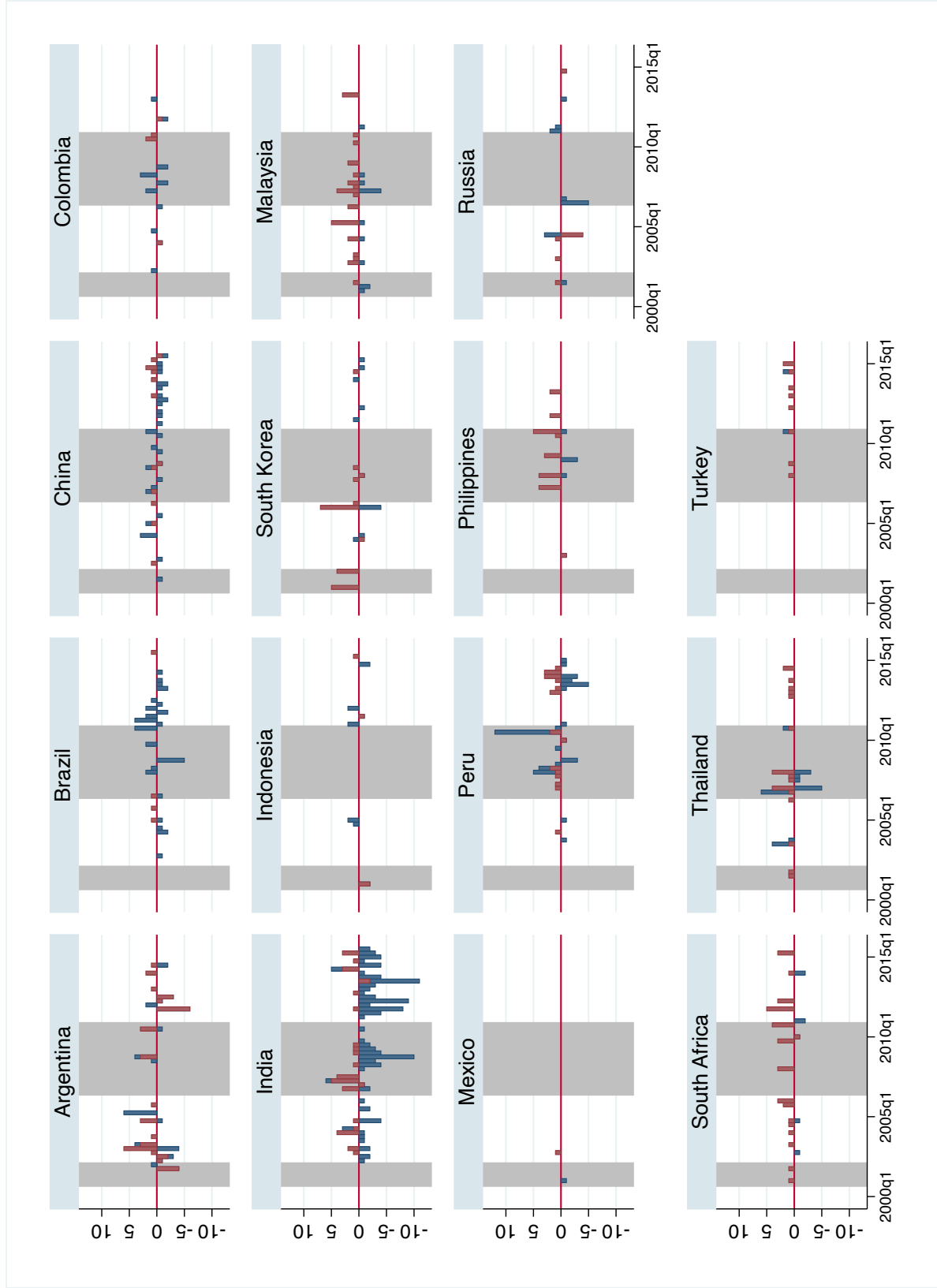
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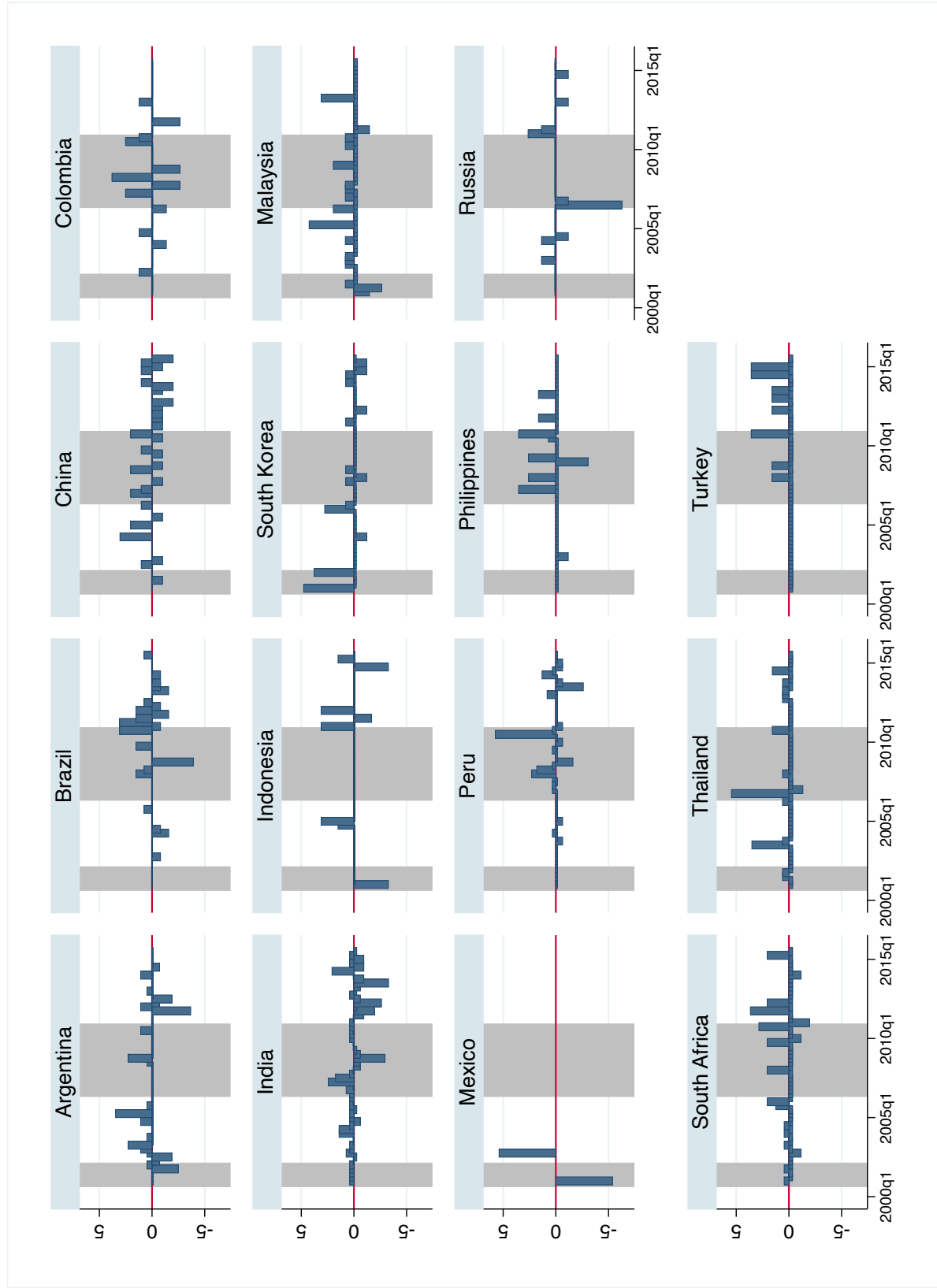
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Figure 1: Z-scores of $NIT_{c,t}$ and $NOE_{c,t}$ across countries and time



