Foreign exchange intervention: A new database*

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Abstract

We construct a novel database of monthly foreign exchange interventions for 49 countries over up to 22 years. We build on a text classification approach that extracts information about interventions from news articles and calibrate our procedure to data about actual interventions. This new dataset allows us to document stylized facts about the use of foreign exchange interventions for countries that neither publish their data nor make them available to researchers. Moreover, we provide evidence on how foreign exchange interventions are used in conjunction with capital controls and macroprudential policy.

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1 Introduction

The continued rise of financial globalization and the related openness of countries have brought new challenges for economic policymaking. Many countries believe they need better shields against volatile international capital flows and the resulting instabilities of their domestic economy. These challenges have prompted recent policy responses such as foreign exchange (FX) interventions, capital controls, and macroprudential regulations. At the same time, the international policy debate has become more open to applying these tools. The new stance of the IMF (2012, 2022), for example, states that measures to impact capital flows can be useful in realizing macroeconomic and financial stability during surges of capital flows, even as pre-emptive measures.

In contrast to this interest of policymakers, there is a lack of broad and reliable FX intervention data. Therefore, this paper's main contribution is to introduce a new database containing an FX intervention proxy that provides more reliable information about FX interventions than what has typically been used in much literature so far, e.g., pure changes in reserves. This new proxy is built on publicly available news articles and reserve data and hence it can be made publicly available. We implement a classification algorithm to predict when public news indicates an intervention has occurred. The algorithm creates a quantitative representation of the words in individual news items and then uses the resulting matrix to calculate the optimal criteria to classify whether a news item contains relevant information about foreign exchange intervention. This algorithm is trained and tested on the dataset of hand-coded news of Fratzscher et al. (2019), hereafter FGMSS, and captures 99% of relevant news at the monthly frequency. We show that this news-based approach, i.e., the "news proxy," delivers a more precise measure for FX interventions than reserve changes. Then, we use this algorithm to construct proxies for FX interventions for a broader set of countries and a longer time series compared to the data in FGMSS. As a result, we get a set of 49 country-specific time series of approximate FX interventions over the period from 1995 to 2016.

We use these new data to provide two novel findings. First, we report stylized facts about the use of FX interventions for 49 countries depending on various market characteristics and exchange rate regimes. Results extend those in FGMSS for a larger dataset and provide information on how our FX intervention proxy represents actual interventions. Second, we study the occurrence of FX interventions in conjunction with other common tools of capital account management, i.e., capital controls and macroprudential regulations. While these tools have been analyzed in isolation in prior research (e.g., Jeanne and Korinek, 2010; Jeanne, 2012; Klein and Shambaugh, 2015; Ghosh et al., 2017; Bianchi and Mendoza, 2018; Korinek, 2018), there has been little attempt to analyze them jointly (exceptions being Gosh et al., 2017, and Basu et al., 2020). We find that the adoption of these three tools is positively correlated and each seems to play a specific role: the most fundamental decision is about (typically) persistently used capital controls. Then, macroprudential measures form the next step, and finally, higher frequency FX interventions are the most flexible instrument of capital account management. These interactions suggest that an impact analysis of one instrument should control for the use of other instruments to avoid confounding effects.

FX interventions are an established policy tool that has been used in all kinds of exchange rate regimes (Eichengreen, 2019). At the beginning of the floating era in the 1970s and 1980s, there was some agreement that interventions may have a signaling effect (Ghosh, 1992) and a small portfolio effect (Dominguez and Frankel, 1993), thus giving FX interventions some role in managing international capital flows. Doubts about the effectiveness of FX interventions increased with the rapid growth of global financial markets. The global financial crisis of 2008/09 changed the assessment again. Recently, several studies have applied an event study or a matching approach, providing evidence that FX interventions can be effective (e.g., Dominguez, 2020). Accordingly, FX interventions seem to smooth exchange rate fluctuations and also impact the level and trend of exchange rates to some degree (e.g., Fatum and Hutchison, 2003; Fratzscher et al., 2019). Much of the new attention towards FX interventions is due to the increased relevance of emerging markets in the world economy, where interventions are quite frequently used (Menkhoff, 2013; Frankel, 2019), while central banks in the US, the Euro area and the UK hardly intervene anymore.

The use of FX interventions has also gained from new theoretical work that extends the view that FX interventions can provide more freedom for monetary policy (Klein and Shambaugh, 2015). For example, Cavallino (2019) shows that, in his model, a mix of monetary policy and FX intervention (as an alternative to capital controls) is an optimal policy response to portfolio flow shocks. Hassan et al. (2022) argue that intervention can achieve lower risk-free interest rates, higher capital accumulation, and higher wages because keeping a currency close to that of a larger anchor currency helps the domestic currency depreciate less in bad times.

In some contrast to the politically and theoretically motivated interest in FX interventions, there is a lack of empirical studies systematically analyzing their impact on exchange rates and capital flows. Despite a long tradition of country studies relying on precise FX intervention data, there is a gap regarding cross-country studies. The latter typically must rely on changes in foreign currency reserves as a proxy for interventions ("reserve proxy"). The disadvantage of this approach is that there are large differences between reserve changes and interventions, as reserve changes may occur for many reasons, only one of which is interventions.

