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Abstract

This paper takes a new approach to assess the benefits of using different policy tools—macroprudential and monetary policies, foreign exchange interventions, and capital controls—in response to changes in financial conditions. Starting from quantile regressions, we evaluate policies across the full distribution of future output growth and inflation using loss functions. Tightening macroprudential policy dampens downside risks to growth from loose financial conditions, and is beneficial in net terms. By contrast, tightening monetary policy entails net losses. These findings also hold when reacting to easing global financial conditions, while buying foreign exchange or tightening capital controls yields only small net benefits.

JEL Classification: E52, E58, F31, G28, E01, O24, G21

Keywords: monetary policy, macroprudential policy, FX intervention, capital controls, cost-benefit analysis

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I. INTRODUCTION

An active debate in academia and policy circles centers on which policies should be used to address financial stability risks (e.g., Adrian and Liang 2018). Should macroprudential policy be the first line of defense? Or should monetary policy help "lean against the wind" of building financial vulnerabilities? What are the costs and benefits of using one set of policies versus the other?

In the eyes of many policymakers, macroprudential policies are preferable, since they can be better targeted at emerging risks. Monetary policy, on the other hand, is a blunt tool, which comes with potentially large costs to the economy at large (see Yellen, 2014, and references therein). Moreover, a key benefit of macroprudential policy is that it can directly strengthen resilience to future shocks, by bolstering the balance sheets of borrowers and lenders, something which monetary policy cannot do. However, as argued by many, macroprudential policy is subject to "leakage effects" (Bengui and Bianchi 2018), reducing its effectiveness, while monetary policy has the advantage of "getting into all the cracks" (Stein 2013). More broadly, since macroprudential policy is relatively new, knowledge about its overall benefits and costs, and how these compare to other policies, is only gradually accumulating.

Financially integrated open economies face the additional challenge of how to respond to an easing of global financial conditions that might drive up the exchange rate and stimulate capital inflows and domestic credit. As is by now acknowledged by many, flexible exchange rates typically do not fully insulate the domestic economy from the effects of such swings in global financial conditions (Obstfeld 2015; Rey 2013; Nelson 2020). And in practice, emerging markets in particular have been using a range of policies, often also including foreign exchange intervention and capital controls, when confronted with rapidly changing global financial conditions.

This paper proposes a new empirical approach to assess the costs and benefits of using different policy tools to dampen the buildup of financial vulnerabilities from a loosening in domestic and global financial conditions. Building on the study by Adrian, Boyarchenko, and Giannone (2019), it estimates the policy effects on the entire distributions of future real GDP growth and inflation, and then evaluates their net benefits using quadratic loss functions. This new approach relates to and advances on various strands of the existing literature.

First, a small number of studies examine whether monetary policy should lean against the wind in an empirical cost-benefit framework that compares the benefits of raising policy rates—lowering the probability of a future crisis—to its short-term costs—namely inducing higher unemployment (IMF 2015, Svensson 2017a). These studies have generally concluded that the costs of leaning outweigh its benefits[1]. While offering some useful insights, the approach has several limitations (see Adrian and Liang, 2018, and Svensson's 2017b response). For one, it assumes a binary partition of "crisis" versus "no crisis" states, while financial stability policies may be beneficial to mitigate the probability and severity of a continuum of outcomes, including standard recessions, financial recessions and all-out crises (Claessens, Kose, and Terrones, 2011). Moreover, this literature has struggled to pin down the effects of changes in policy rates on crisis probabilities, where several and potentially opposing effects may be at work. Finally, it relies on assumptions on the cost of crises, and is subject to subtle arguments as to how a policy of leaning against the wind might itself affect the severity of crises—for example, does leaning create policy space for rate cuts, or does it weaken the economy, thereby exacerbating a crisis?[2]

Second, a growing literature examines empirically the effectiveness of macroprudential policy in achieving its objectives (see the studies covered in the survey by Galati and Moessner 2018). Most of these studies find that macroprudential policies can slow credit growth, with effects generally measured as stronger for borrower-based tools, such as loan to value (LTV) and debt service to income (DSTI) constraints. Some studies also consider costs, such as adverse short-run effects on consumption and growth (Alam et al. 2019, Richter, Schularick, and Shim 2019). However, this literature has not yet advanced to a comprehensive assessment of the costs and benefits of macroprudential policy. For one, while increasing resilience of financial institutions and borrowers to future shocks is a primary objective of macroprudential policy, with only very few exceptions (e.g., Jiménez et al. 2017) the literature has not yet attempted to quantify these effects. Second, and relatedly, empirical studies have so far mostly offered estimates of the effects on intermediate targets (e.g., credit growth) and have not yet attempted a quantitative assessment of the effects on the ultimate objectives of macroprudential policy: to reduce tail risks to future output growth.

A third group of studies introduces a macroprudential policy tool into DSGE models, using a loss function that is typically augmented to include the volatility of credit in addition to output and inflation (e.g., Angelini et al. 2014). These studies generally conclude that when macroprudential policy is available to control the volatility of credit, monetary policy is best focused on output and inflation. While intuitive, a key limitation of the approach is that the transmission of the macroprudential tool is stylized, often amounting to introducing a wedge between interbank and lending rates. In reality, by

[1] Similarly, Schularick et al. (2020), using data from 1870 onward, find that discretionary leaning-against-the-wind policies during credit- and asset price booms were more likely to trigger crises than prevent them.

[2] A related group of papers have studied the issue using New-Keynesian DSGE models that include the possibility of crises. In these models, the extent to which monetary policy should lean against the wind depends on specific conditions (Adam and Woodford 2018, Gourio, Kashyap, and Sim 2018, and Ajello et al. 2019).

contrast, the transmission of macroprudential policy to financial stability also includes a resilience effect, and the effect on credit dynamics differs across tools. A second important limitation is that the volatility of credit is an ad-hoc addition to the loss function, whereas the ultimate objective of macroprudential policy is to avoid adverse effects of financial shocks on output (Adrian and Liang, 2018).

Lastly, a large body of literature has covered policy choices of small open economies, and emerging markets in particular, when faced with external shocks. Largely, the prescription has been that monetary policy should focus on domestic inflation while the exchange rate should be left to float (see, among many others, Clarida, Galí and Gertler, 2000; and Devereux, Lane, and Xu, 2006). More recently, many models have started to build in financial frictions (e.g. Aoki, Benigno, and Kiyotaki 2016; Céspedes, Chang and Velasco, 2017; and Adrian et al. 2020), and partly find justification for Pigouvian taxes on capital inflows (e.g., Korinek, 2018), or the use of foreign-exchange intervention that builds reserves and deploys these to limit disruptive deprecation in the event of outflows. However, empirical estimation of the benefits of these tools remains an unfinished task.

The starting point for the novel empirical approach developed in this paper is an intertemporal trade-off where improving financial conditions today can also lead to an increase in financial vulnerabilities that ultimately puts future growth at risk. Easy financial conditions tend to boost output growth in the short term but are associated with greater downside risks to growth in the medium term (Adrian et al., 2019, forthcoming).[3]

Using our new framework, we ask: which policies can ameliorate the trade-off? In a first step, we employ quantile regressions to compare how policies affect the trade-off between current financial conditions and the expected distribution of future GDP growth and inflation. This analysis uses quarterly data for financial conditions, economic growth and policy indicators for 37 advanced- and emerging market economies over the period 1990 to 2016. To identify the effect of policies on the trade-off, we examine policy surprises, constructed as deviations from estimated policy rules. In a second step, to obtain estimates of the impact of policies on the entire probability distribution of future GDP growth, we fit the empirical conditional quantiles to a known distribution function (skewed-Normal). The third and final step is to feed these distributions into a standard loss function and compare losses with- and without policy actions.

Relative to the existing literature, the approach developed in this paper makes at least three important advances. First, it extends beyond examining the effects of macroprudential policies on intermediate outcomes, by offering a framework that allows an assessment of effects on the ultimate objective, namely to contain tail risks to real economic outcomes. Second, it moves beyond the measurement of costs and benefits using a binary partition into crisis and non-crisis states, by considering instead the whole

[3] This insight is formalized in internally coherent models with rational expectations by Adrian et al. (2020).

future distribution of output growth and measuring costs and benefits across all relevant states of the world. Third, it does not make any simplifying and potentially counterfactual assumptions about the transmission of macroprudential policy (or monetary policy). If macroprudential policy affects the ultimate objectives of the policymaker both by slowing credit growth and by bolstering the resilience of borrowers and banks to future shocks, then both these benefits would come through in the estimated impact on tail risks to GDP.

We conduct this analysis both for changes in domestic and global financial conditions, considering that changes in global financial conditions can more readily be argued to be exogenous for a small open economy. For an easing of global financial conditions, we also consider foreign-exchange intervention and capital flow management policies that countries might want to use to 'lean against' the resulting appreciation and increase in capital inflows. We finally evaluate the interactions between monetary- and macroprudential policies, by examining the impact on the loss functions of a joint use of both sets of policies.

Overall, despite stark differences in the methods used, our results on the effectiveness of macroprudential policy line up with and strengthen the tentative conclusions reached by the existing literature. We find strong and new evidence that macroprudential policy lessens the trade-off between presently looser financial conditions and greater future downside risks to growth. The average tightening of macroprudential measures is associated with large loss reductions, and these benefits are found to be pronounced in particular for the tightening of borrower-based tools, such as caps on LTV and DSTI.

Moreover, tightening borrower-based macroprudential policies when vulnerabilities (as measured by credit aggregates or asset prices) are high is more decisively associated with a reduction in losses than when vulnerabilities are still low. However, financial-institutions-based tools, such as capital and liquidity tools, appear to be most useful in building resilience even when vulnerabilities are still modest.

By contrast, a tightening of monetary policy does not appear to be able to improve the trade-off between loose financial condition today and future tail risks to GDP growth. Indeed, on net, a tightening of monetary policy to counter loosening financial conditions is consistently associated with higher losses over the policy horizon. This confirms the notion that the economic costs of using tighter monetary policy to lean against the wind outweigh any associated financial stability benefit.

These results largely extend when we consider potential responses to changes in global financial conditions. A tightening of macroprudential policies appears to be the most effective response to an easing of global financial conditions. Leaning against such easing with foreign-exchange interventions entails much smaller (but positive) net benefits over the policy horizon. Likewise, tightening CFMs to counter loose global financial conditions seems to bring only a weak reduction in the loss function. Finally, again, a tightening of monetary policy leads to higher losses, and is therefore the least beneficial.

The results are broadly robust to alternative specifications of loss functions, including an asymmetric loss function that penalizes downward deviations more than upward ones.

The remainder of the paper is organized as follows. In Section II we provide more detail on the econometric approach to estimating growth at risk and the data used for the analysis. Section III presents a first comparison of results comparing no-policy outcomes with outcomes where policy is used. Section IV examines impacts on the entire distribution and evaluates loss functions. Section V concludes.

II. EMPIRICAL APPROACH

A. Quantile Regressions

Our approach takes the stylized facts laid out by Adrian et al. (2019, forthcoming) as a starting point: easy financial conditions tend to boost output growth in the short term but tend to be followed by greater downside risks to growth in the medium term.

A first aim is to investigate whether and how different types of policies can ameliorate this trade off. For this purpose, we estimate fixed-effects quantile regressions (FE-QR). For each horizon $h=1 \ldots H$, we use the FE-QR estimator described in Kato et al. (2012):

$$Q_{Y_{i,t+h}}(q|Z_{it}) = \alpha_{0i}^{h}(q) + \beta_1^h(q) f_{it} + \beta_2^h(q) P_{it} + \beta_3^h(q) P_{it} \times f_{it} \boldsymbol{x}_{it} \Gamma^h, \quad (1)$$
$$h = 1 \ldots H, \quad q = 0.05 \ldots 0.95,$$

where $Y_{i,t+h}$ is a measure of either economic activity or inflation in country i and quarter $t+h$, f_{it} is a financial condition index (FCI), P_{it} is the policy variable, $\mathbf{x}$ is a vector of controls including current GDP growth, inflation and credit growth, and Q is the conditional q-th quantile function of $Y_{i,t+h}$, and $Z \equiv [f_{it}, P_{it}, \mathbf{x}_{it}]$.[4]
As our measure of economic activity, we consider a simple proxy of the output gap given by the log level of real GDP (y_{it}) as a deviation from a linear time trend ($\bar{y}_{it}$), that is $Y_{i,t+h} \equiv (y_{it+h} - \bar{y}_{it+h}) - (y_{it} - \bar{y}_{it})$.[5] We also estimate the effects on inflation with an analogous specification. A higher FCI represents looser financial conditions, and a higher level of

[4] Specification (1) assumes that the slope coefficients vary by quantile but not by country. This assumption is dropped later as part of the robustness analysis.

[5] Because of stochastic trends in output, we use $Y_{i,t+h} \equiv (y_{it+h} - \bar{y}_{it+h}) - (y_{it} - \bar{y}_{it})$ instead of $Y_{i,t+h} \equiv (y_{it+h} - \bar{y}_{it+h})$ to ensure stationarity. Our results are not very sensitive to how we detrend output, and qualitatively similar results (available from the authors) are obtained when detrending output with Hamilton's (2018) filter.

the policy variable indicates a tightening (see Section III). Note that the specification assumes symmetric effects for tightening and loosening policy measures.

After estimating the conditional quantile functions given by (1), we are interested in testing the hypothesis that a given policy P changes the effect of f on the distribution of future GDP growth (i.e., the detrended change in log GDP from one to h quarters ahead) and inflation. In particular, in the quantile regressions of future GDP growth, for large h (i.e., at long horizons) and low q (e.g., q=0.1), we expect β_1 to be negative—looser financial conditions today are associated with a fatter left tail of distribution of GDP growth. For a policy P to be effective in containing this buildup of risk, β_3 would need to be positive at the same horizon and for the same quantiles. However, the required inference to test this hypothesis is complicated by the possibility that our data may feature significant serial correlation. We take this into account by calculating the standard errors and confidence bands of the estimators of the parameters in (1) using Hagemann's (2017) cluster-robust bootstrap.[6]

B. Integrating and Computing Loss Functions

However, to obtain a full picture of the effects of policies, it is not sufficient to focus on how policies can change downside risk to GDP (or inflation). For example, the policies may affect both the left and right tails of the conditional distribution of future GDP growth. In addition, they may shift the entire distribution, not just change its dispersion or the shape of its tails.

Our analysis therefore uses summary statistics of the conditional distributions of GDP growth and inflation obtained at various horizons and aggregates them into a loss function which is intended to represent the policymaker's preferences over economic outcomes. Here, we use a quadratic loss function as do New Keynesian models. The period loss function ℓ_t is:

$$\ell_t = \omega_y \left(y_{t+h} - \bar{y}_{t+h} \right)^2 + \omega_\pi \pi_{t+h}^2, \qquad (2)$$

where $\left(y_{t+h} - \bar{y}_{t+h} \right)$ is our measure of detrended GDP, π_{t+h} is quarterly inflation, and ω_y and ω_π are weights. The comparison of policies is then based on the expected discounted value of future losses, written as follows:

$$L_0\left(\Theta\right) = \sum_{h=0}^{H} \beta^h \hat{E}_t \left(\ell_{t+h} \mid P_t = 0, \Theta \right), P_t \in \left\{ MPM_t, MP_t, FXI_t \right\}, \qquad (3)$$
$$\text{and } \Theta = \left[\theta^1 \quad \theta^2 \quad \ldots \quad \theta^H \right]$$

[6] Both the QE-FR and Hagemann's cluster-robust bootstrap estimator are implemented in Koenker's (2019) `quantreg` library for R. For the bootstrap we use country clusters.

for the case of no policy action. In (3), θ^h is the vector of parameters describing the conditional distribution function of h-step ahead detrended output and π is the inflation rate. Similarly, when a given policy is being used, we have:

$$L_1(\Theta) = \sum_{h=0}^{H} \beta^h \hat{E}_t \left(l_{t+h} \mid P_t = \sigma_P, \Theta \right), \quad (4)$$

where σ_p is the sample standard deviation of the relevant policy shock. The net benefit of policy P is then given by $(L_1\text{-}L_0)/\ L_0$ from (3) and (4).