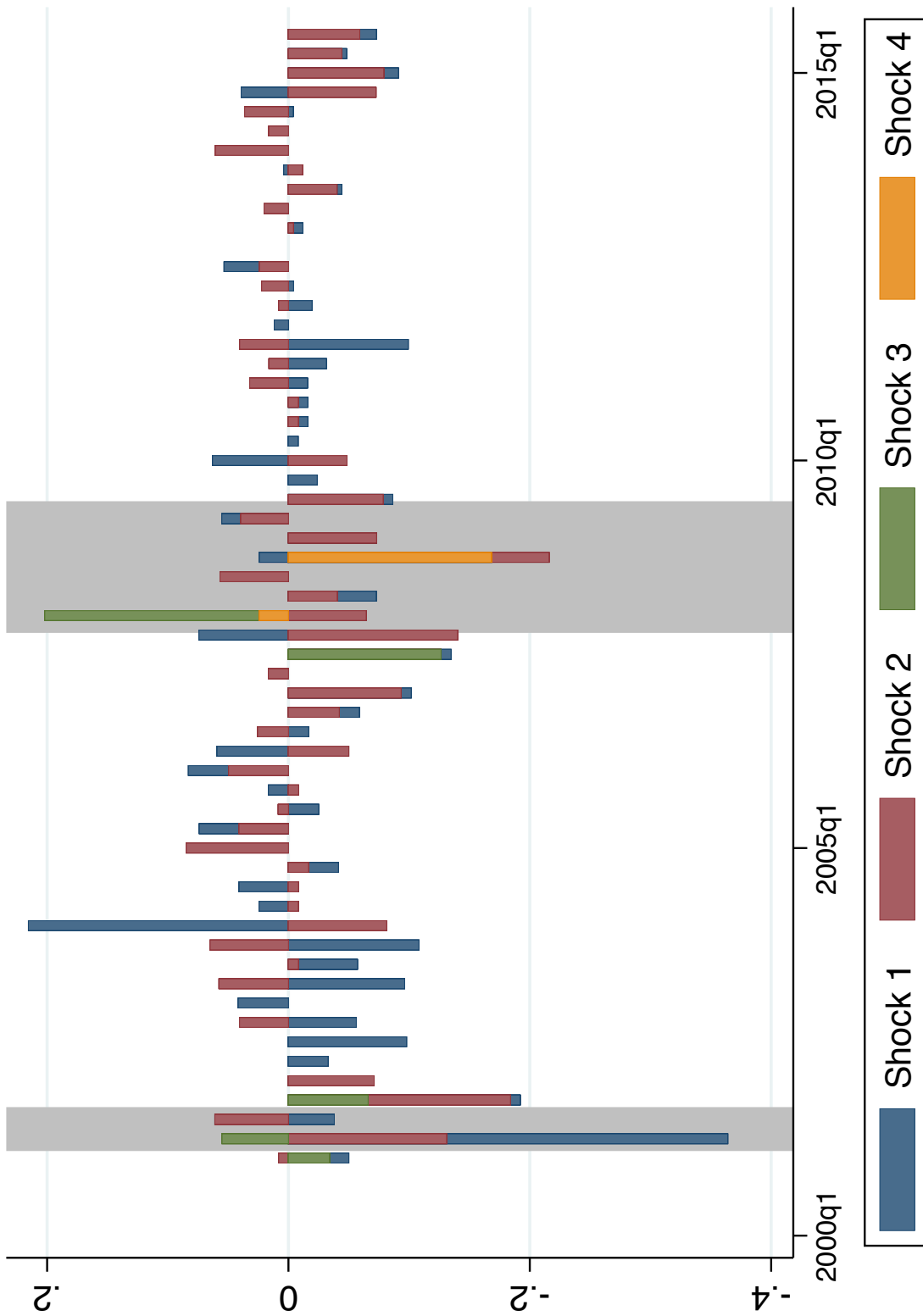
Note: $NIT_{c,t}$ (in ■) and $NOE_{c,t}$ (in ■) are the net number of inflow tightening actions imposed on non-residents and the net number of outflow easing actions imposed on residents, respectively, calculated according to the description in section 2.1, using the data of [Pasricha et al. \(2018\)](#).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