Our research is mainly related to the empirical literature on FX interventions. There has so far been no comprehensive, publicly available database on FX interventions, except for the very recent study by Adler et al. (2021) that we refer to in Sections 2.2 and 2.3 (and which extends data provided by the Federal Reserve Bank of St. Louis via its FRED database). Instead, researchers follow three strands to analyze FX interventions: (i) case studies based on true FX intervention data, (ii) case studies relying on reserve-based proxies to approximate (unavailable) true FX intervention data, and (iii) a few attempts of cross-country analysis. Let us discuss these three strands briefly. First, studies based on true intervention data are typically country case studies because only very few countries make their intervention data publicly available (e.g., Fischer and Zurlinden, 1999; Melvin et al., 2009; Chamon et al., 2017; Kuersteiner et al., 2018). While these studies can often rely on quite detailed data, it remains unclear to which extent their results can be generalized. Second, due to the very restricted data availability, researchers often cannot work with true intervention data but use proxies for FX interventions. The two kinds of publicly available proxies are based either on news, such as reports about FX interventions in newspapers (Klein, 1993; Fischer, 2006), or on data about reserve changes (e.g., Blanchard et al., 2015; Daude et al., 2016; Adler et al., 2019; Adler et al., 2021). News-based proxies have so far been used for country case studies because the data are laborious to compile. Reserve-based proxies are attractive in this respect as they are readily available. However, they can change for several different reasons, and FX interventions are but one of those reasons. Empirically, reserves change basically every month, whereas true FX interventions change much less frequently (only every fifth month on average) and do not follow regular patterns, as we document in this paper. Hence, while reserve changes often are the only available data for empirical research, they may not be very reliable as a proxy for FX interventions. Third, from a research perspective, it is desirable to have reliable cross-country datasets. In practice, however, the problems mentioned above apply: either one has good data but for only very few countries (Dominguez and Frankel, 1993; Dominguez, 2003; Menkhoff et al., 2021), or else one has many countries but relies on FX reserves (Blanchard et al., 2015; Daude et al., 2016), or one has good data on sterilized FX interventions and many countries but data are confidential (Fratzscher et al., 2019). Our new database is designed to provide researchers with a broad cross-section of FX intervention proxy data that are more reliable than changes in reserves.

This paper consists of four further sections. In Section 2, we describe the development of the new database on FX interventions and show its relation to actual interventions. We then document the resulting stylized facts in Section 3. In Section 4, we analyze these data to examine relations between FX interventions and two other tools of capital account management, i.e., capital controls and macroprudential policies. Section 5 concludes.

2 Creating the new database

In Section 2.1, we detail the construction of our news-based proxy for FX interventions. Section 2.2 presents several proxies based on data about international reserves. We analyze the suitability of the news-based proxy and the widely used reserve change data to pin down intervention activity and compare their performance to each other in Section 2.3. Finally, we provide a summary of the salient characteristics of our new FX intervention database in Section 2.4.

2.1 The news-based proxy for FX interventions

If researchers aim for more general insights based on the analysis of many countries, they must rely on publicly available proxies. Two kinds of data can be used as proxies: first, publicly available changes in FX reserves, and second, published news about interventions.

Reserve data and news data as proxies for FX interventions. For any cross-country study, data on reserves have the great advantage of wide availability. Accordingly, reserve data are the proxy of choice in macro-oriented studies that want to exploit cross-country variation (e.g., Blanchard et al., 2015; Daude et al., 2016; Adler et al., 2019; Adler et al., 2021). Nevertheless, it is well-known that reserves change for various reasons unrelated to FX interventions (see, e.g., Neely, 2000). These include (i) the central bank acting as an agent for the government regarding its FX transactions, (ii) valuation changes in reserve holdings, and (iii) domestic monetary policy operations that may affect reserve holdings. It is an empirical question to which degree reserve changes do capture FX interventions. Central banks may sometimes deliberately choose forms of interventions that do not show up in reserves immediately. However, most of the recent research on the effectiveness of FX intervention suggests that FX interventions will lose much of their effectiveness if there is no signal to the market. Thus it is to be expected that FX interventions that are to some degree surprising, such as in flexible exchange rate regimes, will often be accompanied by communication. That can be either explicit communication of the central bank or implicit communication, i.e., that the central bank accepts that market participants learn about the FX intervention.

This important role of communication is picked up by the news-based approach to identifying FX interventions (Klein, 1993; Fischer, 2006; Dominguez and Panthaki, 2007). While news data will tentatively underreport interventions, in particular the smaller ones (Klein, 1993), and may not work well at an intra-day frequency (Fischer, 2006), news data have the potential advantage that there is hardly any reason to report intervention incorrectly, so one of the major drawbacks of reserve-change-based proxies should not apply. Unfortunately, news data have to be extracted from respective databases, access to which is costly and their coverage of many smaller economies used to be patchy. Extracting and then manually coding individual news items is very laborious and thus often not feasible. However, two changes have made news data a far more attractive source for quantitative research recently: first, the coverage of news across countries has improved over time, and, second, there is the option to apply text classification approaches to extract the information of interest efficiently from huge amounts of news data (see, e.g., Hansen et al., 2018).

Processing news data using text classification. We use news from Factiva, a major platform that was jointly created by Reuters and Dow Jones. We download headlines of articles indicating FX interventions that have been sampled using a standardized protocol (details in Appendix A) that FGMSS also used. All news items for the time in which actual intervention data were available are hand-coded according to this protocol.[1] The coding captures rumors, reports and official confirmations of intervention. This is the first out of five steps to creating the final database, see Figure 1.