The first step is to choose the weights ω_y and ω_π in (2). We start with a simple quadratic loss function using output only (i.e., with ω_y =1 and ω_π =0). We then consider ω_y=0.542 and ω_π =1, which are Debertoli et al.'s (2018) optimal weights when economic activity is measured as a deviation from trend output.[7]

The next step is to estimate the moments of the conditional distribution of GDP growth (and inflation) using the empirical quantile functions estimated in Section II A. We follow Adrian et al. (2019) and use a minimum distance estimator to fit the estimated conditional quantiles to a theoretical distribution. Unlike them, however, for computational ease, we use the Skewed-Normal distribution (Azzalini 1985) instead of the Skewed-t distribution.[8] The moments θ of the skewed-Normal distribution are estimated as follows:

$$\hat{\theta}^h = \underset{\theta \in \Theta}{\arg\min} \sum_{q=1}^{19} \left(EQF_h(\overline{x}, q) - SkewNQF(\theta) \right)^2, \quad (5)$$

for each h=1…H, where *EQF* is the empirical conditional quantile function at quantiles *q=5, … ,95* estimated using (1) and *SkewNQF* is the quantile function of a skew-normal distribution. We then calculate confidence intervals for $(L_1\text{-}L_0)/\ L_0$ using the bootstrap.[9]

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[7] These weights are optimal in the context of a standard New Keynesian model.

[8] The Skewed-Normal is nested in the family of Skewed-t distributions (Azzalini 2013). In the Skewed-Normal, only three parameters need to be estimated—location, scale, and skewness—and the excess kurtosis of the distribution is a function of skewness.

[9] The loss functions in (4)-(6) are linear combinations of the various $\hat{\theta}_h$ and these come from correlated samples because the underlying quantile regressions use the same right-hand-side variables and the dependent variables (cumulative GDP growth at *h=1…H*) are correlated. Therefore, we calculate the confidence intervals for $(L_1\text{-}L_0)/\ L_0$ with a country-level cluster bootstrap of the entire sample ($Y_1 … Y_H$ and all left-hand-side variables. The bootstrap uses 400 replications and the confidence bands are calculated with the percentile bootstrap.

III. DATA

Our sample includes a large set of variables capturing financial and macroeconomic conditions and policy actions, summarized in Table 1. The data are quarterly and go from 1990 to 2016, but the coverage varies by country and policy variable. The sample includes 37 economies (see Table 2), of which 16 are classified as emerging markets and the rest as advanced economies. The criterion for inclusion is data availability.

A. Financial and Macroeconomic Conditions

Macroeconomic conditions are measured by real GDP growth and inflation from the IMF's World Economic Outlook database. Financial conditions broadly refer to the ease of obtaining finance. A key component of this is the price of risk—the excess return required for an investor to hold one additional unit of risk (Sharpe 1964). We focus on the price of risk and disregard other variables that capture vulnerabilities, such as leverage and credit growth since these will be considered explicitly in our analysis. Our financial conditions index is based on IMF (2018) and uses the same underlying data. Please see Appendix A for the details.

B. Policy Shocks

To properly measure the effects of different policies tools—monetary- and macroprudential policies, foreign exchange interventions, and capital flow management policies—it is critical to obtain changes in the policy variables that do not reflect endogenous reactions to changes in the economic and financial environment (Ramey, 2016). We achieve this by estimating policy reaction functions for each policy instrument, country by country, that condition on those economic and financial variables, and using the residual of such regressions as the policy shock. Tables 1 and 2 show the summary statistics of each policy shock.

Macroprudential Policy

Macroprudential policy refers to the use of primarily prudential tools to limit systemic risk. Depending on the nature of systemic risk, different instruments have been used across economies. While some macroprudential policy instruments overlap with those of other policies, the defining feature is the objective to limit system-wide financial risks.

Our indicator of macroprudential policy draws from the dummy-type policy action indicators contained in Alam et al.'s (2019) new and comprehensive Integrated Macroprudential Policy (iMaPP) database. We consider three broad categories of macroprudential measures: the overall category, and its sub-categories of borrower-based measures and financial-institution-based measures. Please see Appendix A for the definitions.

The construction of macroprudential policy shocks then involves two steps. First, for each category of macroprudential measures, we estimate the following ordered probit regression:

$$mpm_{it}^{*} = \mu_{0i} + \mu_1 cgap_{it-1} + \mu_2 hgap_{it-1} + \mu_3 \sum_{j=1}^{4} I_{i,t-j}^{mpm} + \varepsilon_{it}^{mpm}, \qquad (6)$$

where mpm_{it}^{*} is the latent variable behind the categorical macroprudential indicator I_{it}^{mpm} , which takes values *{-2,-1,0,1,2}* if, all in net terms, there were more than one loosening actions, one loosening action, no change, one tightening action, or more than two tightening actions in the quarter t, respectively. *cgap* is the credit-to-GDP gap, *hgap* the house price gap, and μ_{0i} are country fixed effects.[10] For both credit and house prices, our gap measure is the deviation from the trend, using Hamilton's (2018) approach with eight quarter lags.

The policy shock is then recovered as the difference between the actual value of the macroprudential indicator and its estimated conditional expectation:

$$\begin{aligned} \hat{\varepsilon}_{it}^{mpm} &= I_{it}^{mpm} - \hat{E}_{t-1}\left[I_{it}^{mpm}\right] \\ &= I_{it}^{mpm} - \textstyle\sum_{k=-2}^{2} \hat{p}_k(\boldsymbol{x}_{it-1})\, k, \end{aligned}$$

where $\hat{E}_{t-1}\left[I_{it}^{mpm}\right]$ is the sample analogue of the expected policy action indicator, conditional on the quarter *t-1* information, and $\hat{p}_k(\boldsymbol{x}_{it-1})$ is the estimated probability of $I_{it}^{mpm} = k$, with $k \in$ *{-2,-1,0,1,2}*, conditional on the right-hand side variables ($\boldsymbol{x}_{it-1}$) of equation (6).

Monetary Policy

As an indicator of monetary policy we use the policy rate as defined in the IMF's International Financial Statistics, except for the euro area, Japan, United Kingdom, and the United States, for which we use Krippner's (2015) shadow short rates to account for both conventional and unconventional monetary policy.[11]

Our main measure of the monetary policy shock is the residual of a Taylor-type rule for each country in the sample. Specifically, we run the following regression for each country:

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[10] In this case, we can estimate the ordered probit with fixed effects because the number of observations per cross-sectional unit is large (greater than 50).

[11] We prefer Krippner's (2015) shadow rate to Wu and Xia's (2016) shadow policy rate because the former has data for the four major central banks and has been shown to be more robust and stable over time, especially when used in first differences (Avdjiev et al. 2019).

$$\Delta r_{it} = \alpha_{0i} + \alpha_{1i} E_t \Delta y_{it+12} + \alpha_{2i} E_t \pi_{it+12} + \sum_{j=1}^{2} \alpha_{3ij} \Delta y_{it-i} + \sum_{j=1}^{2} \alpha_{4ij} \Delta p_{it-j} + \sum_{j=1}^{2} \alpha_{5ij} \Delta neer_{it-j} + \sum_{j=1}^{2} \alpha_{6ij} r_{it-j} + \varepsilon_{it}^{r}, \quad (7)$$

where Δr, Δy, Δp, and $\Delta neer$[12] denote the quarter-on-quarter changes in the monetary policy rate, the log of real GDP, the log of the consumer price index (CPI), and the nominal effective exchange rate. $E_t\Delta y_{t+12}$ and $E_t\Delta p_{t+12}$ are the 12-month ahead market forecasts of GDP growth and inflation, respectively, as measured by Consensus Forecasts. For the forecasts, although we would ideally like to use central bank forecasts as in Romer and Romer (2004), these are generally not available. By using market forecasts, we implicitly assume that central banks and markets have the same information set, as corroborated by Coibion and Gorodnichenko (2012).

For each country, the estimated residual of (7) is the monetary policy shock.[13] In other words, deviations from the Taylor-type rules are intended to capture the non-systematic part of monetary policy actions. Since the overall magnitude of the shocks is very different across countries, we standardize the residuals on a country-by-country basis. Therefore, a unit monetary policy shock signifies a one standard deviation shock in each country.

Foreign Exchange Interventions

Foreign exchange interventions (FXIs) refer to purchases and sales of foreign exchange by central banks. As the actual intervention data is limited to some countries, we construct a proxy by taking the change in the central bank's net foreign assets, adjusted for valuation changes and interest income flows, as suggested by Dominguez (2012) and Adler, Lisack, and Mano (2019). Please see Appendix A for the details on the FXI variables.

We construct the FXI shock using the actual data when available and the proxy variable otherwise. The shock is obtained as the residual of an OLS regression using the following linear rule for each country *i*:

$$FXI_{it} = \gamma_{0i} + \boldsymbol{x}'_{it}\gamma_{1i} + \gamma_{2i} egap_{it-1} + \gamma_{3i}\sigma(e)_{it-1} + \varepsilon_{it}^{FXI}, \quad (8)$$

[12] For robustness, we also consider the policy surprise measures based on a high-frequency identification method for selected countries. Please see Section V.B and Appendix A.

[13] For euro area countries, before 1999 we use the residual estimated with data for each country up to that year. After 1999, for all euro area countries, we use the residual obtained from estimating (7) with euro area data.

where FXI_{it} is our measure of foreign exchange interventions in percent of GDP, which is positive (negative) when the central bank conducts net purchases (sales) of foreign currency in that quarter. The vector $\mathbf{x}$ includes the same covariates used in the first column of Table 2 in Forbes and Klein (2015),[14] *egap* is country i's dollar exchange rate deviation from the trend using Hamilton's (2018) approach with eight quarter lags, and *σ(e)* is the quarterly nominal effective exchange rate volatility calculated from daily data.

Capital Flow Management Measures

Capital flow management measures (CFMs) refer to policy actions that are designed to limit capital flows. We construct the policy shock of CFMs using the changes index by Baba et al. (forthcoming), which is based on the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). Their CFM changes index captures all instances of tightening and easing of capital controls,[15] and as such goes beyond the recording of the existence or absence of certain types of controls that underlies most existing indices of CFMs. Please also see Appendix A.

The CFM shock is obtained in two steps, as for the macroprudential policy shock. First, we estimate the following ordered probit model with country fixed effects:

$$CFM_{it}^{*} = \gamma_{0i} + \boldsymbol{x}_{it}'\gamma_1 + \gamma_2 egap_{it-1} + \gamma_3 \sigma(e)_{it-1} + \varepsilon_{it}^{CFM}, \quad (9)$$

where CFM_{it}^{*} is the latent variable behind the categorical CFM indicator (I_{it}^{CFM}) which takes value *1* (*-1*) for one tightening (loosening) action, *2* (*-2*) for more than one tightening (loosening) actions, and *0* for no change, all in net terms, in each quarter *t*. The controls $\boldsymbol{x}_{it}$ are the same as the ones used for the FXI specification. As in the case of macroprudential policy shocks, the CFM policy shocks are obtained as the difference between the actual and predicted categorical indicators.

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[14] The variables are the log of the VIX, the change in the U.S. policy interest rate, the change in capital inflows as a percentage of GDP, inflation, a commodity price index, the Economist All-Commodity Dollar index (in logs) interacted with a dummy equal to 1 if a country is a major commodity exporter ((food exports+fuel exports)/merchandise exports >0.3), reserves as a percent of GDP, Chin and Ito's (2006) index of capital account openness, and the log of the average of the six indexes of institutional quality from the World Bank's Worldwide Governance Indicators database, the rate of exchange rate depreciation against the U.S. dollar, and the interest rate differential against the U.S.'s policy rate. For the United States, we use the exchange rate and the interest rate differential against the euro, respectively.

[15] The index does not include CFMs that do not discriminate on the basis of residency but are still designed to limit capital flows, for example certain prudential measures.

IV. Results

A. Effects of Policies on the Intertemporal Tradeoff

We start by examining the estimated effects of each policy in response to easy financial conditions on the conditional quantiles of future (detrended) GDP growth and inflation—i.e., $\beta_1^h(q) + \beta_3^h(q) \cdot P$ of equation (1) where P takes the value of one or zero. In Figure 1, we show the estimated changes in the 10th percentile of those variables after a one standard deviation loosening in financial conditions assuming that there is no policy change (blue line) or that a given policy is tightened (red line).

First, looking at the case with no policy change (blue line), we confirm the stylized facts laid out by Adrian et al. (2019). The left-hand side panels of Figure 1 show the well-documented intertemporal tradeoff between looser domestic financial conditions today and greater downside risks to economic growth in the medium term. On the other hand, as shown on the right-hand side panels, there is no apparent intertemporal tradeoff for inflation, which could be explained by the fact that most countries in our sample have well-anchored inflation expectations.

Next, comparing the cases with- and without policies, several interesting findings emerge. The top left panel of Figure 1 shows that tightening macroprudential policy mitigates (but does not eliminate) the tradeoff for output growth: the tail risk deterioration due to the FCI loosening is less marked in the medium term. This effect, moreover, appears to come at little cost in the short term—tightening macroprudential policy does not offset the stimulating effects of easier financial conditions on output, although these short-term effects are mostly not statistically significant. Furthermore, the policy tightening itself does have a contractionary effect on output growth: when we examine the change in the 50th percentile of output and inflation to a macroprudential policy tightening shock— i.e., $\beta_2^h(q) + \beta_3^h(q) \cdot f$ of equation (1)—we tend to find contractionary effects on output (and prices, to some extent). These results are reported in Figure B.2 in Appendix B and, although the magnitude of these effects does not appear large, they are in line with the literature (e.g., Richter et al. 2019).

Turning to the effect of a monetary policy tightening, we find quite different results. The left panel of Figure 1 shows, if anything, a worsening of the underlying trade-off, by further worsening the tail risk statistically significantly in the medium term. The policy effects on inflation are ambiguous, though.

Finally, when we move from the tail of the distribution to median growth (see Figure B.1 in Appendix B), we find that the intertemporal tradeoff documented by Adrian et al. (2019) is absent, in that the effect of easing financial conditions on median output is positive through the entire horizon. In addition, tighter macroprudential policy does not seem to reduce that positive effect of easing financial conditions on median economic activity, while tighter monetary policy appears, if anything, to worsen the median outlook. These findings are in line with the view that macroprudential policy is effective in dampening downside risks to GDP growth whereas monetary policy is a blunt tool (Yellen, 2014).

Figure 1. Response of Tail Risk of GDP and Inflation to Domestic FCI

Note: The charts show the change in tail risk to GDP growth (i.e., the detrended change in log GDP from one to *h* quarters ahead) and inflation associated with looser domestic financial conditions, conditional on there being a policy change. Tail risk to GDP growth is measured by the 10th percentile of the future detrended GDP growth. Inflation is the quarterly change in log CPI. A square marker means that the effect of policy is significantly different than zero at least at the 10 percent significance level. Inference is based on standard errors clustered at the country level based on Hagemann's (2017) wild bootstrap approach. The horizontal axis shows the number of quarters since the time of a loosening shock to domestic financial conditions.

B. Net Benefits of Policies

Changes in Domestic Financial Conditions

Next, we move beyond the effects at specific quantiles to consider the net effects of policies across the entire distribution of future output by using our loss function approach. This compares losses conditional on easing financial conditions when policies are used, versus when no policy action is taken. As our benchmark, we use the quadratic loss function (1), which measures costs and benefits using output and price volatility.

The estimates in Table 3 (left panel) suggest that tightening macroprudential policies when domestic financial conditions loosen reduces losses by about 9 percent, in the case of quadratic policymaker preferences. However, in line with Svensson's (2017a) results, we do not find that leaning against loose domestic financial conditions through monetary policy reduces losses—in fact, monetary policy tightening seems to increase losses by about 12 percent.

The results in favor of macroprudential policy are stronger and more statistically significant for borrower-based measures (between -6.5 and -10 percent) than for financial institution-based measures (at most -5.3 percent), even if our estimates are not sufficiently precise to establish that these two types of policies have different effects at the usual levels of statistical significance.[16] These findings are in line with those by Alam et al. (2019), who report that the borrower-based measures have larger intended effects on credit but smaller unintended side effects on consumption.

Examining these results further, we find that the sharp contrast between the net benefits of different policies mostly comes from their opposite effects on output volatility, while all policies have little effects on price volatility. With tighter macroprudential policy, the distribution of future output gaps shrinks, as evident in the increase of its 10^{th} percentile (Figure 1, top left panel).[17] On the other hand, leaning against the wind with monetary policy increases output volatility (Table 3).

These empirical findings are in line with arguments advanced in the literature that leaning against the wind using monetary policy can be counterproductive, and that macroprudential policy is preferred for this purpose (e.g., Svensson, 2017a; Schularick et al., 2020). For example, Alpanda and Zubairy (2017) show that tighter borrower-based macroprudential measures can reduce economic volatility by reducing financial accelerator effects through tighter borrowing constraints, whereas the active use of monetary policy to lean against the wind can increase the volatility of output, and thereby result in welfare losses. More generally, the DSGE literature points to increases in the volatility of the output gap as a drawback of leaning against the wind with monetary policy (e.g., Gourio, Kashyap, and Sim, 2018), while borrower-based macroprudential

[16] The standard errors around our estimates are fairly conservative because of the bootstrap methods. Even so, many results turn out to be highly statistically significant.