Figure 2: Z-scores of $NNKIR_{c,t}$ across countries and time



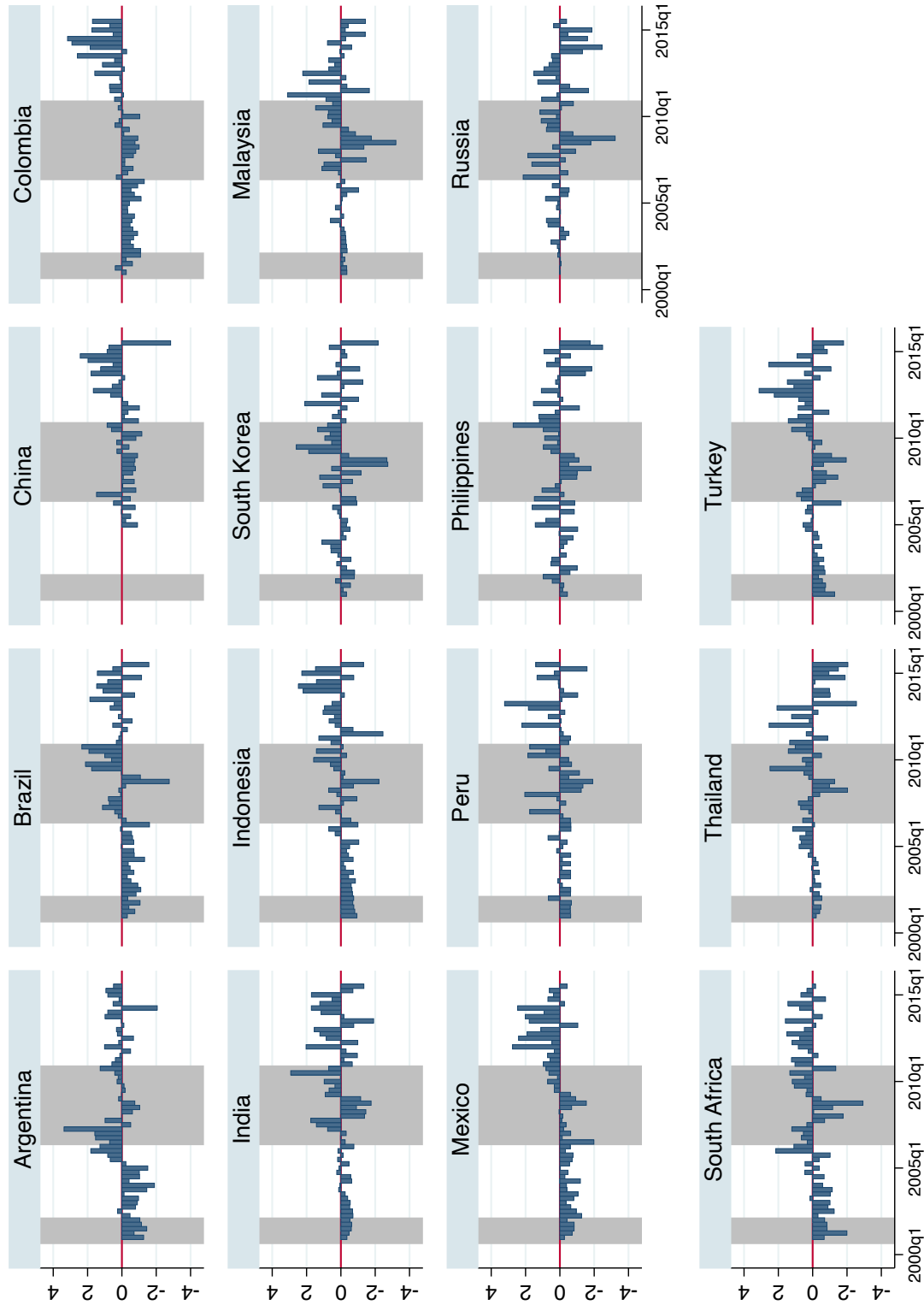
Note: $NNKIR_{c,t}$ is the number of net-net capital inflow reducing actions calculated according to the description in section 2.1, using the data of [Pasricha et al. \(2018\)](#). NBER recessions are indicated by the shaded grey time periods.

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



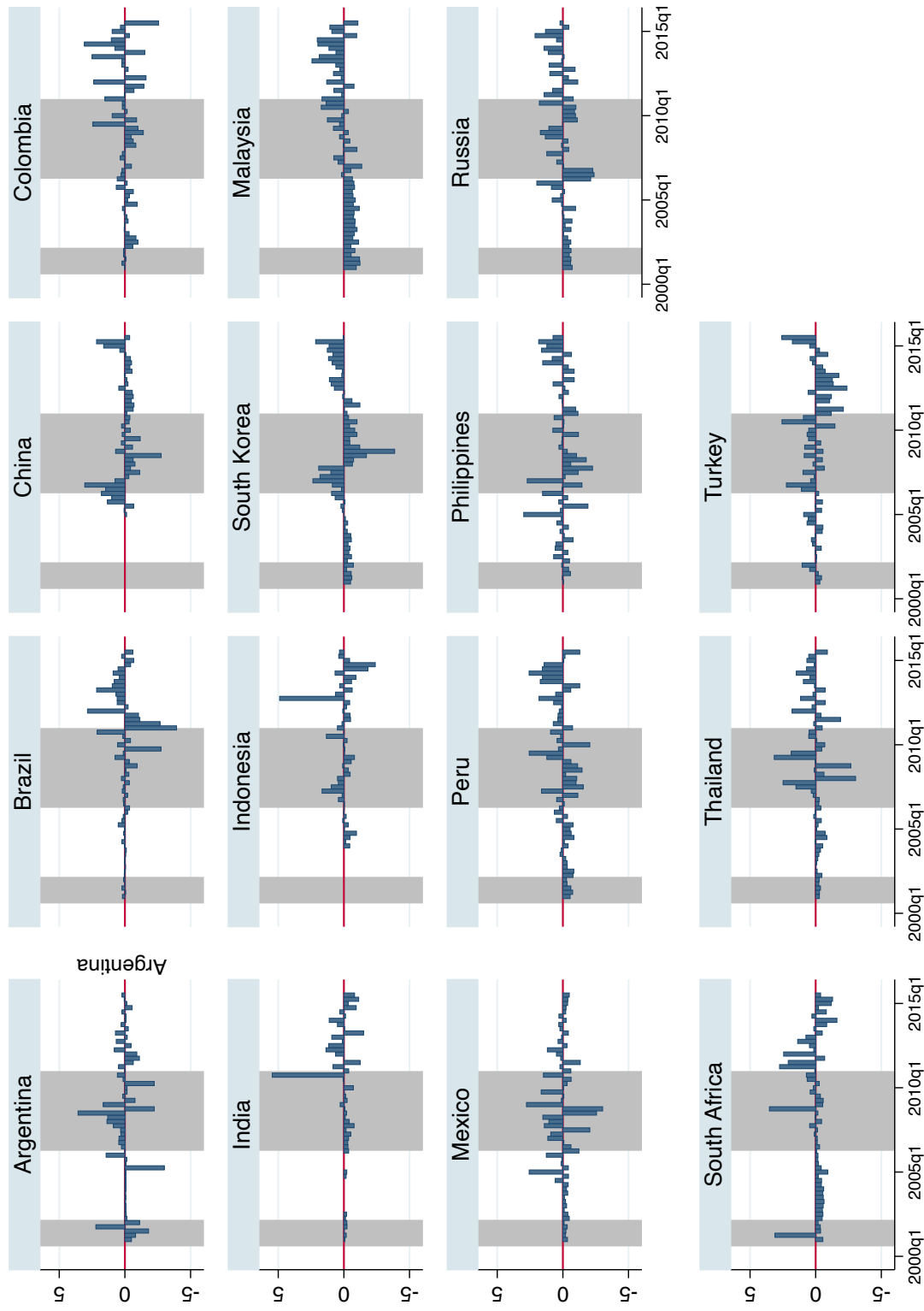
Note: y_t^1 , y_t^2 , y_t^3 and y_t^4 are calculated as the change in the two-year Treasury yield 10 minutes before and 20 minutes after the first, second, third and fourth FOMC announcements, respectively. These changes are recorded as percentage point changes. NBER recessions are indicated by the shaded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