[Figure 1 about here]

There are not enough news items to exploit for six out of the original 33 countries used in FGMSS (Azerbaijan, Bolivia, Costa Rica, Georgia, Kyrgyzstan, and Moldova). Although some of these countries intervene regularly, we only find an average of eight news items in the Factiva database for each of them using our search query. We there-

[1]For most countries, this means that all relevant news items according to the filter that were published on Factiva in 1995-2011 have been hand-coded.

fore remove these countries from our database. For the rest of the countries, we compile all Factiva news reports (step 2 according to Figure 1). This involves detecting and deleting common words that do not convey meaning (e.g.,“and''), stemming (i.e., reducing “intervene'', “intervenes'', and “intervention'' to the common root “interven*'') and summarizing the occurrence of individual terms in a text in matrix form. This matrix can then be used in quantitative models to classify news into those indicating intervention and those that do not.[2]

For this classification, we use an algorithm called a “Support Vector Machine” (available from the open-source python package “sklearn'') to classify news stories into those that report FX interventions and those that do not.[3] A support vector machine separates the data into two groups using a hyperplane. Figure 2 illustrates this. In the two-dimensional case shown in the figure, this results in a line drawn to best separate the two groups. The points closest to the line are called the support vectors. Mathematically, the algorithm chooses the line such that the margin between the support vectors of the two groups is maximized.

[Figure 2 about here]

We train the algorithm with hand-coded data in which research assistants have manually conducted the same classification we seek to automate using the algorithm. We then use 10-fold cross-validation to train the algorithm. That means we randomly divide the complete dataset into ten sub-samples, each consisting of ten percent of the original

[2] Note that our algorithm does not attempt to distinguish between sterilized and unsterilized intervention. That is mainly because this distinction is seldom made in the financial press. It seems reasonable to expect that interventions discussed in the press are generally sterilized, at least in part, given that they are considered and discussed in the news as an instrument different from monetary policy. In any case, relative to the data used in Fratzscher et al. (2019) that only include sterilized interventions, it remains possible that a small fraction of unsterilized intervention operations picked up by the algorithm generates measurement error in the resulting proxy FX intervention we provide. In the news data used in this paper, only 17 out of the over 29,000 news items contain the substring “unsteril”. All of these concern Japan and some state that the Bank of Japan did not leave recent intervention unsterilized. However, the unsterilized interventions were confirmed or hinted at in the news from September 2001, May 2002, and September 2010; in each case covered by several news items. Three monthly data points in our final dataset will thus contain unsterilized intervention. This should not systematically affect any results that make use of the full dataset we provide.

[3] The SVM is known to yield better performance than other approaches that can run on a quantitative representation of the text data, such as simple logistic regressions or multinomial logit. For more details, see also Appendix B.

data. Iteratively, nine of these samples are then used to train the algorithm, and the remaining ten percent of the data are used to assess out-of-sample performance. The parameters that optimize out-of-sample performance are chosen automatically by the algorithm and used to classify all observations. To provide a systematic overview of the resulting algorithm for detecting FX intervention information in publicly available news, we first compare manual and automatic classification before using the classified news data in combination with reserve data.[4,5]

Quality of automated news classification. Comparing the performance of the chosen algorithm to the manual classification as used in the FGMSS data, we see that 94 percent of all truly available (non-) intervention news items are correctly classified. A success rate of 94 percent may be acceptable even from human coders. Then we aggregate this daily information at the monthly frequency, calculating the incidence and number of news items suggesting intervention for each country and month. This aggregation to monthly frequency reduces the impact of errors in those cases where the algorithm has missed information on intervention because, typically, intervention is mentioned in more than one news item. Therefore, even 99 percent of the aggregate manual coding can be reproduced at the monthly frequency. Overall, the use of the algorithm to classify news that indicate FX interventions seems to be successful.

Estimating intervention volumes. While the main contribution of the news-based proxy is to determine the incidence of FX interventions, news can also be used to better estimate intervention volumes. Of course, news items do not inform about volumes by themselves. However, the frequency of news signals the intensity of FX interventions. We use this signal to adjust the volume provided by changes in FX reserves. We expect that larger interventions (by the standard of the currency) trigger more news reports, while

[4]A practical problem when using news data is the assignment of news to specific intervention days. While it is often possible to assign retrospective reports or confirmations to the intervention days when coding manually, a machine learning algorithm will struggle to do this reliably because this task requires a detailed understanding of the text. Since reserve changes are merely available monthly, this problem is not that pressing for our paper because we aggregate news data up, thus reducing the possible assignment error to a minimum.