[17] Mendicino et al. (2019) show in a DSGE model that higher capital requirements can generate welfare gains in the long run, making banks safer, while entailing transition costs.

tools in particular are typically found to offer a better trade-off in terms of output foregone (e.g., Alpanda, Capeau and Meh, 2018).[18]

Global Financial Shocks

Next, we consider shocks to global financial conditions instead of changes to the domestic FCI. We do this mainly to be able to also compare macroprudential policy to FXI and CFMs, policies that are more likely to be used to lean against external shocks than against domestic ones.[19] Moreover, changes in global financial conditions are exogenous for small open economies, allowing for a cleaner identification of the effects of policies.

We therefore expand the previous specification to include global financial conditions (which we proxy with financial conditions in the United States, which is now excluded from the sample) as follows.

$$Q_{\Delta y_{i,t,t+h}}\left(q \mid Z_{it}\right)=\alpha_{0i}^{h}\left(q\right)+\beta_{1}^{h}\left(q\right)f_{it}+\beta_{2}^{h}\left(q\right)g_{it}+\beta_{3}^{h}\left(q\right)P_{it}+\beta_{4}^{h}\left(q\right)P_{it}\times g_{it}+\mathbf{x}_{it}\Gamma, \quad h=1,\ldots,H,\ q=0.05,\ldots,0.95, \tag{10}$$

where g is the global FCI. We then proceed as before to estimate the effect of policies conditional on an easing of financial conditions and compare the loss functions with- and without policy actions.

We first calculate the effect of a one-standard deviation loosening in global financial conditions on the GDP-at-risk (10th percentile of future detrended GDP). We find that the effect of macroprudential policy tightening conditional on easing of global financial conditions is by and large unchanged relative to what we obtained for domestic financial conditions, while monetary policy now appears to reduce, rather than increase, downside tail risks for GDP at the 10th percentile (see Figure B.3 in Appendix B).

In addition, Figure 2 shows that intervening in the foreign exchange market to buy foreign currency does not affect the intertemporal tradeoff—the effect of looser global

[18] The ineffectiveness of tighter monetary policy to lean against the wind can also be understood in the context rational bubbles (Gali, 2014). In this setting, although an interest hike could depress the fundamental component of asset prices, it would also relax the requirement that the bubble component grow at most at the real rate of interest, and the effect of monetary policy on financial stability would depend on which component dominates.

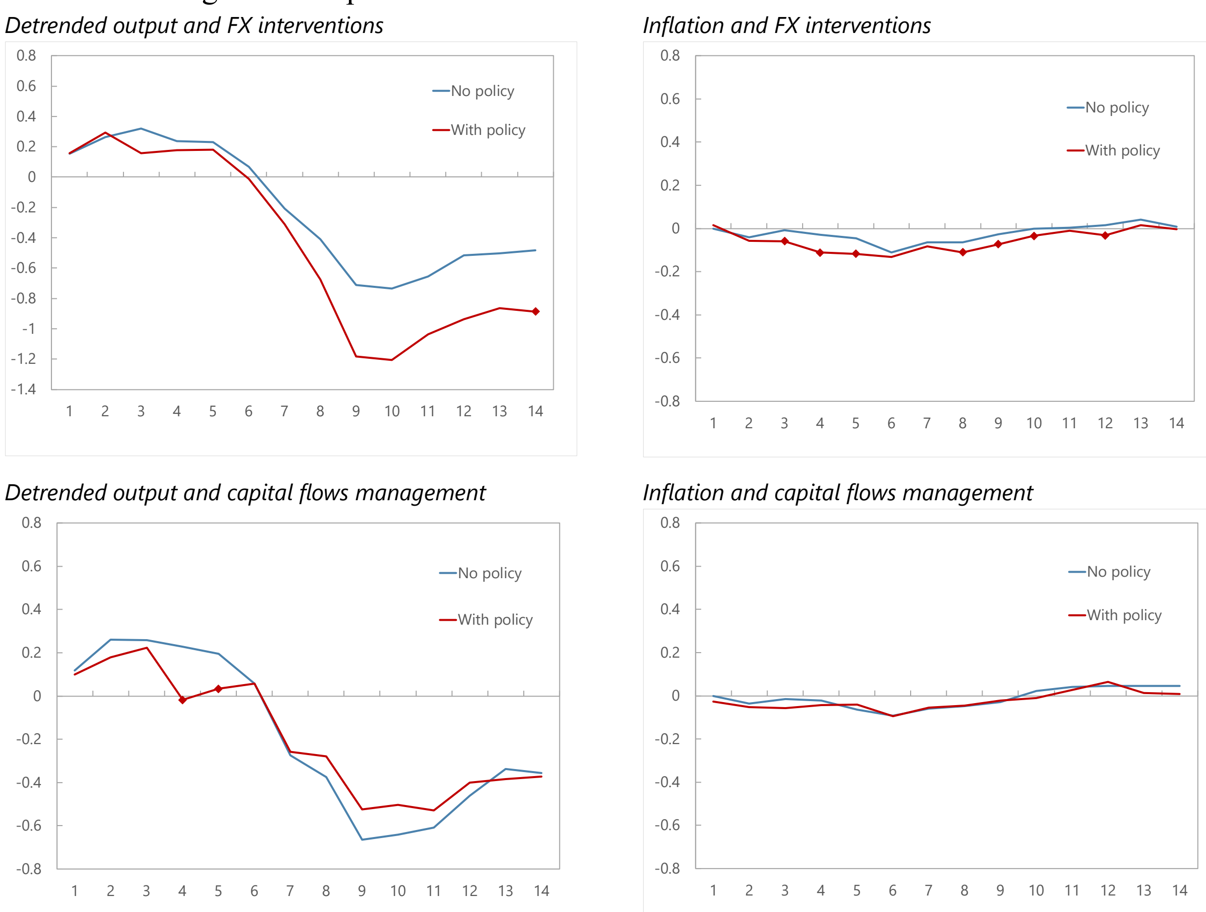
[19] Theoretical predictions regarding the optimality and welfare effects of FXI and CFM depend on the specific features of the models, including the characteristics of the assumed frictions. See, for example Chang (2018), Cavallino (2019), and Rebucci and Ma (2019).

financial conditions on tails risks to GDP does not change—and the same seems to be true for adopting new measures which impede capital inflows.

Moving from specific quantiles to the estimation of losses over the entire distribution, we find that loss reductions from tightening macroprudential measures are again substantial (Table 3, right panel). However, we find again that leaning against easing financial conditions with tighter monetary policy does not yield net gains when considering all the effects on the entire distribution.

Borrower-based macroprudential policies continue to have the largest beneficial effect. Loss reductions due to borrower-based macroprudential actions range between 9.6 and 10.7 percent, depending on the loss-function weights for economic activity and inflation, while tightening financial institution-based policies brings smaller gains (at most a 6.8 percent reduction).

Figure 2. Response of Tail Risk of GDP and Inflation to Global FCI



Note: The charts show the change in tail risk to GDP growth (i.e., the detrended change in log GDP from one to *h* quarters ahead) and inflation associated with looser global financial conditions, conditional on there being a policy change. Tail risk to GDP growth is measured by the 10th percentile of the future detrended GDP growth. Inflation is the quarterly change in log CPI. A square marker means that the effect of policy is significantly different than zero at least at the 10 percent significance level. Inference is based on standard errors clustered at the country level based on Hagemann's (2017) wild bootstrap approach. The horizontal axis shows the number of quarters since the time of a loosening shock to global financial conditions.

In addition, using FX purchases (to prevent a local currency appreciation) or tightening CFMs to counter loose global financial conditions entail very small effects on the distribution of output, which are never statistically different than zero. These findings are broadly consistent with the empirical literature, which so far has found mixed evidence for these policies (e.g., Rebucci and Ma 2019).

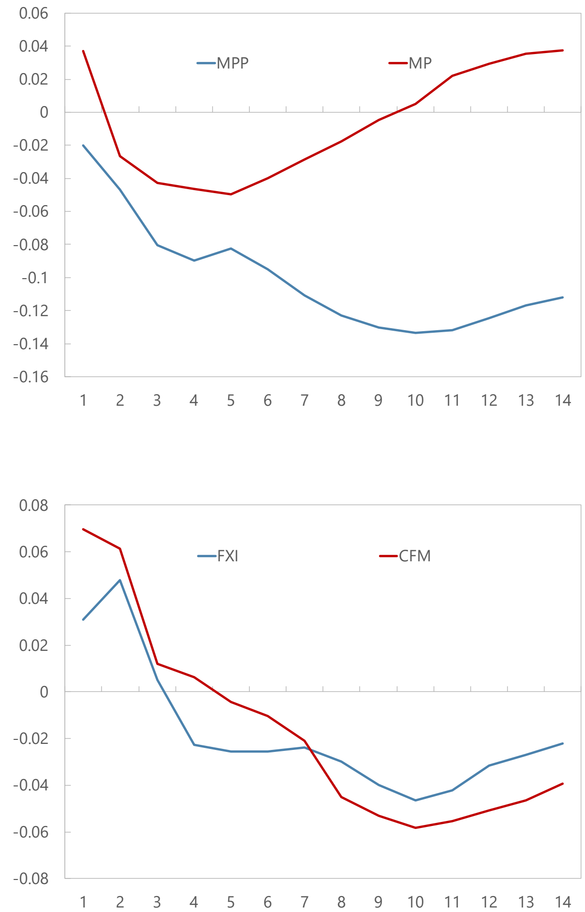
Changes in the Loss Function Over the Forecasting Horizon

How do the changes in the loss functions evolve over the forecasting horizon? To address this question, we calculate a loss differential $\Delta L=(L_1(\Theta)-L_0(\Theta))/L_0(\Theta)$ using expressions (3) and (4) at each horizon $H=1,\ldots,14$. For brevity, we do this only for a period loss function ℓ_t (see equation (2)) with unit weight on output and zero weight on inflation, and only for the case of an easing of global financial conditions. The exercise aims to show how the changes in the expected loss from a given policy tightening are distributed over the 14 quarters.

Three main patterns emerge (Figure 3). First, macroprudential policy reduces losses in a uniform way until the benefits peak after around 10 quarters. Therefore, while the net benefits of macroprudential policy are realized fully in the medium term, they start accruing in the short term. Monetary policy tightening, by contrast, appears to reduce losses initially, and starts to induce increases in losses from about 5 quarters out, suggesting that any initial benefits from tightening are being eroded by the effect of tighter policy on output volatility over the medium term.

Second, borrower-based macroprudential policy has a more persistent beneficial effect on net losses than financial-institution-based macroprudential policy (not shown, but available from the authors). Third, we find that for FXI and CFM (and also for financial-institution-based macroprudential policy) about half the reduction in the loss function up to 10 quarters ahead is reversed after 14 quarters. This suggests that gains associated with the use of these policies are largely temporary, while the benefits of borrower-based macroprudential tools are longer lasting.

Figure 3. Time Profile of Cumulated Loss Changes



Note: The charts show the cumulated change in the loss function when comparing a scenario of loose financial conditions without policy tightening to one where policy is tightened. The period loss function is given by

$$l_t = \omega_y \left(y_t - \bar{y}_t\right)^2 + \omega_\pi \pi_t^2,$$

with $\omega_y=1$ and $\omega_\pi=0$, and the cumulated loss differential at each horizon $H=1, \ldots, 14$ is given by

$$\Delta L = \sum_{h=0}^{H} \beta^h \left(\hat{E}_t\left(l_{t+h} \mid P_t = \sigma_P\right) - \hat{E}_t\left(l_{t+h} \mid P_t = 0\right) \big/ \hat{E}_t\left(l_{t+h} \mid P_t = 0\right)\right),$$

where P is a one-standard deviation shock policy tightening or 0. The horizontal axis shows the number of quarters since the time of a loosening shock to global financial conditions.

C. Effects of Policies Conditional on the Level of Financial Vulnerabilities

The effect of some policies may depend on the level of financial vulnerabilities. For instance, the impact of a loosening shock to the FCI may depend on the degree of existing financial sector leverage. The optimal policy response to loosening financial conditions, in turn, may then be a function of the existing level of credit. Similarly, it is conceivable that the beneficial effect of policies may depend on whether asset prices are already elevated.

In particular, it has been argued that macroprudential policy are needed more urgently when the level of credit is already high, since risks to output are then greater (Biljanovska, Gornicka, and Vardoulakis 2019). Alternatively, with loosening financial conditions, tightening policy to lean against the wind may have a more beneficial effect when private sector leverage is still low, since leaning can then still reduce the further build-up of risks. We test these hypotheses with a modified version of (1) as follows.

$$
\begin{aligned}
Q_{Y_{i,t,t+h}}(q \mid Z_{it}) = {} & \alpha_{0i}^{h}(q) + \beta_1^h(q) f_{it} + \beta_2^h(q) Vul_{it} + \beta_3^h(q) P_{it} + \beta_4^h(q) P_{it} \times f_{it} \\
& + \left(\beta_5^h(q) P_{it} + \beta_6^h(q) P_{it} \times f_{it}\right) Vul_{it} + \mathbf{x}_{it}\Gamma, \\
& h = 1, \ldots, H,\ q = 0.05, \ldots, 0.95,
\end{aligned}
$$

where *Vul* is measure of financial vulnerabilities. We use alternatively the credit-to-GDP ratio (a measure of leverage), and the house price index calculated by the BIS (both in logs).

When looking at quantiles, we find that tighter macroprudential policies are more strongly associated with a reduction in tail risks to GDP growth—measured by the 10th percentile of the distributions of future GDP growth—when credit levels or house prices are high (Figure 4). The figure also shows that using monetary policy to lean against the wind is not associated with a reduction in GDP at risk, irrespective of the level of credit.

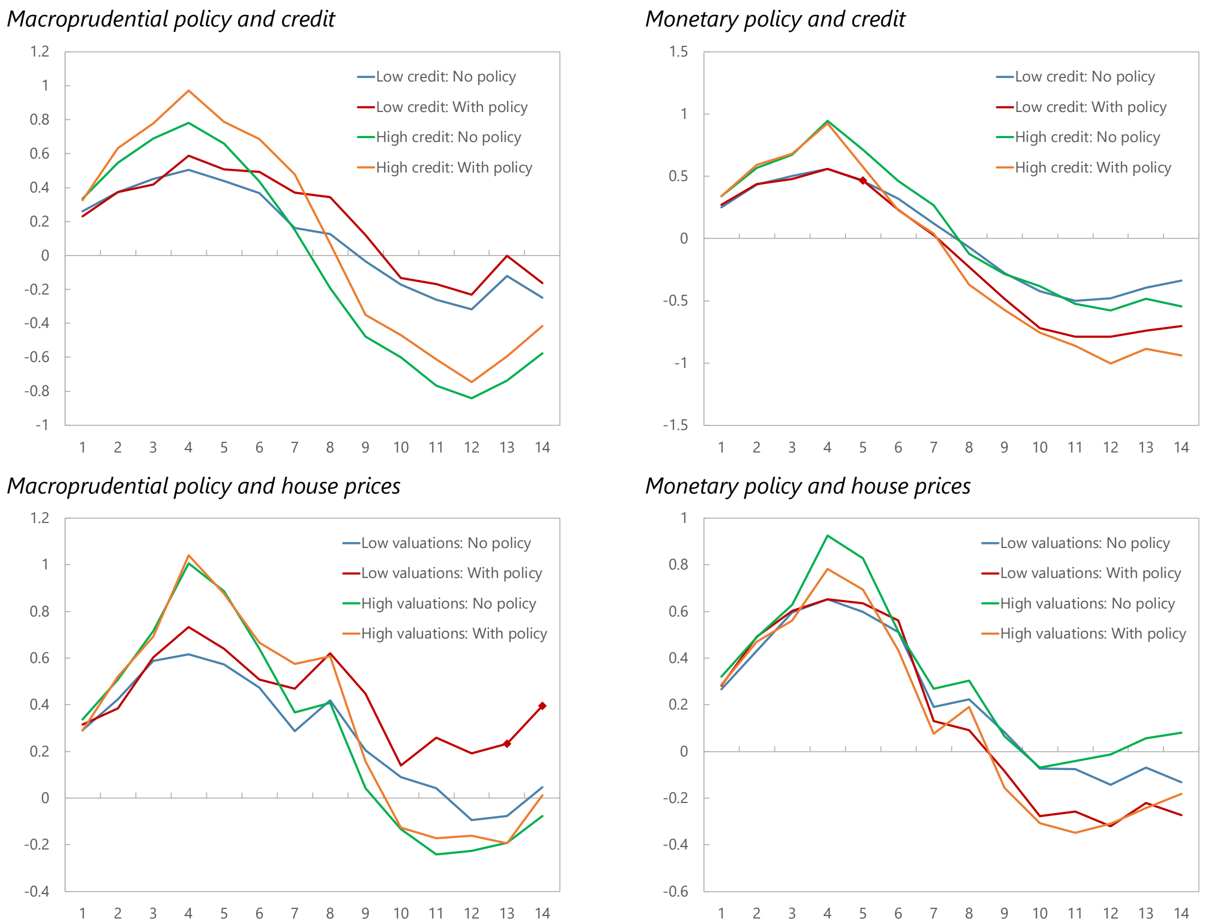
When estimating the effects of these policies on the loss functions, the basic results are confirmed, even as an interesting nuance emerges (Table 4). The relative effectiveness of tightening macroprudential policy tools depends both on the level of vulnerability—measured by the level of credit and real estate valuations—and on the type of policy—borrower-based versus financial-institutions based.