Figure 4: Z-scores of $P_{c,t}^L$ across countries and time



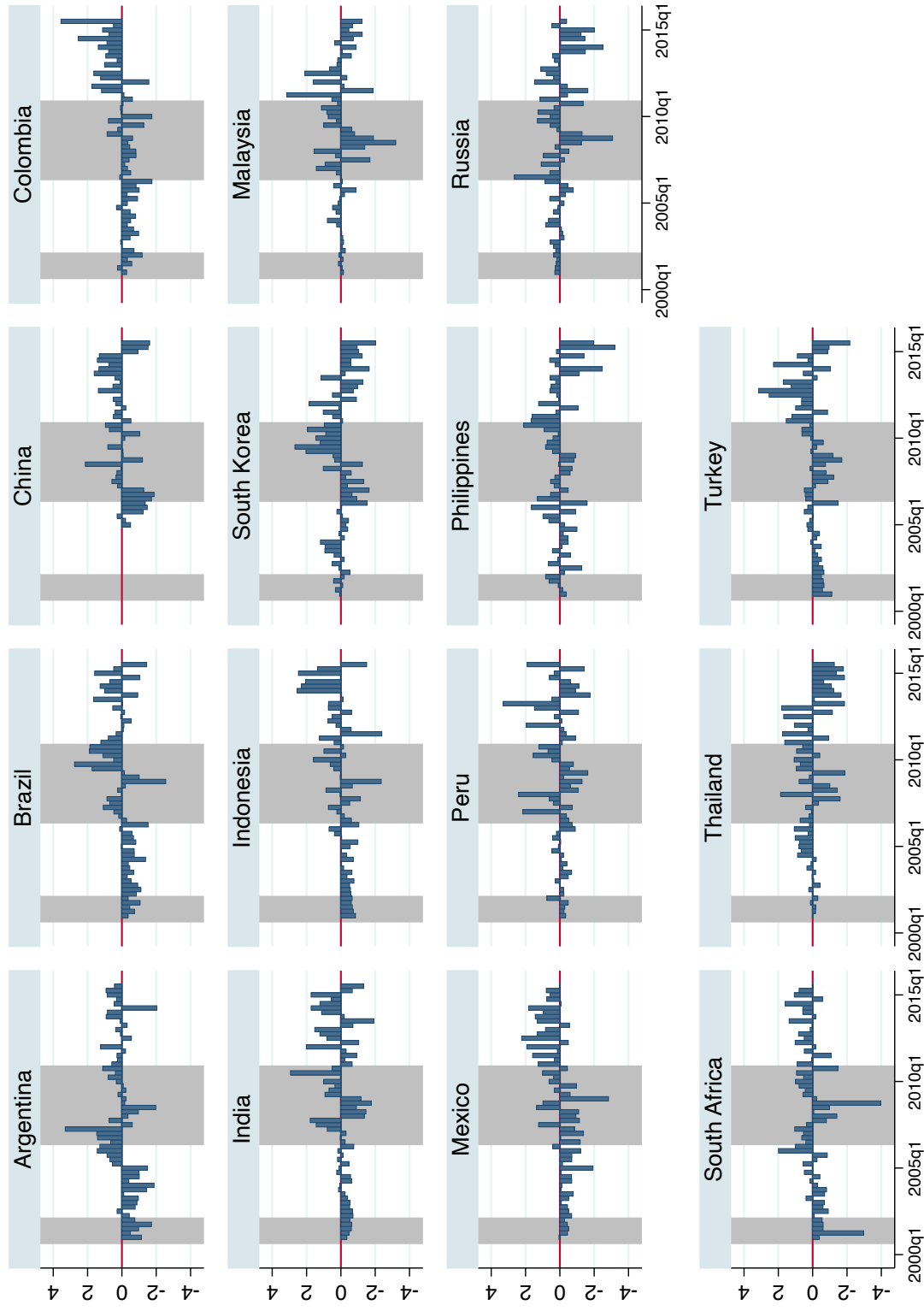
Note: $P_{c,t}^L$ is the portfolio liabilities flows data from IFS, as discussed in section 2.3. Z-score is calculated as $P_{c,t}^L$ minus the country-specific sample mean and then divided by country-specific sample standard deviation. NBER recessions are indicated by the shaded grey time periods.