[5]We also assessed whether other information regarding the circumstances of intervention can be obtained from the short news items we use. These attempts were unsuccessful and are summarized in Appendix C.

small interventions will receive far less attention.[6]

To implement this, we normalize the number of news for each country to get a time series of the relative frequency of news per month for each country, indicating the size of interventions. Then we use the above-mentioned FGMSS data universe of actual FX interventions to construct an adjustment factor so that the difference in logs between actual interventions and reserve changes[7] gets minimized by relying on the frequency of news as further information. Our sample shows that reserve changes should be adjusted downward by about 40 percent on average. Since adjustment factors differ by exchange rate regime, we estimate them separately to correct intervention volumes.[8]

Definition of news-based proxy. Having classified and aggregated news data, we get a binary indicator that captures whether Factiva news items have provided any evidence of intervention during a respective month. The incidence information is thus based on an aggregate of news-based information, which is the result of step 2 in creating the database (see Figure 1). We then use adjusted reserve changes as introduced above for those months with intervention according to the binary proxy. The proxy for currency c in month t can thus be written as

[6] In Table A4 in the Appendix, we show that this relationship holds in the Fratzscher et al. (2019) subset of the data for which actual intervention amounts are available. On average, a one percent higher share of the intervention news of a given country in a given month of the sample period is associated with a one percent higher share of the total absolute intervention volume in that month.

[7] We use the $RAXGFX\_USD$ series from the IFS, which provides foreign exchange reserves excluding Gold and Special Drawing Rights in US Dollars.

[8] The underlying regressions are shown in Table A5, columns 7-10.

FXI incidence:

$$\text{News-based intervention dummy}_{ct} \quad = \begin{cases} 1 \text{ if news dummy}_{ct} = 1 \\ 0 \text{ otherwise} \end{cases}$$

FXI volume:

$$\text{News-based intervention proxy}_{ct} \quad = \begin{cases} \text{Adjusted reserve change}_{ct} \text{ if news dummy}_{ct} = 1 \\ 0 \text{ otherwise.} \end{cases}$$

2.2 Proxies based on reserve changes

Reserve changes are the most common measure for FX interventions in the literature. The definition closest to FX interventions in available statistics is the change in total foreign exchange reserves, excluding Gold, Special Drawing Rights, and IMF reserve position. We call this measure "reserve proxy." As reserves change every month for various reasons unrelated to FX interventions, a possible adjustment is cutting off those rather minor changes. Thus, we introduce a second measure, i.e., reserve changes with a calibrated cutoff which we base on the size of the absolute reserve change. Specifically, we use the share of true interventions (according to FGMSS data) to define a threshold value. In the sample we use to develop and calibrate our proxy,[9] the FGMSS data show interventions in 30.6 percent of months. Hence, out of all the reserve changes (close to 100 percent of months), we define the 30.6 percent largest reserve changes per country as FX interventions.

Earlier literature has aimed to control those determinants of reserve changes that are not due to FX interventions and thus isolate the effect of "active management" (Dominguez et al., 2012). Neely (2000) discusses these determinants and compares ad-

[9]As explained in detail below, this sample consists of 27 countries with sufficient intervention news and availability of reserve data that overlap with the true intervention data from Fratzscher et al. (2019).

justed reserve changes to true published intervention data. He finds that the precision of Swiss reserve data improves by deseasonalizing (as some monetary policy operations at particular times can affect reserves) and that the German reserve data need to be adjusted for reserve flows during crises of the European Exchange Rate Mechanism. By contrast, efforts to adjust for valuation changes of reserves affect the coefficient of correlation with true interventions by one to two percent, and in one of three cases in the wrong direction. Dominguez et al. (2012) extend this approach, excluding reserve changes due to valuation changes in reserves (as Neely, 2000) and also due to investment income flows. Unfortunately, neither valuation changes nor investment income are directly provided but have to be approximated based on quarterly data and several far-reaching assumptions, including that all countries within the groups of advanced or emerging economies would use the same currency allocation in their reserves. Similar to Neely (2000), the figures by Dominguez et al. (2012) document the development of raw and adjusted FX reserves for some countries and indicate relatively small differences. The most recent effort in this direction is Adler et al. (2021), who also quantify valuation changes and investment income and find that the contribution towards estimating FX interventions by these adjusted reserve changes is positive but rather small. In their study of 23 countries, this adjustment improves the R-squared by one percentage point to 0.304.

To come closer to true FX interventions, Adler et al. (2021) propose and implement further adjustments to strip changes in central bank's FX positions from noise. Their Table 4 shows that changes in central bank positions relative to the IMF, i.e., probably mostly IMF loans, are important in explaining official FX intervention data. While changes in positions relative to other non-residents are not relevant by themselves (these include shifts between reserves and less liquid non-reserve assets), they counterbalance to some extent changes in positions relative to residents, which are very important. The latter include non-intervention operations of the government or domestic banks via the central bank accounts. When controlling for these three sources of noise for estimating FX intervention in a set of 23 countries over up to twenty years, the R-squared increases from 0.294 when just considering changes in reserves to 0.464 when also controlling for investment income, valuation changes, and the three positions just mentioned.

While these adjustments seem reasonable, they cannot overcome two limitations of the data: first, the meaning of FX interventions and how they are implemented can differ across central banks, so there is no uniform objective. Adler et al. (2021) consequently apply their definition, but central banks and governments may operate differently. Second, the adjustments for investment income and valuation changes are documented in detail and can thus be replicated, but the other adjustments – which are more important – are less transparent and can be motivated by confidential IMF information. Still, we also use these data, forming "adjusted reserve proxies," in the subsequent section.