In particular, tightening borrower-based macroprudential policies is more strongly associated with a reduction in losses when credit and asset prices are high (high vulnerabilities) than when vulnerabilities are low. By contrast, tightening financial-institutions-based macroprudential appears to have larger benefits when credit or asset prices are still low.

This suggests that when the levels of credit or asset prices are high, financial-institutions-based tools (such as capital requirements) that tackle risks only indirectly by affecting the supply of credit are not sufficient, and borrower-based tools that more directly increase borrowers' resilience to shocks are required. By contrast, when credit is low, measures that reduce the further build-up of credit by affecting financial institutions can still be effective, while avoiding efficiency costs from the imposition of borrower-based tools. Overall, the results are suggestive of the dual role of macroprudential policy in both leaning against the wind and building resilience.

By contrast, the effects of monetary policy appear to be independent of financial vulnerabilities. The quadratic loss functions increase by similar amounts when monetary policy is tightened, regardless of credit levels (Table 4), and the differences in the changes of the loss functions between the low and high vulnerability cases are not statistically different than zero at conventional levels of significance. This suggests that the adverse effects of tighter monetary policy on the volatility of output are independent of the level of credit, whereas the effects of tighter policy in reducing the further supply of credit are relatively small (see Gourio, Kashyap, and Sim 2018).

Figure 4. Response of Tail Risk of GDP to Domestic FCI at Different Levels of Vulnerabilities



Note: The charts show the change in tail risk to GDP growth (i.e., the detrended change in log GDP from one to *h* quarters ahead) associated with looser domestic financial conditions, conditional on there being a policy change and on the level of credit or house prices. Tail risk to GDP growth is measured by the 10th percentile of the future detrended GDP growth. A square marker means that the effect of policy is significantly different when credit or house prices are low (25th percentile) or high (75th percentile) at least at the 10 percent significance level. Inference is based on standard errors clustered at the country level based on Hagemann's (2017) wild bootstrap approach. The horizontal axis shows the number of quarters since the time of a loosening shock to domestic financial conditions.

V. ROBUSTNESS

A. Alternative Loss Functions

As an extension, we calculate the net benefit of each policy using alternative specifications for the ad-hoc loss functions. First, we consider loss functions which are linear-quadratic in output (in addition to being quadratic in inflation), to address the concern that the quadratic loss function may miss out the level effects on output by focusing on its volatility. The introduction of a level (linear) term of output in the policymaker's preferences can be justified with a micro-founded New Keynesian model with a distorted steady state (Benigno and Woodford 2005). The loss function becomes

$$\ell_t = \omega_y \left[\left(y_{t+h} - \bar{y}_t \right)^2 - \left(y_{t+h} - \bar{y}_t \right) \right] + \omega_\pi \pi_t^2 .$$

Including a linear term of output in the loss function yields the same results as those obtained with the pure quadratic losses in the sense that the order of loss reductions among policies is preserved (Table 5). This is likely because this linear-quadratic loss function can be rewritten as the pure quadratic loss function (without a linear term), involving only a shift of the loss function (Benigno and Woodford 2005).

Second, we also consider the case of a policymaker with asymmetric preferences. That is, policymakers may have loss aversion and dislike bad outcomes more than they like good ones. A flexible loss function that accommodates such asymmetry is the linex loss function proposed by Varian (1975) and used to model central bank preferences by Ruge-Murcia (2003) for monetary policy and Bahaj and Foulis (2017) for macroprudential policy, for example. For simplicity we focus only on output and disregard inflation. The period loss is as follows:

$$\ell_t = \frac{(e^{a\tilde{y}_{t+h}} - a\tilde{y}_{t+h} - 1)}{a^2}, \text{where } \tilde{y}_{t+h} \equiv (y_{t+h} - \bar{y}) \quad (11)$$

This loss function includes (4) as a special case when a→0 and covers the case of loss aversion when *a<0*. Also, for simplicity, we use *a=-1* and, as before, assume that potential output grows at a constant rate. To be able to use write the loss function (11) as a function of the moments of the conditional distribution of future GDP growth, we do a fourth order Taylor expansion according to which (4) can be approximated as a function of the conditional variance, skewness, and kurtosis of detrended GDP at each horizon *h*, as follows.

$$E_t(\ell_{t+h}) \cong \frac{1}{2} E_t(\tilde{y}_{t+h})^2 - \frac{1}{3!} E_t(\tilde{y}_{t+h})^3 + \frac{1}{4!} E_t(\tilde{y}_{t+h})^4$$

The results with asymmetric preferences also confirm our findings based on standard quadratic loss functions (Table 5). Borrower-based macroprudential policies remain the most effective in terms of the associated reduction in the loss functions, while monetary policy remains ineffective, and FX purchases and CFM have mostly insignificant effects.

B. Alternative Measures of Monetary Policy

Our results so far suggest that, compared to monetary policy, macroprudential policy is associated with larger reductions in the loss function when financial conditions are loose. Importantly, the results so far suggest that tightening monetary policy to work against loose financial conditions actually increases the loss functions.

However, when it comes to monetary policy shocks, it is notoriously difficult to overcome the associated identification challenges (Ramey 2016). A strand of literature which has dealt with this problem with some success uses the response of asset prices (money market rates, bond yields, or interest rate futures) following a monetary policy announcement (Kuttner 2001 and Gürkaynak et al. 2005). Accordingly, the monetary policy shocks are measured as monetary policy surprises (i.e., the component of monetary policy which was unanticipated by financial markets).

For some advanced economies, especially for the United States and the euro area, deep and sophisticated financial markets require (and the existence of intraday data allow) the surprise to be measured within relatively short windows after the announcement (5, 15, or 30 minutes). Unfortunately, for most emerging markets and many smaller advanced economies, such data do not exist or are of dubious quality (e.g., the data only exist at most at the daily frequency and market functioning is weak). Still, we check the robustness of our findings (i.e., the relative ranking of macroprudential and monetary policies) using high-frequency measures obtained from a variety of sources (see Appendix A).[20]

Qualitatively, the results are unchanged: as per our loss-function-based metric, macroprudential policy is still preferred to monetary policy. The last row of Table 3 shows that leaning against the wind with monetary policy is associated with a very small reduction in the loss function (1 percent for loose domestic FCI and at most 2.5 percent for loose global FCI). This finding is robust to using alternative specifications for the loss function and, for the most part, is not caused by sample composition effects.[21]

[20] We are able to gather data for 27 of the 37 countries in our sample, but the data have some important shortcomings which are discussed in the Appendix.

[21] For the sample for which we have data for monetary policy surprises, leaning against the wind with macroprudential policy reduces losses between 3.5 (global FCI) and 5 percent (domestic FCI). Still, we prefer to use the benchmark results for macroprudential policy as comparison because of the bigger sample, given that these policy tools are infrequently used. Results available from the authors.

C. Advanced- vs. Emerging Market Economies

We also check if our results are driven by our choice of pooling advanced- and emerging market economies. There are two reasons why this choice may confound the results. First, the intertemporal tradeoff between current financial conditions and future downside risks may be different across these two types of economies (see Adrian et al., forthcoming). This suggests a potential bias caused by the assumption of homogenous slopes in the linear quantile regressions. Second, the types of macroprudential policies used differs between emerging market- and advanced economies; for example, the use of mortgage-related measures is much more common in advanced economies given the bigger role of mortgage lending in these countries. Moreover, the use of policies such as CFMs or FXI is more common among emerging economies than in advanced ones. Thus, the estimated beneficial effect of certain policies could be just capturing those group-specific intertemporal tradeoffs.

However, our results by group of country broadly support our benchmark findings (Table 6): macroprudential policy is generally associated with larger reductions in the loss function than any other policy. Interestingly, financial-institution-based macroprudential policies and CFMs seem to work better in emerging markets than in advanced economies, whereas FX purchases again do not seem to reduce losses.

D. Common Factors and Unobserved Heterogeneity

Macroeconomic and financial conditions are potentially correlated across countries, reflecting the role of global investors shaping global financial conditions and the global credit cycle. Our analysis, up to this point, did not explicitly control for the importance of these factors, which we now do.

First, we capture these common factors as time fixed effects, in addition to country fixed effects, as a two-way error structure. Unfortunately, under the assumption of fixed *N*, Kato and other's (2012) FE-QR estimator that we used before is no longer consistent with two-way fixed effects. However, we can still estimate the country fixed effects as before (i.e., as dummy variables) and, under the assumption that the time fixed effects are constant across quantiles, use Koenker's (2004) penalized fixed effects estimator.[22] The results, shown in Table 7 (panel A), are qualitatively similar to those of Section IV, with macroprudential policy reducing losses and monetary policy increasing them.

For our benchmark results, we have also assumed that the slope coefficients of the quantile regressions are homogenous across countries and that the error structure is the only source of heterogeneity. However, assuming homogenous slopes will produce biases

[22] For this effect, we use the `rqpd` library in R. We also did this exercise using Canay's (2011) two-step estimator, with similar results (available from the authors).

in the estimation if current financial conditions transmit differently to future output growth distributions in different countries. We check for the robustness of our findings against this type of misspecification using Ando and Bai's (2019) frequentist approach to panel quantile models with unobserved heterogeneity and common factors.[23] The model that we estimate is a slightly modified version of (3),

$$Q_{\Delta y_{i,t,t+h}}\left(q \mid Z_{it}\right) = \varphi(q)' \lambda_i^h(q) + \beta_{1i}^h\left(q\right) f_{it} + \beta_{2i}^h\left(q\right) g_{it} + \beta_{3i}^h\left(q\right) P_{it} + \beta_{4i}^h\left(q\right) P_{it} \times g_{it} + \mathbf{x}_{it}\Gamma_i,$$
$$h = 1,\ldots,H,\ q = 0.1,\ldots,0.9,$$

where φ and λ are quantile-specific vectors of unobservable factors and factor loadings, respectively.[24] The results are in Table 7 (panel B) and are broadly in line with the benchmark results: macroprudential policy reduces losses, borrower-based measures reduce them by more, and monetary policy does not seem to do the same.

VI. Conclusions

In this paper, we have proposed a novel approach to evaluate the effects of "leaning against the wind" in response to changes in domestic and global financial conditions. We have assessed the impact of different policies on the entire future probability distributions of growth and inflation outcomes, evaluating them using a range of standard- and nonstandard loss functions.

We found that overall, the balance of trade-offs favors the use of macroprudential policies, both in response to changes in domestic financial conditions and to global financial shocks. When credit is high, tightening borrower-based measures appears to be more advantageous than tightening financial-institutions based macroprudential measures, and the converse seems true when credit is low.
By contrast, the trade-off for monetary policy tightening to lean against the wind generally appears to be unfavorable, since monetary policy is associated with higher losses.

Since many emerging markets have been using CFMs and foreign-exchange intervention in response to global financial conditions, we also investigated the role of these policies. Foreign-exchange interventions and CFMs appear to entail some reductions in the loss function. These effects are, however, considerably smaller than those associated with the use of macroprudential policy, and not generally statistically significant.

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[23] We adapt their source code available here.

[24] We use the same number of factors (five) for all policy shocks. Because Ando and Bai's (2019) approach requires the country-by-country estimation of the conditional quantiles, we restrict the sample so that we have at least 30 observations per country, which implies a reduction in the country coverage from 37 to 31. For the same reason, we reduce the number of quantiles to 9.

Our results should be seen as first insights using a novel approach, rather than settling these complex issues. For instance, it is possible that FXI and CFMs entail benefits in certain circumstances, even if their effects on output growth on average are small. Using these tools to mitigate adverse shocks could also have greater benefits than using them to lean against easing financial conditions. Further research is needed to explore these questions in more depth.

In addition, drawing direct policy recommendations from our findings would clearly not be immune to Lucas's (1976) critique—that the effect of policies may come to depend on the way they are used. However, under certain circumstances, applying regression methods to past data can be optimal for decision making (Kocherlakota 2019). More generally, this paper stands in the tradition of using macroeconometric models for policy evaluation, as in Sims (1980), Jordà (2005), and Angrist and Kuersteiner (2011).

REFERENCES

Adam, Klaus, and Michael Woodford. 2018. "Leaning Against Housing Prices as Robustly Optimal Monetary Policy," NBER Working Paper No. 24629

Adler, Gustavo, Noemie Lisack, and Rui Mano. 2019. "Unveiling the effects of foreign exchange intervention: A panel approach." *Emerging Markets Review*, Vol. 40: 100620.

Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone. 2019. "Vulnerable Growth." *American Economic Review*, Vol. 109(4): 1263-89.

Adrian, Tobias, Fernando Duarte, Nellie Liang, and Pawel Zabcyk. 2020. "Monetary and Macroprudential Policy with Endogenous Risk." CEPR Discussion Paper No. 14435

Adrian, Tobias, Federico Grinberg, Nellie Liang, Sheheryar Malik, and Eva Yu. Forthcoming. "The Term Structure of Growth-at-Risk." *American Economic Journal: Macroeconomics*..

Adrian, Tobias, and Nellie Liang. 2018. "Monetary Policy, Financial Conditions, and Financial Stability." *International Journal of Central Banking* 14(1): 73-131.

Ajello, Andrea, Thomas Laubach, David López-Salido, and Taisuke Nakata. 2019. "Financial Stability and Optimal Interest Rate Policy," *International Journal of Central Banking* 15(1): 279-326.

Alam, Zohair, Adrian Alter, Jesse Eiseman, Gaston Gelos, Heedon Kang, Machiko Narita, Erlend Nier, and Naixi Wang. 2019. "Digging Deeper—Evidence on the Effects of Macroprudential Policies from a New Database." IMF Working Paper No. 19/66. (Washington: International Monetary Fund).

Alpanda, Sami, and Sarah Zubairy. 2017. "Addressing Household Indebtedness: Monetary, Fiscal or Macroprudential Policy?" *European Economic Review* 92: 47-73.

Alpanda, Sami, Gino Cateau, and Cesaire Meh. 2018. "A policy model to analyze macroprudential regulations and monetary policy." *Canadian Journal of Economics*, 51 (3), 828-863

Ando, Tomohiro, and Jushan Bai. 2019. "Quantile co-movement in financial markets: A panel quantile model with unobserved heterogeneity." *Journal of the American Statistical Association,* article in press.

Angelini, Paolo, Stefano Neri, and Fabio Panetta. 2014. "The Interaction between Capital Requirements and Monetary Policy." *Journal of Money, Credit, and Banking* 46 (6): 1073-1112.

Angrist, Joshua D., and Guido M. Kuersteiner. 2011. "Causal Effects of Monetary Shocks: Semiparametric Conditional Independence Tests with a Multinomial Propensity Score." *Review of Economics and Statistics* 93, no. 3: 725-747.

Aoki, Kasuke, Gianluca Benigno, and Nobuhiro Kiyotaki, 2016. “Monetary and Financial Policies in Emerging Markets,” unpublished manuscript.

Avdjiev, Stefan, Valentina Bruno, Catherine Koch, and Hyun Song Shin. 2019. “The Dollar Exchange Rate as a Global Risk Factor: Evidence from Investment." *IMF Economic Review* 67, no. 1: 151-173.

Azzalini, Adelchi. 1985. “A Class of Distributions Which Includes the Normal Ones.” *Scandinavian Journal of Statistics* 12, No. 2: 171-178.

———, 2013. *The Skew-Normal and Related Families*. Vol. 3. Cambridge University Press.

Baba, Chikako, Ricardo Cervantes, Salim Darbar, Annamaria Kokenyne, and Viktorya Zotova. Forthcoming. “New Measures of Capital Flow Restrictions — AREAER Indices.” IMF Working Paper. (Washington: International Monetary Fund).

Bahaj, Saleem, and Angus Foulis. 2017. “Macroprudential Policy Under Uncertainty." *International Journal of Central Banking* 13, No. 3: 119-154.

Bengui, Julien, and Javier Bianchi. 2018. “Macroprudential Policy with Leakages.” NBER Working Paper No. 25048. National Bureau of Economic Research.

Benigno, Pierpaolo, and Michael Woodford. 2005. “Inflation stabilization and welfare: The case of a distorted steady state.” *Journal of the European Economic Association* 3, no. 6: 1185-1236.