Figure 5: Z-scores of $P_{c,t}^A$ across countries and time



Note: $P_{c,t}^A$ is the portfolio assets flows data from IFS, as discussed in section 2.3. Z-score is calculated as $P_{c,t}^A$ 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 6: Z-scores of $P_{c,t}^N$ across countries and time



Note: $P_{c,t}^N$ is the net-net portfolio flows data from IFS, as discussed in section 2.3. Z-score is calculated as $P_{c,t}^N$ 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.

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%
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%
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%
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 [Pistricha 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					
	$NIT_{c,t}$		$NOE_{c,t}$		$NNKIR_{c,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
y_{t-1}^1	-0.328 (0.331)		0.016 (0.290)		-0.274 (0.307)	
y_{t-1}^2	-0.513* (0.278)		-1.645*** (0.574)		-1.713** (0.762)	
Δr_{t-1}^{shadow}		-0.036 (0.046)		0.015 (0.039)		-0.052 (0.037)
$\pi_{c,t-1}$	-0.062** (0.029)	-0.063** (0.030)	0.015 (0.036)	0.014 (0.038)	-0.019 (0.021)	-0.025 (0.022)
$g_{c,t-1}$	0.049* (0.027)	0.049* (0.028)	0.021 (0.033)	0.012 (0.034)	0.077*** (0.023)	0.071*** (0.024)
$\Delta(CA/GDP^*)_{c,t-1}$	-0.020 (0.038)	-0.018 (0.037)	0.018 (0.019)	0.021 (0.021)	0.028 (0.035)	0.034 (0.034)
$\Delta \ln s_{c,t-1}$	-0.084** (0.034)	-0.082** (0.033)	-0.143*** (0.033)	-0.141*** (0.033)	-0.176*** (0.033)	-0.172*** (0.033)
Observations	841	841	841	841	841	841
Countries	15	15	15	15	15	15
R^2	0.015	0.015	0.027	0.020	0.046	0.039
Standard error type	Driscoll and Kraay (1998) (12 quarters)					

Note: The regressions shown in this table take the general form of equation 1. See section 2.1 for the definitions of $NIT_{c,t}$, $NOE_{c,t}$ and $NNKIR_{c,t}$. y_{t-1}^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_{t-1}^2 is the second. $\Delta r_{c,t-1}^{shadow}$ 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_{t-1}^1 , y_{t-1}^2 and $\Delta r_{c,t-1}^{shadow}$ 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^2 s are overall R-squareds.

Table 3: Causal effect of capital control actions on portfolio flows

	Dependent variable		
	$P_{c,t+1}^L$	$P_{c,t+1}^A$	$P_{c,t+1}^N$
	(1)	(2)	(3)
$NIT_{c,t}$	-0.815*** (0.280)		
$NOE_{c,t}$		-0.050 (0.165)	
$NNKIR_{c,t}$			-0.403*** (0.108)
$\pi_{c,t} - \pi_{c,t}^{U.S.}$	-0.065 (0.062)	-0.038 (0.028)	-0.008 (0.029)
$g_{c,t} - g_{c,t}^{U.S.}$	0.074 (0.048)	-0.052** (0.026)	0.079*** (0.031)
$\Delta (CA/GDP^*)_{c,t}$	0.040 (0.027)	-0.101*** (0.038)	0.002 (0.034)
$\Delta \ln s_{c,t}$	-0.064 (0.052)	0.014 (0.024)	-0.038 (0.045)
four lags of dependent variable are included			
Observations	795	765	795
Countries	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)		
S-H J -statistics p-value	0.663	0.758	0.675

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. $P_{c,t+1}^L$, $P_{c,t+1}^A$ and $P_{c,t+1}^N$ the net portfolio liability flows, net portfolio asset flows, and net-net portfolio flows, respectively, as detailed in section 2.3. $NIT_{c,t}$, $NOE_{c,t}$ and $NNKIR_{c,t}$ are the net inflow tightening actions, net outflow easing actions and net-net inflow reducing measures, respectively, 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; $\ln s_{c,t-1}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. All variables 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: Causal effect of $NIT_{c,t}$ on portfolio liability flows

	Dependent variable				
	$P_{c,t+1}^L$		$\left(\frac{P^L}{GDP^*}\right)_{c,t+1}$		$P_{c,t+1}^L$
	No instruments (1)	Key result: GMM-FE (2)	Key result: GMM-FE (3)	Weighted version of $NIT_{c,t}$ (4)	"concerns abroad" meetings removed control (6)
$NIT_{c,t}$	0.024 (0.029)	-0.815*** (0.280)	-0.628** (0.259)		-0.535** (0.251)
$WNIT_{c,t}$				-0.810*** (0.298)	-0.806* (0.457)
$\Delta \ln REER_{c,t}$					0.045 (0.070)
$\pi_{c,t} - \pi_{c,t}^{U.S.}$	0.022 (0.039)	-0.065 (0.062)	-0.062 (0.050)	-0.080 (0.067)	-0.047 (0.046)
$g_{c,t} - g_{c,t}^{U.S.}$	0.004 (0.054)	0.074 (0.048)	0.068 (0.048)	0.085* (0.051)	0.022 (0.031)
$\Delta (CA/GDP^*)_{c,t}$ (0.024)	0.017 (0.027)	0.040 (0.027)	0.035 (0.025)	0.036 (0.022)	0.050** (0.033)
$\Delta \ln s_{c,t}$ (0.047)	-0.057 (0.052)	-0.064 (0.047)	-0.093** (0.045)	-0.069 (0.041)	-0.040
four lagged dependent variables are included					
Observations	795	795	795	795	795
Countries	15	15	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)				
S-H J -statistics p-value	n/a	0.663	0.671	0.688	0.630

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. $P_{c,t+1}^L$ is the net portfolio liability flow detailed in section 2.3. $NIT_{c,t}$ is the net inflow tightening actions and $WNIT_{c,t}$ is its weight version, both from [Pasticha 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; $\ln s_{c,t-1}$ is the quarterly log difference in the nominal exchange rate, which is the units of the local currency per U.S. dollar. $REER_{c,t}$ is the real effective exchange rate. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). In column (5), the Excess Bond Premium (EBP) of [Gilchrist and Zakrajsek \(2012\)](#) is used as the instrumental variable. 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: Asymmetric monetary policy shocks