2.3 Judging the quality of proxies

Developing a proxy for foreign exchange intervention can be seen as a standard problem of information retrieval, i.e., to retrieve the months of actual interventions from all months by relying on imperfect signals. The goal of any proxy is to realize a high share of correct predictions relative to the possible mistakes. To evaluate this, we can use a simple matrix (see Table A1 in the Appendix) that relates actual interventions to predicted interventions. The resulting four fields are "true positive" (A: actual intervention and predicted intervention), "false positive" (B: no intervention but predicted intervention), "false negative" (C: intervention not predicted) and "true negative" (D: no intervention and no prediction).

To condense information from this table, we consider not only "accuracy," i.e., the share of correctly predicted cases, but also two more informative aggregated success measures: (i) The "probability of detection" is the share of correctly predicted interventions over all actual interventions (A/(A+C)); (ii) the "probability of false alarm" is the share of false positives denominated by all actual non-intervention (B/(B+D)). Why these measures? First of all, there is a trade-off between type I and type II errors (i.e., B and C) because a measure that will detect a very large share of interventions tends to predict too many interventions and thus comes at the cost of a higher rate of false alarm. We prefer a low probability of false alarm because this ensures that results are largely based on true FX interventions and thus informative. A way to combine both measures is the "noise-to-signal-ratio," defined as ((B/(B+D))/((A/(A+C)) and prominently used by Kaminsky et al. (1998). A low ratio is desirable.

Reserve-based proxies indicate too many interventions. It is known that reserve-based proxies indicate too many interventions because reserve positions change due to many reasons, only one of them being FX interventions (we provide the case of Japan as an illustration in Appendix Figure A3). One way to address this problem is to eliminate some noise by considering only the larger FX interventions. Before we show the performance of the further measures introduced in Section 2.2 (the 30.6 percent cutoff and the adjusted reserve proxy), we provide a sense for the consequence of this procedure. We start by considering all reserve changes and then order all interventions across all countries according to their size relative to the respective GDP. We start by dropping the single smallest FX intervention volume (relative to domestic GDP), then the second smallest etc, until there is just the largest intervention left in the sample. As shown in Figure 3, dropping more and more small interventions will indeed increase the share of correctly identified FX interventions (the solid line in Figure 3). When using no cutoff for reserve changes (at the very left of the figure), about every third month with reserve changes is indeed a month with actual intervention. This share of correctly identified FX interventions will never reach more than about 60 percent. However, at this point, only about 10 percent of actual FX interventions will be detected (the dashed line).[10]

[Figure 3 about here]

Intervention news comes with actual interventions. News reports about interventions typically cover actual intervention. The most widely available form of news about FX intervention is a report that market participants have noticed that the central bank intervened in the market, i.e., a rumor. Although rumors might be seen as unreliable, all of them have made it across the filter of a financial journalist reporting on them (as reported by Factiva).

[10] There are no substantial improvements of the reserve proxy based on other cutoff definitions we have tried. First, we used a cutoff defined separately by intervention direction, and, second, in terms of the log absolute reserve change instead of relative to a country's GDP.

To better understand what triggers news on FX interventions, we study the determinants in Appendix D. We test, for example, whether interventions in larger markets, under certain exchange rate regimes, and in countries with freer press receive more coverage. A plausible result is that larger reserve changes or larger intervention volumes increase the probability of any relevant news. In larger countries, there are more news covering an intervention of a given size, but due to aggregating news at the monthly level, the impact on our proxy is small, and smaller than one might expect ex-ante.

Comparing the proxies of reserve changes and intervention news. We compare the proxies based on the FGMSS data in two steps. First, we start with descriptive statistics for the three proxies based on the (raw) reserve data. Panel A of Table 1 informs about the distribution of actual and classified FX interventions for these proxies. This highlights the very small share of false positives for the news proxy. Second, we now compare additional proxies for several criteria (step 4 according to Figure 1). This extended comparison not only considers the raw reserve data but also the adjusted reserve data as compiled by Adler et al. (2021) and provides the basis for Panel B of Table 1. Panel B presents "condensed" information regarding the six covered proxies on the following criteria (as introduced above): the share of correctly predicted FX interventions, also known as accuracy (i.e., the information used in Figure 3), then our two core criteria, i.e., the probability of detection and the probability of false alarm, the combination of the two core criteria, i.e., the noise-to-signal-ratio, and finally a simple correlation with actual interventions and two R-squared measures.

[Table 1 about here]

As we aim for a comparison of (raw) reserves and adjusted reserves (i.e., the Adler et al. 2021 data) within the FGMSS dataset, we need to complement in Table 1 the Adler et al. (2021) data with raw reserve data where necessary, i.e., in particular before the year 2000. The first three columns present results for the proxies based on raw reserve data, i.e., the reserve proxy, the reserve proxy cutoff and the respective news proxy. The share of correctly predicted FXI is 31 percent for the reserve proxy (as shown in Figure 3 above), 65 percent for the reserve proxy cutoff, and 75 percent for the news proxy. These numbers can be directly calculated from Panel A. For example, 30.75 percent accuracy of the reserve proxy means that (1,309 + 6) correct classifications relate to 4,276 total cases. The raw reserve-based proxies indicate intervention quite reliably: the probability of detection for the first two measures is 100 and 43, respectively, indicating that once a cutoff is imposed, interventions will be missed. By contrast, the probability of false alarm is almost 100 and 25 percent, showing that eliminating small reserve changes reduces false alarm but comes at the cost of not detecting all interventions anymore. The value of defining some cutoff to reduce the noise created by ever-changing reserves is indicated by the noise-to-signal ratio, which is far lower for the cutoff variant. If researchers do not focus on intervention incidence but calculate the overall correlation coefficients or overall R^2, shown at the bottom of the table, this poor performance in the information content of proxies becomes masked. Yet, to estimate policy impacts or effectiveness, reducing noise is important, so researchers should also assess the incidence information of their proxies.