Biljanovska, Nina, Lucyna Gornicka, and Alexandros Vardoulakis. 2019. “Optimal Macroprudential Policy and Asset Price Bubbles.” IMF Working Paper No. 19/184. International Monetary Fund.

Canay, Ivan A., 2011. “A Simple Approach to Quantile Regression for Panel Data.” *The Econometrics Journal* 14, no. 3: 368-386.

Cavallino, Paolo, 2019. “Capital Flows and Foreign Exchange Intervention.” *American Economic Journal: Macroeconomics*, Vol. 11(2), 127-70.

Céspedes, Luis Felipe & Chang, Roberto & Velasco, Andrés, 2017. "Financial intermediation, real exchange rates, and unconventional policies in an open economy," *Journal of International Economics*, Vol. 108(S1): 76-86.

Chang, Roberto. 2018. “Foreign Exchange Intervention Redux,” NBER Working Paper No. 24463.

Chinn, Menzie D. and Hiro Ito, 2006. “What Matters for Financial Development? Capital Controls, Institutions, and Interactions.” *Journal of Development Economics*, Volume 81, Issue 1, Pages 163-192.

Claessens, Stijn, M. Ayhan Kose, and Marco E. Terrones. 2011. “Financial Cycles: What? How? When?” In *International Seminar on Macroeconomics*, Volume 7, No. 1: 303-344. Chicago, IL: University of Chicago Press.

Clarida, Richard, Jordí Gali and Mark Gertler, 2000. “Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory”, *The Quarterly Journal of Economics*, Vol 115 (1), 147-180.

Coibion, Olivier, and Yuriy Gorodnichenko, 2012. “What Can Survey Forecasts Tell Us about Information Rigidities?” *Journal of Political Economy*, Volume 120, No. 1: 116–159.

Debortoli, Davide, Jinill Kim, Jesper Lindé, and Ricardo Nunes. 2018. “Designing a Simple Loss Function for Central Banks: Does a Dual Mandate Make Sense?” *The Economic Journal* 129, no. 621: 2010-2038.

Devereux, Michael B., Philip R. Lane and Juanyi Xu, 2006. “Exchange Rates and Monetary Policy in Emerging Market Economies,” *The Economic Journal*, 116 (April), 478–506.

Dominguez, Kathryn ME, 2012. “Foreign Reserve Management During the Global Financial Crisis.” *Journal of International Money and Finance* 31, no. 8: 2017-2037.

Forbes, Kristin J., and Michael W. Klein. 2015. “Pick Your Poison: The Choices and Consequences of Policy Responses to Crises.” *IMF Economic Review* 63, no. 1: 197-237.

Galati, Gabriele, and Richhild Moessner. 2018. “What Do We Know About the Effects of Macroprudential Policy?” *Economica* 85(340): 735-770.

Galí, Jordi. 2014. “Monetary Policy and Rational Asset Price Bubbles.” *American Economic Review* 104, no. 3: 721-52.

Gourio, Francois, Anil K. Kashyap, and Jae W. Sim. 2018. “The Tradeoffs in Leaning Against the Wind.” *IMF Economic Review* 66:70-115.

Gürkaynak, Refet S., Brian Sack, and Eric Swanson. 2005. “The sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models.” *American Economic Review* 95, no. 1: 425-436.

Hagemann, Andreas. (2017). “Cluster-Robust Bootstrap Inference in Quantile Regression Models.” *Journal of the American Statistical Association*, 112(517), 446-456.

Hamilton, James D. 2018. “Why you should never use the Hodrick-Prescott filter.” *Review of Economics and Statistics* 100, no. 5: 831-843.

International Monetary Fund (IMF), 2015. “Monetary Policy and Financial Stability.” *IMF Policy Paper*. Washington, D.C.

———, 2018. “A Decade after the Global Financial Crisis: Are We Safer?” in *Global Financial Stability Report— A Decade after the Global Financial Crisis: Are We Safer?* October. Washington, D.C.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina, 2017. “Macroprudential Policy, Countercyclical Bank Capital Buffers, and Credit Supply:

Evidence from the Spanish Dynamic Provisioning Experiments." *Journal of Political Economy* 125(6): 2126-2177.

Jordà, Òscar. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review* 95, no. 1: 161-182.

Kato, Kengo, Antonio F. Galvão Jr, and Gabriel V. Montes-Rojas. 2012. "Asymptotics for panel quantile regression models with individual effects." *Journal of Econometrics* 170, no. 1: 76-91.

Kocherlakota, Narayana R., 2019. "Practical Policy Evaluation." *Journal of Monetary Economics* 102: 29-45.

Koenker, Roger, 2004. "Quantile Regression for Longitudinal Data." *Journal of Multivariate Analysis* 91, no. 1: 74-89.

Koenker, Roger, 2019. *Quantreg: Quantile Regression*, R package version 5.40.

Korinek, Anton. 2018. "Regulating Capital Flows to Emerging Markets: An Externality View." *Journal of International Economics* 111: 61-80.

Krippner, Leo. 2015. *Zero Lower Bound Term Structure Modeling: A Practitioner's Guide*. Berlin: Springer.

Kuttner, Kenneth N. 2001. "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market." *Journal of Monetary Economics*, 47(3): 523–44.

Lucas, Robert E., 1976. "Econometric Policy Evaluation: A Critique." In *Carnegie-Rochester Conference Series on Public Policy*, vol. 1, no. 1: 19-46.

Mendicino, Caterina, Kalin Nikolov, Javier Suarez, and Dominik Supera, 2019. "Bank Capital in the Short and in the Long Run." *Journal of Monetary Economics*, in press.

Nelson, Edward, 2020. "The Continuing Validity of Monetary Policy Autonomy under Floating Exchange Rates," *International Journal of Central Banking*, vol.16: 81–123.

Obstfeld, Maurice, 2015. "Trilemmas and Trade-offs: Living with Financial Globalization," BIS Working Papers No. 480.

Ramey, Valerie A. 2016. "Macroeconomic Shocks and Their Propagation." In *Handbook of Macroeconomics*, vol. 2: 71-162. Elsevier.

Rebucci, Alessandro, and Chang Ma. 2019. "Capital Controls: A Survey of the New Literature," NBER Working Paper No. 26558.

Rey, Hélène, 2013. "Dilemma not trilemma: the global financial cycle and monetary policy independence", in: "Global dimensions of unconventional monetary policy," proceedings of the Federal Reserve Bank of Kansas City Jackson Hole symposium, 2013: 285–333.

Richter, Björn, Moritz Schularick, and Ilhyock Shim. 2019. "The Costs of Macroprudential Policy." *Journal of International Economics* 118: 263-282.

Romer, Christina D., and David H. Romer. 2004. "A New Measure of Monetary Shocks: Derivation and Implications." *American Economic Review* 94 (4): 1055-1084.

Ruge-Murcia, Francisco J. 2003. "Does the Barro–Gordon Model Explain the Behavior of U.S. Inflation? A Reexamination of The Empirical Evidence." *Journal of Monetary Economics* 50, no. 6: 1375-1390.

Schularick, Moritz, Lucas Ter Steege and Felix Ward, 2020. "Leaning Against the Wind and Crisis Risk," CEPR Discussion Paper DP14797

Sharpe, William F, 1964. "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk." *The Journal of Finance* 19, no. 3: 425-442.

Sims, Christopher A., 1980. "Macroeconomics and Reality." *Econometrica* 48, No. 1: 1-48.

Schularick, Moritz, Lucas Ter Steege, and Felix Ward, 2020. "Leaning Against the Wind and Crisis Risk." CEPR Discussion Paper DP14797.

Stein, Jeremy C., 2013. "Overheating in Credit Markets: Origins, Measurement, and Policy Responses." Speech at the *Restoring Household Financial Stability after the Great Recession: Why Household Balance Sheets Matter* research symposium sponsored by the Federal Reserve Bank of St. Louis, St. Louis, Missouri, February 17, 2013.

Svensson, Lars EO, 2017a. "Cost-benefit analysis of leaning against the wind." *Journal of Monetary Economics* 90: 193-213.

———, 2017b. "How Robust Is the Result That the Cost of "Leaning Against the Wind" Exceeds the Benefit? Response to Adrian and Liang." CEPR Discussion Paper No. 11744. (London: Centre for Economic Policy.)

Varian, Hal R., 1975. "A Bayesian Approach to Real Estate Assessment," *in: Studies in Bayesian Econometrics and Statistics in Honor of Leonard J. Savage*, eds. Stephen Fienberg and Arnold Zellner, Amsterdam: North- Holland, 195-208.

Wu, Jing Cynthia, Xia, Fan Dora, 2016. "Measuring the macroeconomic impact of monetary policy at the zero-lower bound." *Journal of Money, Credit, and Banking* 48 (2–3): 253–291.

Yellen, Janet Louise, 2014. *Monetary Policy and Financial Stability*. Michael Camdessus Central Banking Series—Inaugural Lecture, July 2, 2014. International Monetary Fund.

Table 1. Summary Statistics

Variable	Observations	Average	Standard Deviation	Median	Minimum	Maximum
Detrended output	2,876	-0.03	1.11	0.02	-8.08	7.21
Quarterly inflation	2,876	0.66	0.87	0.55	-3.07	9.84
Financial conditions index	2,876	-0.07	0.94	-0.20	-2.74	6.11
Real GDP growth*	2,876	2.97	4.68	2.86	-22.29	26.89
YoY Inflation	2,876	2.72	2.51	2.23	-6.32	16.37
Growth in credit*	2,876	0.64	2.46	0.50	-7.60	10.60
Credit to GDP (logs)	2,876	4.78	0.58	4.93	3.00	5.99
House prices (logs)	2,876	5.03	0.67	4.90	3.16	8.45
Output gap	2,808	0.00	0.04	0.00	-0.20	0.33
MPM All	2,876	0.01	0.48	-0.05	-2.51	2.24
MPM Borrower-Based	2,876	0.00	0.23	-0.01	-2.07	1.99
MPM FI-Based	2,876	0.00	0.40	-0.03	-2.58	2.17
MP	2,852	-0.03	0.95	-0.05	-5.74	9.05
FXI	2,259	0.00	0.01	0.00	-0.09	0.14
CFM	2,259	-0.02	0.52	0.03	-2.00	2.30

* Winsorized at the top and bottom 0.5 percent.

Note: "MPM All", "MPM Borrower-Based", and "MPM FI-Based" stand for the macroprudential policy shocks for all instruments, borrower-based instruments, and financial-institution-based instruments, respectively; "MP" stands for the monetary policy shock; "FXI" stands for the foreign exchange intervention shock; and "CFM" stands for the capital flow management measure shock. Please see Appendix A for details.

Table 2. Policy Shock Size by Country

Country	Observations	MPM All	MPM Borrower-Based	MPM FI-Based	MP	FXI	CFM
Australia	103	0.38	0.00	0.19	1.03	0.13	0.58
Austria	103	0.29	0.00	0.14	0.93	0.09	0.22
Belgium	98	0.34	0.01	0.17	0.95	0.09	0.27
Brazil	59	0.96	0.13	0.47	1.01	0.17	0.95
Canada	103	0.53	0.34	0.14	0.98	0.19	0.50
Chile	55	0.13	0.13	0.00	1.04	0.19	0.69
China	42	1.23	0.55	0.41	1.04	0.05	0.96
Colombia	76	0.43	0.23	0.11	0.95		
Denmark	103	0.24	0.17	0.17	1.04	0.11	0.03
Finland	103	0.34	0.14	0.17	0.95	0.09	0.25
France	103	0.22	0.00	0.14	0.97	0.09	0.31
Germany	102	0.28	0.00	0.10	0.95	0.10	0.22
Hong Kong SAR	103	0.56	0.47	0.21	1.05	0.14	0.46
Hungary	71	0.50	0.35	0.00	1.00	0.15	0.52
India	27	0.97	0.34	0.43	1.03	0.14	1.06
Indonesia	55	0.61	0.27	0.13	1.02	0.16	0.80
Ireland	78	0.30	0.16	0.16	0.94	0.16	0.09
Italy	103	0.35	0.10	0.17	0.96	0.10	0.16
Japan	103	0.24	0.00	0.10	1.22	0.12	0.27
Kazakhstan	39	0.42	0.16	0.22	1.05		
Korea	103	0.74	0.58	0.19	1.04	0.20	0.98
Malaysia	102	0.58	0.22	0.14	1.02	0.19	0.82
Mexico	43	0.41	0.00	0.26	1.00	0.09	0.57
Netherlands	103	0.39	0.25	0.10	0.94	0.15	0.03
Norway	103	0.43	0.22	0.32	1.05	0.13	0.22
Peru	71	0.75	0.12	0.17	1.01		
Philippines	31	0.40	0.18	0.18	0.79	0.09	0.70
Poland	68	0.59	0.24	0.21	1.04	0.16	0.51
Russia	59	0.89	0.00	0.50	0.90	0.19	0.91
Singapore	103	0.52	0.33	0.10	1.05	0.14	0.48
South Africa	103	0.24	0.00	0.19	1.03	0.11	0.85
Spain	103	0.36	0.10	0.22	0.98	0.08	0.22
Sweden	103	0.34	0.14	0.26	1.03	0.11	0.25
Switzerland	103	0.31	0.00	0.24	1.03	0.11	0.31
Turkey	23	1.00	0.29	0.50	1.03	0.19	0.64
United Kingdom	103	0.33	0.10	0.26	1.02	0.09	0.03
United States	103	0.32	0.10	0.17	1.05	0.06	0.03

Note: The table shows one standard deviation of each policy shock. "MPM All", "MPM Borrower-Based", and "MPM FI-Based" stand for the macroprudential policy shocks for all instruments, borrower-based instruments, and financial-institution-based instruments, respectively; "MP" stands for the monetary policy shock; "FXI" stands for the foreign exchange intervention shock; and "CFM" stands for the capital flow management measure shock. Please see Appendix A for details.

Table 3. Effect of Policy Changes on Loss Functions

The table shows the estimated values of the expected loss given by the following period loss function

$$\ell_t = \omega_y \left(y_{t+h} - \overline{y}_{t+h} \right)^2 + \omega_\pi \pi_{t+h}^2,$$

which are obtained from the following quantile regressions

$$Q_{Y_{i,t+h}} \left(q \mid Z_{it} \right) = \alpha_{0i}^h \left(q \right) + \beta_1^h \left(q \right) f_{it} + \beta_2^h \left(q \right) P_{it} + \beta_3^h \left(q \right) P_{it} \times f_{it} + \mathbf{x}_{it} \Gamma, \text{ and}$$

$$Q_{Y_{i,t,t+h}} \left(q \mid Z_{it} \right) = \alpha_{0i}^h \left(q \right) + \beta_1^h \left(q \right) f_{it} + \beta_2^h \left(q \right) g_{it} + \beta_3^h \left(q \right) P_{it} + \beta_4^h \left(q \right) P_{it} \times g_{it} + \mathbf{x}_{it} \Gamma,$$

$$h = 1, \ldots, H, \; q = 0.05, \ldots, 0.95,$$

for domestic and global FCI shocks, respectively, where $Q_Y(q|.)$ is the conditional quantile function of either cumulative GDP growth (i.e., the detrended change in log GDP) for up to 14 quarters ahead or the inflation rate (change in log CPI) in that quarter, f is a country-specific financial conditions index, g is a global financial conditions index, P is a policy shock, and $\mathbf{x}$ is a vector of controls including current GDP growth, inflation, and credit growth. The exercise shows the results when macroprudential policy, monetary policy, and capital flow measures tighten or when the central bank intervenes in the foreign exchange market by purchasing foreign currency, when financial conditions are loose. MPM All is the shock based on Alam et al.'s (2019) index of 17 macroprudential measures. MPM Borrower-Based and MPM FI-Based are the same as MPM All but only use borrower-based and financial-institution-based prudential measures, respectively. MP is a monetary policy shock calculated as the residual of an estimated Taylor rule. FXI is a measure of FX interventions. CFM is Baba et al.'s (forthcoming) index of capital-flow-management measures. HF MP is a measure of monetary policy surprises based on high-frequency data from multiple sources. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels, respectively. Inference is based on a country-level cluster bootstrap.