	Dependent variable			
	$NIT_{c,t}$	$P_{c,t+1}^L$	$NNKIR_{c,t}$	$P_{c,t+1}^N$
	(1)	(2)	(3)	(4)
y_{t-1}^{1-}	0.065 (0.548)		0.392 (0.514)	
y_{t-1}^{1+}	-0.829 (0.722)		-1.162 (0.982)	
y_{t-1}^{2-}	-0.862* (0.453)		-2.436** (0.956)	
y_{t-1}^{2+}	0.492 (1.958)		-0.794 (2.178)	
$NIT_{c,t}$		-0.861*** (0.247)		
$NNKIR_{c,t}$				-0.434*** (0.093)
$\pi_{c,t-1}$	-0.062** (0.029)		-0.019 (0.021)	
$g_{c,t-1}$	0.054** (0.026)		0.084*** (0.023)	
$\Delta (CA/GDP^*)_{c,t-1}$	-0.019 (0.039)		0.029 (0.036)	
$\Delta \ln s_{c,t-1}$	-0.085** (0.035)		-0.176*** (0.034)	
$\pi_{c,t} - \pi_{c,t}^{U.S.}$		-0.061 (0.053)		-0.004 (0.027)
$g_{c,t} - g_{c,t}^{U.S.}$		0.069 (0.048)		0.079*** (0.030)
$\Delta (CA/GDP^*)_{c,t}$		0.038 (0.026)		-0.006 (0.031)
$\Delta \ln s_{c,t}$		-0.073* (0.044)		-0.049 (0.043)
Observations	841	795	841	795
Countries	15	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)			
R^2	0.016		0.047	
S-H J -statistics p-value		0.812		0.833

Note: The regressions shown in this table take the general form of equation (1) in columns (1) and (3) and of equation (2) in columns (2) and (4). $NIT_{c,t}$ and $NNKIR_{c,t}$ are net inflow tightening actions and net change in inflow reducing actions, respectively, from [Pasricha et al. \(2018\)](#); see section 2.1. y_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_t^2 is the second; variables with superscripts “-” and “+” are the negative and positive parts of the shocks, respectively, as defined in equation (5). $\pi_{c,t-1}$ is the CPI inflation rate calculated as the year-on-year change in the CPI index and $g_{c,t-1}$ is the real GDP growth rate calculated as the year-on-year change in real GDP; the differentials of these variables vis-à-vis those of the U.S. are used in columns (2) and (4). $(CA/GDP^*)_{c,t-1}$ 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_{t-1}^{1-} , y_{t-1}^{1+} , y_{t-1}^{2-} and y_{t-1}^{2+} 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^2 s are overall R-squareds and “S-H J -statistics” is the Sargan-Hansen test of the null that the over-identifying restrictions are valid.

Table 6: Causal effect of $NNKIR_{c,t}$ on net portfolio flows

	Dependent variable				
	$P_{c,t+1}^N$		$\left(\frac{P^N}{GDP^*}\right)_{c,t+1}$		$P_{c,t+1}^N$
	No instruments (1)	Key result: GMM-FE (2)	Key result: GMM-FE (3)	Weighted version of $NNKIR_{c,t}$ (4)	"concerns abroad" meetings removed control (6)
$NNKIR_{c,t}$ 0.011	-0.403*** (0.026)	-0.354*** (0.108)	(0.111)	-0.259** (0.116)	-0.808*** (0.311)
$WNNKIR_{c,t}$				-0.443*** (0.118)	
$\Delta \ln REER_{c,t}$					
$\pi_{c,t} - \pi_{c,t}^{U.S.}$	0.035 (0.036)	-0.008 (0.029)	-0.008 (0.032)	-0.022 (0.030)	-0.009 (0.028)
$g_{c,t} - g_{c,t}^{U.S.}$	0.042 (0.045)	0.079*** (0.031)	0.068** (0.031)	0.088*** (0.030)	0.066** (0.029)
$\Delta (CA/GDP^*)_{c,t}$	0.006 (0.040)	0.002 (0.034)	0.002 (0.026)	0.011 (0.033)	0.019 (0.034)
$\Delta \ln s_{c,t}$	-0.061 (0.057)	-0.038 (0.045)	-0.054 (0.039)	-0.033 (0.043)	-0.014 (0.042)
four lagged dependent variables are included					
Observations	795	795	795	795	795
Countries	15	15	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)				
S-H J -statistics p-value	n/a	0.675	0.593	0.705	0.705

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. $P_{c,t+1}^N$ is the net-net portfolio flow detailed in section 2.3. $NNKIR_{c,t}$ is the net-net inflow reducing actions and $WNNKIR_{c,t}$ is its weight version, both 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 effective exchange rate; $REER_{c,t}$ is the real effective exchange rate. All variables are standardized by the country-specific mean and standard deviation (i.e., z-scores are used in these regressions). In column (5), the Excess Bond Premium (EBP) of [Gilchrist and Zakrajsek \(2012\)](#) is used as the instrumental variable. 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: Longer-term monetary policy shocks

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

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

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

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

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

Table 9: Parsing out prudential policies

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

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

Table 10: FDI and “other” flows

	Dependent variable					
	Liability flows			Net-net flows		
	$P_{c,t+1}^L$ (1)	$FDI_{c,t+1}^L$ (2)	$O_{c,t+1}^L$ (3)	$P_{c,t+1}^N$ (4)	$FDI_{c,t+1}^N$ (5)	$O_{c,t+1}^N$ (6)
$NIT_{c,t}$	-0.815*** (0.280)	1.040*** (0.141)	0.757** (0.328)			
$NNKIR_{c,t}$				-0.403*** (0.108)	0.399** (0.104)	0.187* (0.102)
$\pi_{c,t} - \pi_{c,t}^{U.S.}$	-0.065 (0.062)	0.027 (0.024)	0.036 (0.045)	-0.008 (0.029)	-0.029 (0.027)	-0.008 (0.026)
$g_{c,t} - g_{c,t}^{U.S.}$	0.074 (0.048)	0.044** (0.020)	0.019 (0.028)	0.079*** (0.031)	0.050*** (0.019)	0.033* (0.018)
$\Delta (CA/GDP^*)_{c,t}$	0.04 (0.027)	0 (0.031)	-0.081 (0.056)	0.002 (0.034)	0.057 (0.017)	-0.065*** (0.022)
$\Delta \ln s_{c,t}$	-0.064 (0.052)	0.031 (0.037)	-0.144*** (0.023)	-0.038 (0.045)	0.010 (0.020)	-0.190*** (0.023)
four lags of dependent variable are included						
Observations	795	795	772	795	795	772
Countries	15	15	15	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)					
S-H J —statistics p-value	0.663	0.858	0.582	0.675	0.577	0.519