The news-based proxy in column 3 achieves considerably higher accuracy and a far lower noise-to-signal ratio than the two proxies mentioned above. It thus offers a considerable improvement in estimating the incidence of FX interventions. This is achieved by reducing the probability of false alarm, thus substantially reducing the noise-to-signal ratio. Regarding the volume of interventions, the reserve changes correlate approximately as strongly with actual intervention volumes as for the purely reserve-based proxies but the cutoff variant indicates that this correlation is stronger for larger reserve changes and interventions. Hence, we next assess whether using better reserves data can improve the proxy in its volume dimension.

In Panel B, columns 4 to 6 of Table 1 we rely on the adjusted reserve proxy as developed by Adler et al. (2021). Numbers in the upper part of the table remain unchanged for the news proxy because the new reserves data does not affect our proxy regarding the incidence of interventions. In this respect, we see that the adjusted reserve data do not show significantly better performance than the raw reserves data because the adjusted reserve series changes almost every month. However, when combining this volume dimension with the incidence information of the news-based proxy, one can achieve substantial gains in performance.

Using the adjusted reserve changes improves the R^2 in the volume dimension by almost half from 0.554 to 0.745. Combining news and adjusted reserves results in a more than doubling of the overall R^2, from 0.262 to 0.585. The combined proxy, made up of news-based incidence information and a volume information from adjusted reserves data, thus outperforms reserves-based proxies in all three dimensions – incidence, volume, and overall.[11]

We follow these lessons in the remainder of this research. That means our preferred proxy uses the news-based classification of interventions and the adjusted reserve data of Adler et al. (2021) where available. In cases where this is not available (especially before 2000) we use the simpler volume adjustment explained above. We use this proxy in the remainder of the paper.

Comparing FX intervention proxies across sub-samples. To further test the robustness of the three main proxies, i.e., the reserve proxy, the reserve proxy cutoff and the news proxy, we repeat the above analyses for three disaggregations of the full FGMSS sample: across exchange rate regimes, across volatile vs. calm periods, and the global financial crisis (2008) vs. other years. In short, the pattern of results differs little across these sub-samples. For example, among free-floating regimes, the noise-to-signal ratio is 100 percent for the reserve proxy, 32 percent for the reserve proxy cutoff, and 13 percent for the news proxy.

In Table A7 we provide performance statistics for our adjusted news proxy by exchange rate regime, showing that accuracy is highest for free floaters where the probability of detection is far higher than for other regimes because interventions are clearly more newsworthy.

[11] This result holds qualitatively when we limit the analysis to those country-time data, where the Adler et al. (2021) data are available, in particular covering only the years 2000 to 2011 (see Table A7).

2.4 Characteristics of the new database for FX interventions

The news-based intervention proxy appears to be useful in the data universe of 27 countries over a long sample period (13 years on average across countries). Using the same methodology, we extend the proxy across time and countries (step 5 in Figure 1), thus creating a new database on FX interventions with country-level monthly intervention proxies. Our database includes almost all countries that provide data for monthly foreign currency reserves in the International Financial Statistics (IFS) database of the IMF, and the sample period is 1995-2016 for the majority of countries.

Minimum number of news required. The Factiva news database covers countries to a different extent. A lack of news reports on intervention should hence not be automatically interpreted as evidence of non-intervention. Thus we define a minimum degree of coverage for countries to be considered in our database. We use a simple cutoff of at least ten FX intervention-related news items over the full sample period (the cutoff is varied in a robustness check without changing results qualitatively). This rule results in dropping four countries from the IFS database, i.e., Estonia, Kuwait, Lithuania, and Mongolia.[12] The country in our working sample closest to the cutoff is Iceland, which has been actively building up reserves in the aftermath of the 2008 crisis, with 24 relevant news items.

Coverage over time. The data cover the period 1995-2016. We do not extend the data back to the 1980s because the relevant news coverage of emerging markets during those times was very poor. The panel is unbalanced because some countries do not provide reserve data for the whole period. Since we need those data, it is impossible to create it in full for those cases, i.e., both regarding the incidence and the size of interventions.

Country coverage. Our new intervention proxy covers 48 countries plus the EMU: Argentina, Australia, Brazil, Bulgaria, Canada, Chile, China, Colombia, Croatia, Czech Republic, Denmark, the European Monetary Union (EMU), Hong Kong, Hungary, Iceland, India, Indonesia, Israel, Japan, Kenya, Latvia, Lebanon, Malaysia, Malta, Mex-

[12]This cutoff also implies dropping Azerbaijan, Bolivia, Costa Rica, Georgia, Kyrgyzstan, and Moldova that were part of FGMSS's original 33 countries. Several of these countries are also not in the IFS database, thus lacking comparable monthly reserve data to work with.

ico, New Zealand, Nigeria, Norway, Peru, the Philippines, Poland, Romania, Russia, Saudi Arabia, Singapore, Slovak Republic, Slovenia, South Africa, South Korea, Sweden, Switzerland, Thailand, Turkey, Ukraine, United Kingdom, United States, Uruguay, Venezuela, and Vietnam (see also Table A9). Thus, this dataset includes 37 of the 38 most important currencies covered in the BIS triennial survey (2017), missing only Bahrain. Furthermore, the data also extend to the currencies of Iceland, Kenya, Lebanon, Nigeria, Uruguay, and Venezuela, which are not part of the BIS survey. They include several countries whose individual intervention history ended when they joined the Euro, which applies to Latvia, Malta, Slovak Republic, and Slovenia between 2007 and 2014. Our main working sample thus covers most of the worldwide trade in FX, and the currencies of far over 80 percent of the world economy. In this respect, the new dataset is much more comprehensive than publicly available FX intervention data or the FGMSS data.