	Domestic FCI			External FCI		
	ω_y=1, ω_p=0	ω_y=1, ω_p=1	ω_y=0.542, ω_p=1	ω_y=1, ω_p=0	ω_y=1, ω_p=1	ω_y=0.542, ω_p=1
MPM All	-0.089 ***	-0.085 ***	-0.083 ***	-0.112 ***	-0.107 ***	-0.104 ***
MPM Borrower-Based	-0.100 ***	-0.068 ***	-0.065 ***	-0.107 ***	-0.101 ***	-0.096 ***
MPM FI-Based	-0.053 **	-0.036 **	-0.035 **	-0.068 ***	-0.067 ***	-0.065 ***
MP	0.121 ***	0.115 ***	0.111 ***	0.038 *	0.036 *	0.036 *
FXI	-	-	-	-0.022	-0.021	-0.021
CFM	-	-	-	-0.039	-0.034	-0.030
HF MP	-0.011	-0.011	-0.011	-0.025	-0.023	-0.022

Table 4. Effect of Policy Changes on Loss Functions by Vulnerability

The table shows the estimated values of the expected loss given by the following period loss function

$$l_t = \omega_y \left(y_{t+h} - \bar{y}_{t+h} \right)^2 + \omega_\pi \pi_{t+h}^2,$$

which are obtained from the following quantile regressions

$$Q_{Y_{i,t,t+h}} \left(q \mid Z_{it} \right) = \alpha_{0i}^h \left(q \right) + \beta_1^h \left(q \right) f_{it} + \beta_2^h \left(q \right) Vul_{it} + \beta_3^h \left(q \right) P_{it} + \beta_4^h \left(q \right) P_{it} \times f_{it}$$
$$+ \left(\beta_5^h \left(q \right) P_{it} + \beta_6^h \left(q \right) P_{it} \times f_{it} \right) Vul_{it} + \mathbf{x}_{it} \Gamma,$$
$$h = 1, \ldots, H, \; q = 0.05, \ldots, 0.95,$$

where $Q_Y(q|.)$ is the conditional quantile function of either cumulative GDP growth (i.e., the detrended change in log GDP) for up to 14 quarters ahead, f is a country-specific financial conditions index, g is a global financial conditions index, P is a policy shock, Vul is a measure of financial vulnerabilities (credit-to-GDP, in panel A, or house-price index, in panel B) and $\mathbf{x}$ is a vector of controls including current GDP growth, inflation, and credit growth. The exercise shows the results when macroprudential policy or monetary policy tighten with loose financial conditions. MPM All is the shock based on Alam et al.'s (2019) index of 17 macroprudential measures. MPM Borrower-Based and MPM FI-Based are the same as MPM All but only use borrower-based and financial-institution-based prudential measures, respectively. MP is a monetary policy shock calculated as the residual of an estimated Taylor rule. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels, respectively. Inference is based on a country-level cluster bootstrap.

Panel A.

	Low Credit			High Credit		
	ω_y=1, ω_p=0	ω_y=1, ω_p=1	ω_y=0.542, ω_p=1	ω_y=1, ω_p=0	ω_y=1, ω_p=1	ω_y=0.542, ω_p=1
MPM All	-0.089 **	-0.086 **	-0.084 **	-0.099 **	-0.094 **	-0.090 **
MPM Borrower-Based	-0.033	-0.032	-0.031	-0.083 ***	-0.078 ***	-0.075 ***
MPM FI-Based	-0.076 **	-0.072 **	-0.070 **	-0.028	-0.027	-0.026
MP	0.137 ***	0.132 ***	0.129 ***	0.126 ***	0.120 ***	0.115 ***

Panel B.

	Low Valuations			High Valuations		
	ω_y=1, ω_p=0	ω_y=1, ω_p=1	ω_y=0.542, ω_p=1	ω_y=1, ω_p=0	ω_y=1, ω_p=1	ω_y=0.542, ω_p=1
MPM All	-0.152 ***	-0.144 ***	-0.139 ***	-0.072 **	-0.068 **	-0.066 **
MPM Borrower-Based	-0.123 **	-0.114 **	-0.107 **	-0.074 **	-0.071 **	-0.068 **
MPM FI-Based	-0.085 **	-0.082 **	-0.080 **	-0.031	-0.031	-0.030
MP	0.150 ***	0.145 ***	0.141 ***	0.216 ***	0.208 ***	0.202 ***

Table 5. Effect of Policy Changes with Alternative Loss Functions

The table shows the estimated values of the expected loss given by the following period loss functions

$$\ell_t = \omega_y \left[\left(y_{t+h} - \bar{y}_t \right)^2 - \left(y_{t+h} - \bar{y}_t \right) \right] + \omega_\pi \pi_t^2, \text{ and}$$

$$\ell_t = \frac{\left(e^{a\tilde{y}_{t+h}} - a\tilde{y}_{t+h} - 1 \right)}{a^2}, \text{where } \tilde{y}_{t+h} \equiv \left(y_{t+h} - \bar{y} \right),$$

for the linear-quadratic and asymmetric policymaker preferences, respectively. The loss functions are obtained from the following quantile regressions:

$$Q_{Y_{i,t+h}}\left(q \mid Z_{it}\right) = \alpha_{0i}^h(q) + \beta_1^h(q) f_{it} + \beta_2^h(q) P_{it} + \beta_3^h(q) P_{it} \times f_{it} + \mathbf{x}_{it}\Gamma,$$

$$h = 1, \ldots, H, \; q = 0.05, \ldots, 0.95, \text{ and}$$

$$Q_{\Delta y_{i,t,t+h}}\left(q \mid Z_{it}\right) = \alpha_{0i}^h(q) + \beta_1^h(q) f_{it} + \beta_2^h(q) g_{it} + \beta_3^h(q) P_{it} + \beta_4^h(q) P_{it} \times g_{it} + \mathbf{x}_{it}\Gamma,$$

$$h = 1, \ldots, H, \; q = 0.05, \ldots, 0.95,$$

for domestic and global FCI shocks, respectively, where $Q_Y(q|.)$ is the conditional quantile function of either cumulative GDP growth (i.e., the detrended change in log GDP) for up to 14 quarters ahead or the inflation rate (change in log CPI) in that quarter, f is a country-specific financial conditions index, g is a global financial conditions index, P is a policy shock, and x is a vector of controls including current GDP growth, inflation, and credit growth. The exercise shows the results when macroprudential policy, monetary policy, and capital flow measures tighten or when the central bank intervenes in the foreign exchange market by selling foreign currency, when financial conditions are loose. MPM All is the shock based on Alam et al.'s (2019) index of 17 macroprudential measures. MPM Borrower-Based and MPM FI-Based are the same as MPM All but only use borrower-based and financial-institution-based prudential measures, respectively. MP is a monetary policy shock calculated as the residual of an estimated Taylor rule. FXI is a measure of FX interventions. CFM is Baba et al.'s (forthcoming) index of capital-flow-management measures. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels, respectively. Inference is based on a country-level cluster bootstrap.

	Domestic Shock			External Shock		
	Linear-quadratic		Asymmetric	Linear-quadratic		Asymmetric
	ω_y=1, ω_p=0	ω_y=1, ω_p=1	ω_y=1, ω_p=0	ω_y=1, ω_p=0	ω_y=1, ω_p=1	ω_y=1, ω_p=0
MPM All	-0.080 ***	-0.076 ***	-0.087 ***	-0.100 ***	-0.095 ***	-0.109 ***
MPM Borrower-Based	-0.092 ***	-0.087 ***	-0.098 ***	-0.097 ***	-0.089 ***	-0.100 ***
MPM FI-Based	-0.046 **	-0.045 **	-0.053 *	-0.060 **	-0.058 **	-0.067 ***
MP	0.134 ***	0.126 ***	0.124 ***	0.046 **	0.044 **	0.040 *
FXI	-	-	-	-0.029	-0.027 *	-0.024
CFM	-	-	-	-0.040	-0.033	-0.041

Table 6. Effect of Policy Changes on Loss Functions by Group of Countries

The table shows the estimated values of the expected loss given by the following period loss function

$$\ell_t = \omega_y \left(y_{t+h} - \bar{y}_{t+h} \right)^2 + \omega_\pi \pi_{t+h}^2,$$

which are obtained from the following quantile regressions

$$Q_{Y_{i,t+h}}\left(q \mid Z_{it}\right) = \alpha_{0i}^h(q) + \beta_1^h(q) f_{it} + \beta_2^h(q) P_{it} + \beta_3^h(q) P_{it} \times f_{it} + \mathbf{x}_{it}\Gamma, \text{ and}$$

$$Q_{Y_{i,t,t+h}}\left(q \mid Z_{it}\right) = \alpha_{0i}^h(q) + \beta_1^h(q) f_{it} + \beta_2^h(q) g_{it} + \beta_3^h(q) P_{it} + \beta_4^h(q) P_{it} \times g_{it} + \mathbf{x}_{it}\Gamma,$$

$$h = 1, \ldots, H,\ q = 0.05, \ldots, 0.95,$$

for domestic and global FCI shocks, respectively, where $Q_Y(q|.)$ is the conditional quantile function of either cumulative GDP growth (i.e., the detrended change in log GDP) for up to 14 quarters ahead or the inflation rate (change in log CPI) in that quarter, f is a country-specific financial conditions index, g is a global financial conditions index, P is a policy shock, and $\mathbf{x}$ is a vector of controls including current GDP growth, inflation, and credit growth. The exercise shows the results when macroprudential policy, monetary policy, and capital flow measures tighten or when the central bank intervenes in the foreign exchange market by selling foreign currency, when financial conditions are loose. MPM All is the shock based on Alam et al.'s (2019) index of 17 macroprudential measures. MPM Borrower-Based and MPM FI-Based are the same as MPM All but only use borrower-based and financial-institution-based prudential measures, respectively. MP is a monetary policy shock calculated as the residual of an estimated Taylor rule. FXI is a measure of FX interventions. CFM is Baba et al.'s (forthcoming) index of capital-flow-management measures. The group *advanced economies* includes those considered as advanced economies as per the 2019 World Economic Outlook database; all other economies are included in the group *emerging economies*. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels, respectively. Inference is based on a country-level cluster bootstrap.

	Domestic FCI			External FCI		
	ω_y=1, ω_p=0	ω_y=1, ω_p=1	ω_y=0.542, ω_p=1	ω_y=1, ω_p=0	ω_y=1, ω_p=1	ω_y=0.542, ω_p=1
			Advanced economies			
MPM All	-0.120 **	-0.116 **	-0.113 **	-0.139 **	-0.136 **	-0.133 **
MPM Borrower-Based	-0.141 **	-0.136 **	-0.132 *	-0.142 ***	-0.139 ***	-0.136 ***
MPM FI-Based	-0.027	-0.026	-0.025	-0.046	-0.045	-0.045
MP	0.127 ***	0.124 ***	0.122 ***	0.075	0.075	0.075
FXI	-	-	-	0.051	0.049	0.047
CFM	-	-	-	0.015	0.015	0.015
			Emerging economies			
MPM All	-0.081 ***	-0.078 ***	-0.075 ***	-0.143 ***	-0.062 ***	-0.038 ***
MPM Borrower-Based	-0.067 **	-0.064 **	-0.061 **	-0.136 *	-0.099 *	-0.089 *
MPM FI-Based	-0.074 **	-0.072 **	-0.070 **	-0.132 ***	-0.125 ***	-0.120 ***
MP	0.086 **	0.080 ***	0.077 ***	0.092 *	0.089 *	0.086 **
FXI	-	-	-	0.017	0.014	0.011
CFM	-	-	-	-0.065 *	-0.050	-0.040

Table 7. Effect of Policy Changes on Loss Functions Accounting for Common Factors

The table shows the estimated values of the expected loss given by the following period loss function

$$l_t = \omega_y \left(y_{t+h} - \bar{y}_{t+h} \right)^2 + \omega_\pi \pi_{t+h}^2,$$

which are obtained from the following quantile regressions

$$Q_{Y_{i,t+h}}\left(q \mid Z_{it}\right) = \alpha_{0i}^h\left(q\right) + \lambda_{0i}^h\left(q\right) + \beta_1^h\left(q\right) f_{it} + \beta_2^h\left(q\right) P_{it} + \beta_3^h\left(q\right) P_{it} \times f_{it} + \mathbf{x}_{it}\Gamma,$$
$$h = 1,\ldots, H,\ q = 0.05,\ldots, 0.95,$$

where $Q_Y(q|.)$ is the conditional quantile function of either cumulative GDP growth (i.e., the detrended change in log GDP) for up to 14 quarters ahead or the inflation rate (change in log CPI) in that quarter, α and λ are country and time fixed effects, respectively, f is a country-specific financial conditions index, g is a global financial conditions index, P is a policy shock, and $\mathbf{x}$ is a vector of controls including current GDP growth, inflation, and credit growth. The exercise shows the results when macroprudential policy and monetary policy measures tighten and financial conditions are loose. MPM All is the shock based on Alam et al.'s (2019) index of 17 macroprudential measures. MPM Borrower-Based and MPM FI-Based are the same as MPM All but only use borrower-based and financial-institution-based prudential measures, respectively. MP is a monetary policy shock calculated as the residual of an estimated Taylor rule. The columns in panel A (Common factors) show the results using quantile regressions with individual (country) and (quarter) fixed effects. Time fixed effects are assumed to be pure location shift parameters and estimated using Koenker's (2004) penalized estimator (R library `rqpd`). The columns in panel B (Unobserved heterogeneity) show the results using quantile regressions show the results using quantile regressions with country-specific slope coefficients and five unobserved common factors. These quantile regressions are estimated using Ando and Bai's (2019) procedure and their source code.

Panel A

	Common factors		
	ω_y=1, ω_p=0	ω_y=1, ω_p=1	ω_y=0.542, ω_p=1
MPM All	-0.073	-0.070	-0.067
MPM Borrower-Based	-0.038	-0.035	-0.033
MPM FI-Based	-0.053	-0.051	-0.050
MP	0.142	0.135	0.130

Panel B

	Unobserved heterogeneity		
	ω_y=1, ω_p=0	ω_y=1, ω_p=1	ω_y=0.542, ω_p=1
MPM All	-0.104	-0.108	-0.110
MPM Borrower-Based	-0.477	-0.336	-0.228
MPM FI-Based	-0.129	-0.124	-0.120
MP	0.063	0.060	0.057

Appendix A. Data Sources and Definitions

1. Financial Conditions Index

Since financial conditions are not directly observable, typically they are approximated with an index of financial conditions. These indexes summarize the information of the current state of financial variables that influence and predict future economic activity (Hatzius et al., 2010).

Our financial conditions index (FCI) is based on IMF (2018) and uses the same underlying data. To construct the financial conditions indexes we use up to 10 financial variables, depending on data availability: the real short-term interest rate, the interbank spread, the spreads on local currency and U.S. dollar-denominated sovereign and corporate debt, equity returns (in local currency), the implied volatility of equity returns, the change in a debt-weighted exchange rate index, and the year-on-year growth in real house prices (see Table A.1 for definitions).

In building our country-specific FCI, we deal with missing values and choose the optimal number of factors for each country's FCI. First, concerning missing observations, our financial variable data have two problems: there are many missing variables for several variables; and they are not missing entirely at random since data coverage increases over time. This cautions against the use of simple imputation methods (such as replacing missing values with the sample mean or zeros). Therefore, we use Josse and Husson's (2012a) iterative principal component analysis algorithm to complete the dataset.[1] Second, to determine the optimal number of components to include in the FCI, we use Josse and Husson's (2012b) cross-validation approximation method.[2] The FCI is computed as the sum of the first p principal components, where p is the result of the cross-validation method. For most countries, using two to three factors seems optimal. We use the FCI in the United States as a proxy of global financial conditions.

[1] This is implemented in the *R* package *missMDA* with the function (Josse and Husson 2016).

[2] We prefer this cross-validation method to formal tests of hypothesis methods (e.g., Bai and Ng, 2002) because it does not rely on distributional assumptions nor does it require the number of variables and the length of the sample to be large.