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. $P_{c,t+1}^L$ and $P_{c,t+1}^N$ are net portfolio liability flow and net-net portfolio flow described in section 2.3, while $FDI_{c,t+1}^L$, $O_{c,t+1}^L$, $FDI_{c,t+1}^N$ and $O_{c,t+1}^N$ are the net FDI liability flow, net other liability flow, net-net FDI flow and net-net other flows, respectively, defined in section 4.3. $NIT_{c,t}$ and $NNKIR_{c,t}$ are the net inflow tightening actions and net-net 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 effective exchange rate. 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 11: The exclusion restriction—are U.S. monetary policy shocks transmitted through asset price channels?

	Dependent variable		
	$i_{c,t} - i_{c,t}^{U.S.}$	$r_{c,t} - r_{c,t}^{U.S.}$	$\Delta H_{c,t} - \Delta H_{c,t}^{US}$
	(1)	(2)	(3)
y_{t-1}^1	-1.207* (0.680)	-1.133 (1.350)	0.143 (2.033)
y_{t-1}^2	-0.130 (1.136)	-0.391 (1.568)	0.203 (1.057)
$\pi_{c,t-1}$	0.325*** (0.035)	0.079 (0.071)	0.065 (0.040)
$g_{c,t-1}$	-0.194* (0.106)	0.261*** (0.094)	-0.020 (0.064)
$\Delta (CA/GDP^*)_{c,t-1}$	0.002 (0.035)	-0.114** (0.051)	-0.012 (0.044)
$\Delta \ln s_{c,t-1}$	0.172*** (0.039)	-0.027 (0.056)	-0.017 (0.060)
four lags of dependent variable are included			
Observations	841	657	774
Countries	15	15	15
R^2	0.220	0.081	0.005
Standard error type	Driscoll and Kraay (1998) (12 quarters)		

Note: The regressions shown in this table take the general form of equation 1. $i_{c,t} - i_{c,t}^{U.S.}$, $r_{c,t} - r_{c,t}^{U.S.}$, and $\Delta H_{c,t} - \Delta H_{c,t}^{US}$ are the interest differential, equity return differential, and home price growth differential, respectively; all differentials are taken vis-à-vis the U.S. y_{t-1}^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_{t-1}^2 is the second. $\pi_{c,t-1}$ 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_{t-1}^1 and y_{t-1}^2 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^2 s are overall R-squareds.

Table 12: Interest differential as causal variable and EBP as instrument

	Dependent variable			
	$P_{c,t+1}^L$		$P_{c,t+1}^N$	
	Two causal variables (1)	EBP as an instrument (2)	Two causal variables (3)	EBP as an instrument (4)
$NIT_{c,t}$	-0.722* (0.388)	-0.795*** (0.277)		
$NNKIR_{c,t}$			-0.496*** (0.125)	-0.185* (0.108)
$i_{c,t} - i_{c,t}^{U.S.}$	0.134 (0.308)		-0.171 (0.204)	
$\pi_{c,t} - \pi_{c,t}^{U.S.}$	-0.114 (0.123)	-0.055 (0.051)	0.065 (0.090)	0.005 (0.033)
$g_{c,t} - g_{c,t}^{U.S.}$	0.098 (0.072)	0.081 (0.050)	0.044 (0.053)	0.082** (0.037)
$\Delta (CA/GDP^*)_{c,t}$	0.035 (0.030)	0.034 (0.027)	-0.001 (0.037)	0.022 (0.034)
$\Delta \ln s_{c,t}$	-0.079 (0.066)	-0.084* (0.050)	-0.029 (0.037)	-0.026 (0.042)
four lags of dependent variable are included				
Observations	795	795	795	795
Countries	15	15	15	15
Standard error type	Driscoll and Kraay (1998) (12 quarters)			
S-H J —statistics p-value	0.535	0.736	0.487	0.708

Note: The regressions shown in this table are fixed effects (within transformation) regressions that take the general form of equations (1) and (2), estimated with efficient GMM. $P_{c,t+1}^L$ and $P_{c,t+1}^N$ are net portfolio liability flow and net-net portfolio flow described in section 2.3. $NIT_{c,t}$ and $NNKIR_{c,t}$ are the net inflow tightening actions and net-net 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 effective exchange rate. In columns (1) and (3), $i_{c,t-1} - i_{US,t-1}$, the nominal policy rate relative to the U.S. is also a causal variable of interest in addition to $NIT_{c,t}$ or $NNKIR_{c,t}$. In columns (2) and (4), the Excess Bond Premium (EBP) of [Gilchrist and Zakrajsek \(2012\)](#) is used as the instrumental variable. 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		
	$P_{c,t+1}^N$		$(\frac{P^N}{GDP^*})_{c,t+1}$
	Key result (1)	China excluded (2)	China excluded (3)
$NNKIR_{c,t}$	-0.403*** (0.108)	-0.429*** (0.129)	-0.400*** (0.131)
$\pi_{c,t} - \pi_{c,t}^{U.S.}$	-0.008 (0.029)	-0.020 (0.028)	-0.028 (0.028)
$g_{c,t} - g_{c,t}^{U.S.}$	0.079*** (0.031)	0.073** (0.033)	0.061* (0.034)
$\Delta(CA/GDP^*)_{c,t}$	0.002 (0.034)	0.002 (0.037)	0.000 (0.029)
$\Delta \ln s_{c,t}$	-0.038 (0.045)	-0.038 (0.047)	-0.062 (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. $P_{c,t+1}^N$ 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: Subsamples