3 Stylized facts about FX interventions

In this section, we describe several stylized facts of the new database about FX interventions. These have two purposes. First, stylized facts provide a perspective on FX intervention patterns; second, they allow us to get a better sense of whether there are relevant differences between these proxy data and the actual intervention data from FGMSS.

Frequency of intervention. We know from FGMSS that interventions occur in about 20 percent of months in their sample of 33 countries (the respective number is 30.6 percent for the sample of 27 countries used above). Taking a sub-sample of our data by using all 27 countries that are also included in FGMSS, intervention is estimated to occur in 11.3 percent of months. This indicates that the news-based proxy underestimates the true incidence of interventions. The proxy picks up just over one third of the actual intervention months on average. The precise share of correctly classified months is 27.3 percent, as shown in Table A1. As discussed in Appendix D, this discrepancy is greatest in the most rigid regimes for which we often lack relevant news items that capture interventions because FX intervention seems to be taken for granted in these regimes.

To test whether there is any trend in the frequency of the intervention data, we plot the share of countries with interventions at the monthly frequency over time.[13] If anything, there appears to be a slow decrease in intervention incidence over time (Figure A9 in the Appendix) that is interrupted by the times of the global boom of the mid-2000s and then by the Great Financial Crisis and its aftermath. These simple statistics mask differences by currency regime. For example, broad band regimes were more likely to intervene in FX markets during periods of market turmoil and large capital inflows. The comparison with the same information from actual intervention data of FGMSS suggests that broad swings in intervention activity of country groups can be observed with the help of our proxy even if the proxy misses some intervention episodes.

Interventions come in episodes. As we know from daily data (see, e.g., FGMSS), interventions occur in sequences. According to our proxy, the length of intervention episodes varies: about two-thirds of episodes last only one month. The distribution has a mean of 1.7 months and a long tail. The probability of an intervention being followed by a second intervention month is about 16 percent. In the actual intervention data of FGMSS, this probability is 18 percent. A marked difference is that intervention spells are substantially longer in the actual data, with a mean of 5 months. This is driven by some extremely long intervention spells (e.g., monthly intervention over more than 5 years). Medians are much closer at 1 and 2 months, respectively. Also, it is explained by episodes being at times split up under the proxy and not counted as belonging to the same spell. That happens because longer intervention spells tend not to receive regular monthly coverage in the news database we exploit.

Majority of intervention months are net purchases of foreign currency. We find that, on average, across all regimes, central banks more often build up reserves (60.3 percent of all intervention months) rather than decrease them. Also, the distribution of months with net purchases and net sales for a given central bank in a given year indicates reserve building. When assessing the net reserve change per year, we find net purchases of

[13]Since the proxy somewhat underestimates intervention, we correct the averages over time using the procedure described in Appendix D.

foreign currency in 69 percent of country-year observations. This high share of purchases is expected because having foreign reserves in combination with economic growth and globalization requires buying foreign currency. The share of months with purchases is higher in less rigid regimes like broad bands and free floaters, a fact that is consistent with the confidential intervention data of FGMSS.

Intervention size is imperfectly approximated. Based on the FGMSS country sample, we can compare the difference between our estimated and actual intervention sizes. The actual intervention amounts in the true data are, in absolute value, 1090 million USD in intervention months. According to the news-based estimation procedure, in true intervention months, the adjusted reserves change by 1087 million USD in absolute value. Hence, the proxy is relatively precise on average. In addition to this comes imprecision due to classification errors (false positives and especially false negatives). When assessing the mean absolute reserve change of interventions indicated by our proxy on the same sample, the mean absolute volume is 2145 million USD. That is because the news proxy tends to miss small interventions but is quite good at picking up larger than average interventions because these are more likely to be reported (see Table A3). This leads to an overestimation of the actual intervention size, but for applications where large shocks are of interest, the proxy can be a helpful guide.

More interventions in turbulent times. As can be seen in Table 2, where we provide additional information on the intervention proxy across different regimes, all countries are significantly more likely to intervene in turbulent times (defined here by the VIX deviating more than two standard deviations from its mean), regardless of their exchange rate regime.[14] According to the proxy, free floaters are, for example, more than twice as likely to intervene in a given month if markets are in turmoil. For rigid regimes, the increase in odds is smaller. This makes sense because this regime is expected to intervene more often regardless of market conditions.

[Table 2 about here]

[14] Comparison data can be found in Table A10.