Table A.1 Variable Definitions

Variable	Definition
FCI_{it}	Financial conditions index. Calculated as the weighted sum of the first *N* principle components of a set of up to 11 financial variables for each country. *N* is chosen using Josse and Husson's (2012b) cross-validation method. Each principal component is weighed by its share of the total variance. Missing values of each the underlying financial values are treated with Josse and Husson's (2012a) imputation method. The following financial variables are measured at the country level, when available: the real short-term interest rate, the interbank spread, the term spread, the spread on sovereign local-currency debt, the spread on sovereign dollar-denominated debt, the spread on corporate local-currency debt, the spread on corporate dollar-denominated debt, the average price-to-book ratio of the MSCI country index, the historical or implied volatility of country stock returns, debt-weighted exchange rate returns, and year-on-year growth of house prices (deflated by the CPI). See the Online Annex 1.1 of IMF (2018) for a detailed description of sources. For the analysis of global FCI, the US FCI is used as a proxy for global financial conditions.
y_{it}	The natural log of real GDP. Real GDP data is from the IMF's World Economic Outlook database.
π_{it+h}	Inflation. The h-quarter difference in the natural log of the consumer price index (CPI). The CPI data is from the IMF's World Economic Outlook database.
$I_{it}^{mpm\_A}$	Index of changes in all macroprudential measures. It takes the value of zero for no change, 1 (-1) for one tightening (loosening) action, and 2 (-2) for more than one tightening (loosening) actions, all in net terms, in each quarter and in each country. Data on macroprudential policy actions are from the iMaPP database by Alam et al. (2019).
$I_{it}^{mpm\_B}$	Index of changes in borrower-based macroprudential measures. A subset of $I_{it}^{mpm\_A}$. It takes the value of zero for no change, 1 (-1) for one tightening (loosening) action, and 2 (-2) for more than one tightening (loosening) actions, all in net terms, in each quarter, in each country, and in the subcategory of borrower-based measures. The subcategory consists of the limits to loan-to-value ratios and debt-service-to-income ratios. Data on macroprudential policy actions are from the iMaPP database by Alam et al. (2019).
$I_{it}^{mpm\_F}$	Index of changes in financial institutions-based macroprudential measures. A subset of $I_{it}^{mpm\_A}$. It takes the value of zero for no change, 1 (-1) for one tightening (loosening) action, and 2 (-2) for more than one tightening (loosening) actions, all in net terms, in each quarter, in each country, and in the subcategory of financial-institutions-based measures. The subcategory consists of (1) countercyclical buffers, (2) conservation buffers, (3) capital requirements, (4) leverage limits, (5) loan loss provisions, (6) limits to credit growth, (7)loan restrictions, (8) limits to foreign currency loans, (9) liquidity requirements, (10) limits to the loan to deposit ratio, (11) limits to FX positions, (12) reserve requirements, and (13) measures on systemically

Variable	Definition
	important financial institutions. Data on macroprudential policy actions are from the iMaPP database by Alam et al. (2019).
$\hat{\varepsilon}_{it}^{mpm\_A}$	Aggregate macroprudential policy shock. Calculated as the difference between $I_{it}^{mpm\_A}$ and its prediction estimated with an ordered probit model with the credit-to-GDP house price gaps as explanatory variables.
$\hat{\varepsilon}_{it}^{mpm\_B}$	Borrower-based macroprudential shock. Calculated in the same way as $\hat{\varepsilon}_{it}^{mpm\_A}$ but using $I_{it}^{mpm\_B}$ instead.
$\hat{\varepsilon}_{it}^{mpm\_F}$	Financial institutions-based shock. Calculated in the same way as $\hat{\varepsilon}_{it}^{mpm\_A}$ but using $I_{it}^{mpm\_F}$ instead.
$cgap_{it}$	Credit-to-GDP gap. The residuals of country-level regressions of credit-to-GDP on four lags of itself. Data from the Bank for International Settlements.
$hgap_{it}$	House price gap. The residuals of country-level regressions of a house price index on four lags of itself. Data from the Bank for International Settlements.
$egap_{it}$	Exchange rate gap. The residuals of country-level regressions of country *i*'s dollar exchange rate on four lags of itself. Data from the IMF's International Financial Statistics.
$\sigma(e)_{it}$	The quarterly nominal effective exchange rate volatility calculated from daily data. Data from the IMF's International Financial Statistics.
$\hat{\varepsilon}_{it}^{r}$	Monetary policy shock. Calculated as the standardized residual of an estimated Taylor-type rule. The rule is estimated with the quarterly change of the monetary policy rate (from the IMF's International Financial Statistics) on the left-hand-side and 12-month ahead expected inflation and GDP growth (from Consensus Forecasts) and the lagged policy rate.
FXI_{it}	Foreign exchange interventions as a percent of GDP. The actual FXI data are used for Australia, Brazil, Canada, Chile, Colombia, Denmark, euro area countries (after 1999), Germany (before 1999), Hong Kong SAR, India, Italy (before 1999), Japan, Kazakhstan, Mexico, Peru, Russian Federation, Switzerland (before 2009 and for 2010: Q1 and Q2), Turkey, the United Kingdom, and the United States, as reported in the respective central banks' websites, Cukierman (2019), Frenkel et al. (2001), Goldberg et al. (2013), Henning (2006), Larrain and Saravia (2019), Neely (2011), and the Federal Research Economic Database (FRED). For all countries and periods, interventions are approximated with Adler et al.' (2019) measure of valuation-adjusted changes to central banks' net foreign assets.
$\hat{\varepsilon}_{it}^{FXI}$	Foreign exchange intervention shock. Calculated as the residual of an estimated FXI rule. The rule is estimated using OLS with the FXI variable in percent of GDP on the lag of exchange rate gap (*egap*) and exchange rate volatility (*σ(e)*), as well as the covariates used in the first column of Table 2 in Forbes and Klein (2015). That is, the log of the VIX, the change in the U.S. policy interest rate, the change in capital inflows as a percentage of GDP, inflation, a commodity price index, the Economist All-Commodity Dollar index (in logs) interacted with a

Variable	Definition
	dummy equal to 1 if a country is a major commodity exporter ((food exports+fuel exports)/merchandise exports >30%), reserves as a percent of GDP, Chinn and Ito's (2006) index of capital account openness, and the log of the average of the six indexes of institutional quality from the World Bank's Worldwide Governance Indicators database, the rate of exchange rate depreciation against the U.S. dollar, and the interest rate differential against the U.S.'s policy rate. For the United States, we use the exchange rate and the interest rate differential against the euro, respectively.
I_{it}^{CFM}	Index of changes in capital flow management measures. It takes the value of zero for no change, 1 (-1) for tightening (loosening) actions, and 2 (-2) for more than one tightening (loosening) actions, all in net terms, in each quarter in each country. Data on CFM changes are from Baba et al. (forthcoming).
$\hat{\varepsilon}_{it}^{CFM}$	CFM shock. Calculated as the difference between I_{it}^{CFM} and its prediction, estimated with an ordered probit model with the lag of exchange rate gap (egap) and exchange rate volatility ($\sigma(e)$), as well as the covariates used in the first column of Table 2 in Forbes and Klein (2015), which are listed in the column for $\hat{\varepsilon}_{it}^{FXI}$.

2. Macroprudential Policy

We use Alam and other's (2019) Integrate Macroprudential Policy (iMaPP) database in constructing our categorical macroprudential policy indicators. The iMaPP database provides the dummy-type indices for 17 categories of macroprudential policy instruments,[3] which count the number of tightening and loosening actions in each category in a given month for a given country, from January 1990 through December 2016. For our categorical indicator, we consider three broad categories, instead of individual categories, because some of the measures are only infrequently used in many countries. These three categories are the overall category and its subcategories of borrower-based and financial-institution-based measures.

Using the dummy-type indices from the iMaPP database, we construct our categorical indicator for each category of macroprudential measures—$I_{it}^{mpm\_A}$, $I_{it}^{mpm\_B}$, and $I_{it}^{mpm\_F}$. Each of the indicator is defined to take the value of zero for no change, 1 (-1) for tightening (loosening) actions, and 2 (-2) for more than one tightening (loosening)

[3] The database includes policy instruments that can be both macroprudential policy and other policies, such as capital flow management and monetary policy measures, because instruments can overlap (while the distinction of policies is made by their objectives). For some measures, such as reserve requirements, it is difficult to unambiguously declare them as macroprudential and/or monetary policies and we treat them separately.

actions, all in net terms, in the category in each quarter. Please see Table A.1. for the definitions.

Table A.2. Ordered Probit Regressions for Macroprudential Measures

Variables	(1) $I_{it}^{mpm\_A}$	(2) $I_{it}^{mpm\_B}$	(3) $I_{it}^{mpm\_F}$
Credit gap	0.0066**	0.0124***	0.0051*
	(0.011)	(0.001)	(0.075)
House price gap	0.0004	0.0006	0.0002
	(0.293)	(0.261)	(0.587)
Past policy actions	0.1080***	0.2221***	0.1195***
	(0.000)	(0.000)	(0.000)
α_1	-2.4806***	-3.1003***	-2.6595***
	(0.000)	(0.000)	(0.000)
α_2	-1.6860***	-2.3596***	-1.8421***
	(0.000)	(0.000)	(0.000)
α_3	1.4329***	2.0822***	1.5476***
	(0.000)	(0.000)	(0.000)
α_4	2.0945***	2.8356***	2.2820***
	(0.000)	(0.000)	(0.000)
Observations	2,935	2,935	2,935
Country FE	YES	YES	YES
Number of countries	37	37	37
Pseudo R2	0.0422	0.0572	0.0540

We then proceed to extracting policy shocks for $I_{it}^{mpm\_A}$, $I_{it}^{mpm\_B}$, and $I_{it}^{mpm\_F}$ using the approach described in Section III. B. Specifically, we estimate a panel ordered probit regression with country fixed effects for each one of the macroprudential measures using specification 6. The estimates for each regression are in Table A.2.

3. Monetary Policy

As explained in Section III.B., our baseline measure of the monetary policy shock is obtained as the residual of a Taylor-type rule for each country. As a robustness check, we use the monetary policy surprises based on high-frequency data on interest rate changes around the monetary policy announcement. The high-frequency responses of asset prices to monetary policy announcements come from a variety of sources (see Table A.3). Like for the Taylor rule shock, we use these policy surprises of the United States and euro area for Hong Kong SAR and Singapore, and Denmark and Hungary, respectively, because these countries follow hard pegs or run currency boards.

These surprise measures are not used for the baseline results, because there are several shortcomings. First, the time series are often significantly shorter than what we have for our preferred monetary policy shock measure (from 25 quarters for Switzerland to 108 quarters for the United States). Second, except for Norway, all countries with missing data are emerging markets, which tend to use macroprudential policy more often. Third, the measures come from different data sources and do not follow a homogeneous approach. Finally, the quality of the data is very uneven: we only have truly high-frequency data for the major central banks in advanced economies, while for most emerging markets we use monetary policy surprises sample at the daily frequency.

Table A.3. Data Sources for High-Frequency Monetary Policy Surprises

Country	Observations	Start year	End year	Source of high-frequency data	Comments
Australia	45	2005	2019	Kearns, Schrimpf, and Xu (2018)	Based on intra-day asset price movements
Austria	72	1999	2017	Jarocinski and Karadi (2020)	Based on intra-day asset price movements
Belgium	72	1999	2017	Jarocinski and Karadi (2020)	Based on intra-day asset price movements
Brazil	56	2003	2016	Barbone-Gonzalez (2019)	Based on daily asset price movements
Canada	40	2007	2019	Kearns, Schrimpf, and Xu (2018)	Based on intra-day asset price movements
Chile	56	2003	2017	Pescatori (2018)	Based on daily survey (surprise against median expectation)
China	..				No data available
Colombia	28	2012	2019	Refinitiv Datastream	Based on daily survey (surprise against median expectation)
Denmark	72	1999	2017	Jarocinski and Karadi (2020)	Used euro area shock
Finland	72	1999	2017	Jarocinski and Karadi (2020)	Based on intra-day asset price movements
France	72	1999	2017	Jarocinski and Karadi (2020)	Based on intra-day asset price movements
Germany	72	1999	2017	Jarocinski and Karadi (2020)	Based on intra-day asset price movements
Hong Kong SAR	108	1990	2016	Jarocinski and Karadi (2020)	Used US shock
Hungary	72	1999	2017	Jarocinski and Karadi (2020)	Used euro area shock
India	..				No data available
Indonesia	28	2011	2016	Refinitiv Datastream	Based on daily survey (surprise against median expectation)
Ireland	72	1999	2017	Jarocinski and Karadi (2020)	Based on intra-day asset price movements
Italy	72	1999	2017	Jarocinski and Karadi (2020)	Based on intra-day asset price movements
Japan	50	2004	2019	Kearns, Schrimpf, and Xu (2018)	Based on intra-day asset price movements
Kazakhstan	..				No data available
Korea	28	2011	2019	Refinitiv Datastream	Based on daily survey (surprise against median expectation)
Malaysia	28	2010	2019	Refinitiv Datastream	Based on daily survey (surprise against median expectation)
Mexico	28	2011	2019	Refinitiv Datastream	Based on daily survey (surprise against median expectation)
Netherlands	72	1999	2017	Jarocinski and Karadi (2020)	Based on intra-day asset price movements
Norway	..				No data available
Peru	..				No data available
Philippines	28	2010	2019	Refinitiv Datastream	Based on daily survey (surprise against median expectation)
Poland	..				No data available
Russia	40	2007	2018	Tishin (2019)	Based on daily asset price movements
Singapore	108	1990	2016	Jarocinski and Karadi (2020)	Used US shock
South Africa	28	2010	2019	Refinitiv Datastream	Based on daily survey (surprise against median expectation)
Spain	72	1999	2017	Jarocinski and Karadi (2020)	Based on intra-day asset price movements
Sweden	39	2007	2018	Iversen and Tysklind (2017)	Based on intra-day asset price movements
Switzerland	25	1999	2017	Kearns, Schrimpf, and Xu (2018)	Based on intra-day asset price movements
Turkey	28	2010	2019	Refinitiv Datastream	Based on daily survey (surprise against median expectation)
United Kingdom	72	1997	2015	Miranda-Agripino (2017)	Based on intra-day asset price movements
United States	108	1990	2016	Jarocinski and Karadi (2020)	Based on intra-day asset price movements

4. Foreign Exchange Interventions

We use the actual data of foreign exchange interventions (FXIs) where available and a proxy variable otherwise. The actual FXI data are publicly available only for a small group of countries (Table A.4). For other countries, as a proxy for FXIs, we use the changes in the central bank's net foreign assets adjusted for valuation changes and interest income flows, following Dominguez (2012) and Adler, Lisack, and Mano (2019).

Specifically, our FXI proxy in percent of GDP is constructed as follows:

$$FXI_{it} = (\Delta NFA_{it} - \Delta^{adj} NFA_{it})/GDP_{it},$$

where ΔNFA_{it} denotes the quarter-on-quarter change in the central bank's net foreign assets; $\Delta^{adj} NFA_{it}$ is the adjustment term for valuation changes and income flows; and GDP_{it} is the annual GDP, for country *i* and in quarter *t*. These are all in U.S. dollars.

For the adjustment term, we make a few assumptions. First, for simplicity, we consider adjustments only for the two components of the net foreign assets:

$$\Delta^{adj} NFA_{it} = \Delta^{adj} S_{it} + \Delta^{adj} CD_{it},$$

where S_{it} denotes securities and CD_{it} currencies and deposits. In other words, we assume no valuation changes and no income flows for other components of the net foreign assets. Second, as in Dominguez (2012) and Adler, Lisack, and Mano (2019), we assume that the currency composition is uniform across components of the net foreign assets due to the lack of such granular data. Third, as in these studies, we assume that securities are mostly composed of 10-year government bonds. Forth, for currencies and deposits, we assume that valuation changes are zero and their interest income is based on the 3-month interbank rate, as in Adler, Lisack, and Mano (2019).

Using these assumptions, we compute the adjustment terms as follows.

$$\Delta^{adj} S_{it} = \sum_{c \in C} \left(\frac{R_t^c}{R_{t-1}^c} - 1 \right) \cdot S_{it-1} \cdot \omega_{t-1}^c,$$

$$\Delta^{adj} CD_{it} = \sum_{c \in C} i_{t-1}^c \cdot CD_{it-1} \cdot \omega_{t-1}^c,$$

where $(R_t^c/R_{t-1}^c - 1)$ is the growth rate of the treasury's total return index from Refinitiv Datastream, which captures both valuation changes and income flows; i_{t-1}^c is the 3-month interbank rate from Haver; and ω_t^c is the share of the currency-*c* assets from the IMF's Currency Composition of Official Foreign Exchange Reserves (COFER) database. The set of currency (C) consists of U.S. dollar, Australian dollar, Canadian dollar, British pound, Japanese yen, Swiss Franc, Chinese yuan and Euro.

While there are caveats due to the simplifying assumptions, our FXI proxy variable is reasonably correlated with the actual FXI data for the countries for which actual FXI data are available (Table A.4). The correlations between our FXI proxy and the actual data are reasonably positive for emerging market economies, ranging from 0.30 (Chile) and 0.89 (Russian Federation), while they are more diverse for advanced economies, ranging from -0.05 (Australia) and 0.88 for Switzerland. Fortunately, we have actual intervention for most advanced economies and our coverage is weaker for emerging economies, for which the proxy measure seems to work better.

Table A.4. Correlation Between Actual and Proxy FXI Measures by Country and Group

Country	Country Group	Correlation between actual FXI and proxy	Group Average
Brazil	EM	0.39	0.56
Chile	EM	0.30	
Colombia	EM	0.65	
India	EM	0.83	
Kazakhstan	EM	0.43	
Mexico	EM	0.27	
Peru	EM	0.77	
Russian Federation	EM	0.88	
Turkey	EM	0.52	
Australia	AE	-0.04	0.22
Canada	AE	0.15	
Denmark	AE	0.84	
Japan	AE	-0.03	
Switzerland	AE	0.86	
United Kingdom	AE	-0.04	
United States	AE	0.01	
Eurozone	AE	0.04	

Notes: The correlations are calculated for the actual FXI data and the proxy FXI variable, both in percent of annual GDP.