Regressor	Dependent variable				
	$P_{c,t+1}^N$			$(\frac{P^N}{GDP^*})_{c,t+1}$	
	Key result (1)	Subsample 1 (2)	Subsample 2 (3)	Subsample 1 (4)	Subsample 2 (5)
$NNKIR_{c,t}$	-0.403*** (0.108)	-0.270*** (0.074)	-0.438** (0.171)	-0.566*** (0.091)	-0.316** (0.154)
$\pi_{c,t} - \pi_{c,t}^{U.S.}$	-0.008 (0.029)	0.007 (0.019)	0.064** (0.025)	0.019 (0.025)	0.063*** (0.022)
$g_{c,t} - g_{c,t}^{U.S.}$	0.079*** (0.031)	0.067 (0.045)	0.030 (0.041)	0.116** (0.056)	0.037 (0.039)
$\Delta(CA/GDP^*)_{c,t}$	0.002 (0.034)	0.028 (0.025)	-0.087*** (0.030)	0.018 (0.041)	-0.075*** (0.026)
$\Delta \ln s_{c,t}$	-0.038 (0.045)	0.007 (0.016)	-0.149*** (0.023)	-0.021 (0.023)	-0.138*** (0.020)
lag of dependent variable	four lags included				
Observations	795	344	451	344	451
Countries	15	15	15	15	15
Standard error type	Driscoll and Kraay(1998)(12 quarters)				
S-H J-statistics p-value	0.675	0.824	0.696	0.729	0.719

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. $P_{c,t+1}^N$ 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 2007Q4 and Subsample 2 uses the data from 2008Q1.

Table A.3: Robustness check: Portfolio debt flows and portfolio equity flows

Regressor	Dependent variable				
	$P_{c,t+1}^N$	$P_{c,t+1}^{ND}$	$P_{c,t+1}^{NE}$	$(\frac{P^{ND}}{GDP^*})_{c,t+1}$	$(\frac{P^{NE}}{GDP^*})_{c,t+1}$
	Key result (1)	Net debt flows (2)	Net equity flows (3)	Net debt flows (4)	Net equity flows (5)
$NNKIR_{c,t}$	-0.429*** (0.129)	-0.436*** (0.152)	-0.390*** (0.100)	-0.730*** (0.201)	-0.306*** (0.074)
$\pi_{c,t} - \pi_{c,t}^{U.S.}$	-0.020 (0.028)	-0.009 (0.017)	0.239*** (0.039)	-0.018 (0.022)	0.175*** (0.032)
$g_{c,t} - g_{c,t}^{U.S.}$	0.073** (0.033)	0.111** (0.048)	0.065* (0.038)	0.155** (0.071)	0.032 (0.033)
$\Delta(CA/GDP^*)_{c,t}$	0.002 (0.037)	0.020 (0.029)	0.064* (0.037)	0.020 (0.040)	0.044* (0.026)
$\Delta \ln s_{c,t}$	-0.038 (0.047)	0.058*** (0.017)	0.005 (0.023)	0.054* (0.029)	0.005 (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. $P_{c,t+1}^N$ 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.4: Robustness check: Using Hamilton trend GDP to normalize variables

	Dependent variable		
	$P_{c,t+1}^N$	$\left(\frac{P^N}{GDP^*}\right)_{c,t+1}$	
	Key result (1)	Key result (2)	Hamilton (2018) trend (3)
$NNKIR_{c,t}$	-0.403*** (0.108)	-0.354*** (0.111)	-0.371*** (0.112)
$\pi_{c,t} - \pi_{c,t}^{U.S.}$	-0.008 (0.029)	-0.008 (0.032)	-0.018 (0.034)
$g_{c,t} - g_{c,t}^{U.S.}$	0.079*** (0.031)	0.068** (0.031)	0.073** (0.030)
$\Delta (CA/GDP^*)_{c,t}$	0.002 (0.034)	0.002 (0.026)	0.006 (0.023)
$\Delta \ln s_{c,t}$	-0.038 (0.045)	-0.054 (0.039)	-0.065* (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. $P_{c,t+1}^N$ 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 $P_{c,t}^N$ 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.

Table A.5: Robustness check: Using untransformed variables

	Dependent variable		
	$P_{c,t+1}^N$	$\left(\frac{P^N}{GDP^*}\right)_{c,t+1}$	
	Key result (1)	Key result (2)	No z-scores (3)
$NNKIR_{c,t}$	-0.403*** (0.108)	-0.354*** (0.111)	-0.003*** (0.001)
$\pi_{c,t} - \pi_{c,t}^{U.S.}$	-0.008 (0.029)	-0.008 (0.032)	-0.005** (0.002)
$g_{c,t} - g_{c,t}^{U.S.}$	0.079*** (0.031)	0.068** (0.031)	0.015 (0.009)
$\Delta (CA/GDP^*)_{c,t}$	0.002 (0.034)	0.002 (0.026)	-0.059 (0.070)
$\Delta \ln s_{c,t}$	-0.038 (0.045)	-0.054 (0.039)	-0.001 (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. $P_{c,t+1}^N$ 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), 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.6: Robustness check: Intra-quarter monetary policy shocks added together

	Dependent variable		
	$P_{c,t+1}^N$	$\left(\frac{P^N}{GDP^*}\right)_{c,t+1}$	
	summed shocks (1)	summed shocks (2)	summed shocks (3)
$NNKIR_{c,t}$	-0.403*** (0.108)	-0.233* (0.120)	-0.157 (0.109)
$\pi_{c,t} - \pi_{c,t}^{U.S.}$	-0.008 (0.029)	0.008 (0.032)	0.014 (0.033)
$g_{c,t} - g_{c,t}^{U.S.}$	0.079*** (0.031)	0.082** (0.038)	0.068** (0.037)
$\Delta(CA/GDP^*)_{c,t}$	0.002 (0.034)	0.002 (0.029)	0.003 (0.022)
$\Delta \ln s_{c,t}$	-0.038 (0.045)	-0.029 (0.044)	-0.041 (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_t^1 and y_t^2 , the sum of all monetary policy shocks within quarter t is used as the instrument. $P_{c,t+1}^N$ 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.