5. Capital Flow Management Measures

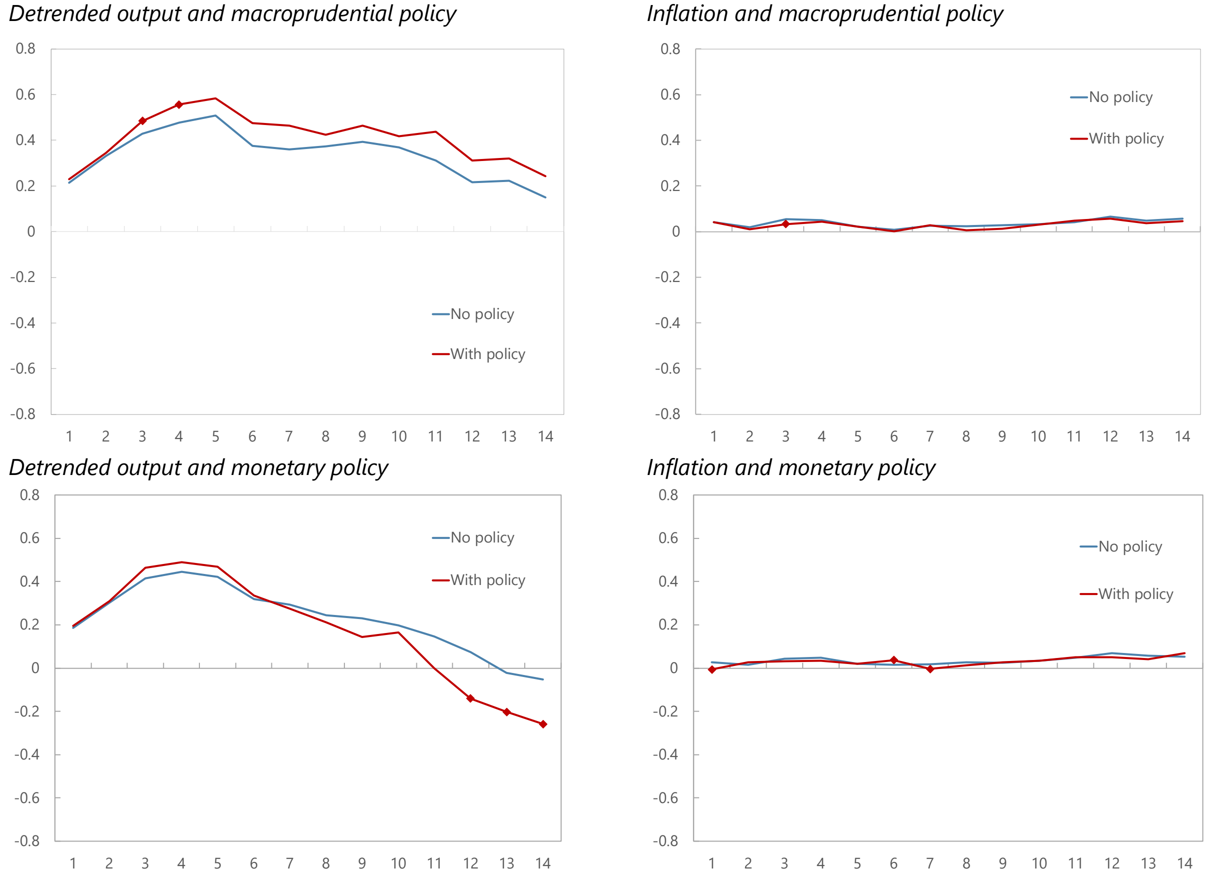
The policy shocks are then calculated as detailed in Section III.B. The estimates of regression (9) are given in Table A.5.

Table A.5. Ordered Probit Regressions for Capital Flow Management Measures

Variables	(1) CFM All
VIX	0.0150***
	(0.001)
Δ FFR	0.1072
	(0.177)
Commodity price index	0.0366
	(0.751)
Commodity producer dummy x Commodity price index	0.0568
	(0.610)
Δ inflation	0.0150
	(0.409)
Real GDP growth	0.0134**
	(0.019)
FX Reserves (percent of GDP)	0.0009
	(0.411)
Institutions	0.4234
	(0.137)
Capital account oppeness	0.2199***
	(0.000)
Inward capital floes (percent of GDP)	-0.0005
	(0.906)
Outward capital floes (percent of GDP)	0.0002
	(0.964)
Δ Exchange rate	-0.9428
	(0.132)
FX volatility	-0.9128*
	(0.079)
Δ Exchange rate x FX volatility	2.4946**
	(0.045)
Δ IR	0.0123***
	(0.005)
α_1	-0.5279
	(0.532)
α_2	-0.1394
	(0.869)
α_3	3.2341***
	(0.000)
α_4	3.6070***
	(0.000)
Observations	2,675
Country FE	YES
Number of countries	37
Pseudo R2	0.0978

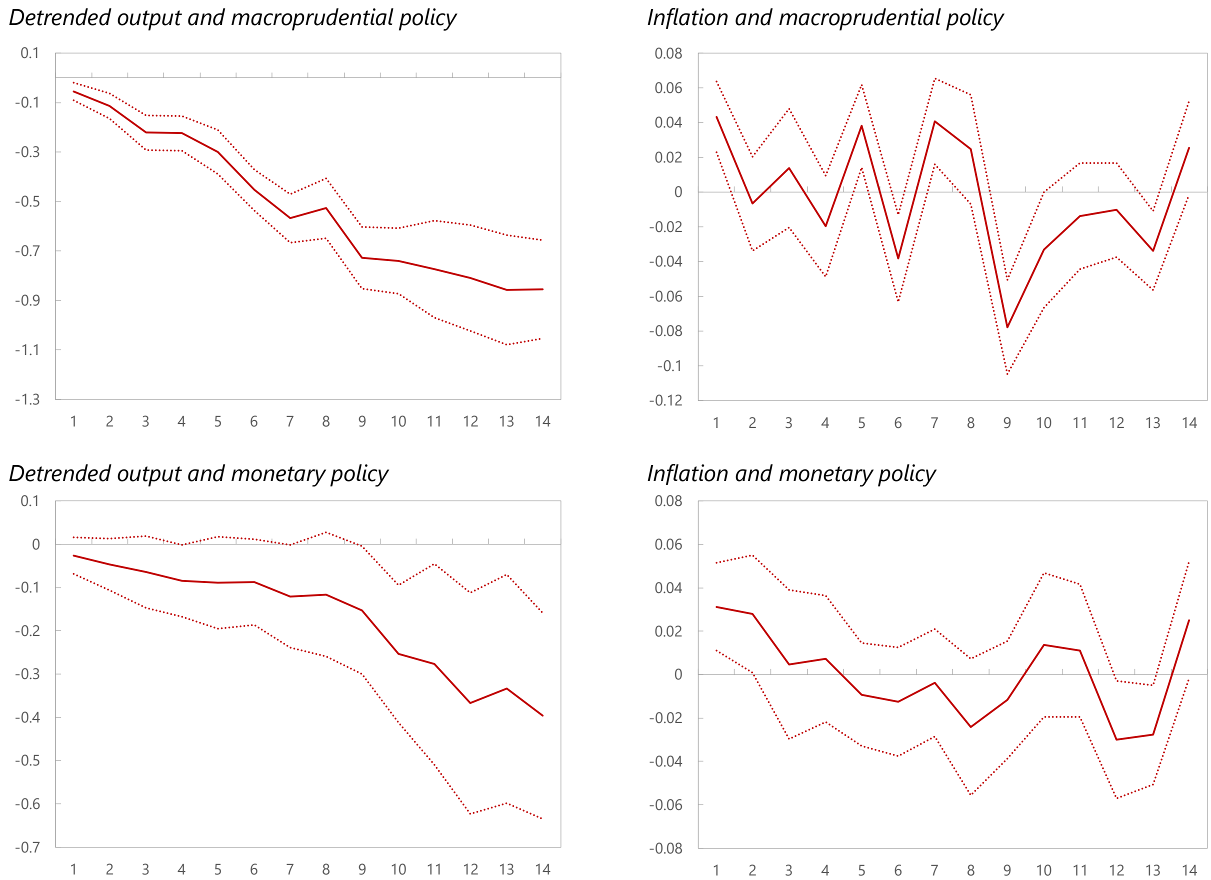
Appendix B. Additional Results

Figure B.1. Response of Median GDP Growth and Inflation to Domestic FCI



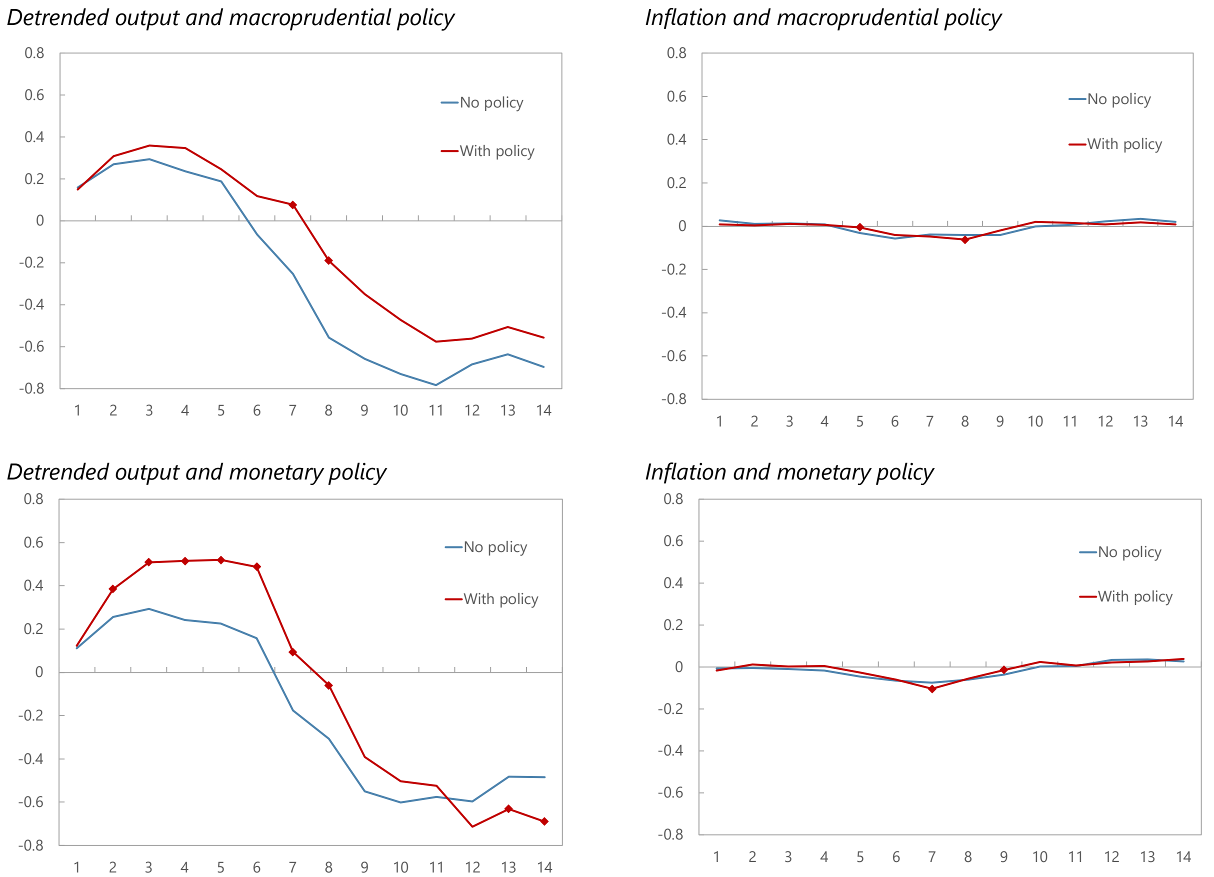
Note: The charts show the change in median GDP growth associated with looser domestic financial conditions, conditional on there being a policy change. GDP growth is measured by future detrended GDP growth. Inflation is the quarterly change in log CPI. A square marker means that the effect of policy is significantly different than zero at least at the 10 percent significance level. Inference is based on standard errors clustered at the country level based on Hagemann's (2017) wild bootstrap approach. The horizontal axis shows the number of quarters since the time of a loosening shock to domestic financial conditions.

Figure B.2. Response of Median GDP Growth and Inflation to Policy Shocks



Note: The charts show the change in median GDP growth associated with looser global financial conditions, conditional on there being a policy change. GDP growth is measured by future detrended GDP growth. Inflation is the quarterly change in log CPI. A square marker means that the effect of policy is significantly different than zero at least at the 10 percent significance level. Inference is based on standard errors clustered at the country level based on Hagemann's (2017) wild bootstrap approach. The horizontal axis shows the number of quarters since the time of a loosening shock to global financial conditions.

Figure B.3. Response of Tail Risk of GDP and Inflation to Global FCI



Note: The charts show the change in tail risk to GDP growth associated with looser global financial conditions, conditional on there being a policy change. Tail risk to GDP growth is measured by the 10th percentile of the future detrended GDP growth. Inflation is the quarterly change in log CPI. A square marker means that the effect of policy is significantly different than zero at least at the 10 percent significance level. Inference is based on standard errors clustered at the country level based on Hagemann's (2017) wild bootstrap approach. The horizontal axis shows the number of quarters since the time of a loosening shock to global financial conditions.

Appendix References

Bai, Jushan and Serena Ng. 2002. "Determining the Number of Factors in Approximate Factor Models," *Econometrica*, 70: 191–221.

Barbone-Gonzalez, Rodrigo, 2019. "Monetary Policy Surprises and Employment: Evidence from Matched Bank-Firm Loan Data on the Bank Lending-Channel." BIS Working Paper No. 799, Bank for International Settlements.

Cukierman, Alex, 2019. "Forex Intervention and Reserve Management in Switzerland and Israel since the Financial Crisis: Comparison and Policy Lessons." *Open Economies Review* No. 30: 403–424.

Frenkel, Michael, Georg Stadtmann, and Christian Pierdzioch, 2001. "The Interventions of The European Central Bank: Effects, Effectiveness, And Policy Implications," *Research Notes* 01-2, Deutsche Bank Research.

Goldberg, Linda S., Cindy Hull, and Sarah Kathryn Stein, 2013. "Do Industrialized Countries Hold the Right Foreign Exchange Reserves?" *Current Issues in Economics and Finance* 19, no. 1: 1-9.

Hatzius, Jan, Peter Hooper, Frederic S. Mishkin, Kermit L. Schoenholtz, and Mark W. Watson. 2010. "Financial conditions indexes: A fresh look after the financial crisis." U.S. Monetary Policy Forum (Chicago: Chicago Booth Initiative on Global Markets) pp. 3-59.

Henning, C. Randall, 2006. "Organizing Foreign Exchange Intervention in the Euro Area." *JCMS: Journal of Common Market Studies* 45, no. 2: 315-342.

Iversen, J., and O. Tysklind, 2017. "The Effect of Repo Rate Path Changes on Asset Prices." Sveriges Riksbank Staff memo.

Jarociński, Marek, and Peter Karadi, 2020. "Deconstructing Monetary Policy Surprises—The Role of Information Shocks." *American Economic Journal: Macroeconomics* 12, no. 2: 1-43.

Josse, Julie and François Husson. 2012a. "Handling missing values in exploratory multivariate data analysis methods." *Journal de la Société Française de Statistique* 153, no. 2: 79-99.

———, 2012b. "Selecting the number of components in PCA using cross-validation approximations." *Computational Statistics and Data Analysis* 56 (6): 1869-1879.

———, 2016. "missMDA: A Package for Handling Missing Values in Multivariate Data Analysis." *Journal of Statistical Software*, 70(1), 1-31.

Kearns, Jonathan, Andreas Schrimpf, and Dora Xia, 2018. "Explaining Monetary Spillovers: The Matrix Reloaded," BIS Working Papers 757, Bank for International Settlements.

Larrain, Catalina and Diego Saravia, 2019. "Interventions in Chile," Chapter 8: 115-35, in *Foreign Exchange Intervention in Inflation Targeters in Latin America*, edited by Marcos Chamon, David Hofman, Nicolás E. Magud, and Alejandro Werner. International Monetary Fund.

Miranda-Agrippino, Silvia, 2017. "Unsurprising Shocks: Information, Premia, and the Monetary Transmission." Bank of England Working Paper No. 626, Bank of England.

Neely, Christopher J. 2011. "A Foreign Exchange Intervention in an Era of Restraint." *Federal Reserve Bank of St. Louis Review* 93, no. 5: 303-24.

Pescatori, Andrea, 2018. "Central Bank Communication and Monetary Policy Surprises in Chile." IMF Working Paper No. 18/156. International Monetary Fund.

Tishin, Alexander, 2019. "Monetary Policy Surprises in Russia," mimeo.