4 Relations between FX interventions, capital controls, and macroprudential policies

Having developed our news-based proxy, we are equipped to analyze linkages between FX interventions, capital controls, and macroprudential regulations. In Section 4.1 we introduce into the different characteristics of these three policy instruments, as these differences motivate our course of empirical analysis. Section 4.2 shows the generally positive correlations between FX interventions and the two regulatory instruments. Section 4.3 examines the dynamic role of FX interventions and macroprudential policies with the help of a panel vector autoregressive (VAR) model, also in countries with or without capital controls.

4.1 Characteristics of the three instruments of capital account management

The capital inflows and outflows of economies are often directly managed by authorities. On the first pages of this paper, we have discussed the stance toward FX interventions, which have become more accepted as a policy tool during the last decade. Now we introduce capital controls and macroprudential policy, and then we compare their characteristics. This sequence implies that we stick to the more traditional understanding that capital controls and macroprudential policies can be separated, while others, such as Erten et al. (2021), use a wider definition of capital controls.

Capital controls are policy measures that aim to directly impact the inflow and outflow of capital by regulating quantities and/or prices. The earlier literature on capital controls has mostly been critical about the consequences of using such tools, the main reason being the potential misuse in trying to avoid otherwise necessary adjustments (see also more recently Klein, 2012). Several studies highlight the distortions created by capital controls (e.g., Costinot et al., 2014; Forbes et al., 2015; Alfaro et al., 2017). At the same time, it has been acknowledged that capital inflows and outflows can be heavy relative to the size and capacity of a domestic financial market (in particular in emerging economies), so controls can be a useful instrument to moderate such extreme flows (e.g., Ostry et al., 2011; Benigno et al., 2016; Dominguez, 2020; Erten et al., 2021).

Relative to capital controls, the literature on macroprudential policies is broader (e.g., Farhi and Werning, 2016). Some papers particularly relevant for us (e.g., Korinek, 2018) highlight the beneficial role of macroprudential policies in managing the capital account. Cerutti et al. (2017a) provide the broadest documentation of macroprudential policies with 64 countries covered at the quarterly frequency and find that these policies can generally impact credit growth. Aside from those few studies that discuss the usefulness of macroprudential regulation to stabilize the economy (and the financial sector in particular), such as Jeanne and Korinek (2017), only a few consider FX transactions. While Korinek (2018) identifies reasons why specific forms of capital inflows to emerging markets might be taxed, Ahnert et al. (2021) show that borrowing in foreign currency is reduced due to stricter macroprudential regulation but that risks may shift from the regulated banking sector to unregulated firms.

Relative to FX interventions, which may be used on a daily basis, regulatory policies (such as capital controls and macroprudential instruments) have a longer horizon. Moreover, capital controls are far more stable over time than macroprudential policies. In particular, capital controls are not cyclical (Fernández et al., 2015). This is already implicit in the granularity at which data are collected on these instruments: yearly for capital controls, quarterly for macroprudential instruments, and daily or monthly for FX interventions (as we use them in the next section). As a concrete example, there are only five observed changes in capital controls for free-floating regimes and a mere six for rigid regimes. We complement these qualitative observations with an empirical view by which we standardize the changes of instruments relative to the overall level of existing policies. For this exercise, we motivate the data on the regulatory policies we use.

Novel databases on capital controls have been built on earlier works (such as Ito and Chinn, 2008), leading us to pick the most comprehensive one that was established by Fernández et al. (2016). Its update covers 100 countries for the years 1995-2015. From our perspective, these data have the disadvantage of being available only at the annual frequency, but we are not aware of a better alternative source for capital control measures. As a measure of the intensity of capital controls we add up different categories to form an overall index.[15]

Regarding data on macroprudential policies, we rely on Cerutti et al. (2017a), who offer extensive coverage across countries, instruments, and over time, spanning the years 2000-2014 at the quarterly frequency for 64 countries. The definition of macroprudential policies is taken from Cerutti et al. (2017a, 2017b) and is a measure of the intensity of macroprudential policy: it adds up the number of measures that are taken in defined categories. A quarter-on-quarter change can then take values 1, 0, and -1, indicating increasing, stable and decreasing macroprudential policies. We reflect the quarterly frequency of the macroprudential policy data by conducting the analysis with quarterly data.

To make the persistence and intensity of changes comparable, we standardize the changes relative to the overall level of existing policies. In the case of foreign exchange interventions, the modal value is zero and the scale (left axis) displays intervention size relative to GDP. The macroprudential policy variable lacks a measure of the level, so we use the best proxy for levels available from the dataset, which is the cumulative change since the start of the sample. The capital controls dataset, by contrast, contains levels. We define the latter two variables' changes on the right axis as changes in the respective index relative to the level. We show the results in Figure 4. The frequency and intensity of fluctuations thus provide an impression of how frequent and intense changes are. Given that the capital controls data are only available at the annual frequency, the fluctuations in the data are obviously less volatile. However, the main point of Figure 4 is that fluctuations are far larger for FX interventions and macroprudential policies on average than for capital controls.

These results indicate that the three instruments may be used in different ways. In particular, capital controls stand out in that they are quite persistent. Thus, countries

[15]There are 14 inflow and outflow controls each, all measured by an index that is scaled between 0 and 1. We add up all inflow and outflow controls, respectively, and divide each resulting aggregate index by 14 such that it is scaled between 0 and 1 again. The resulting sample means for inflow controls and outflow controls are 0.34 and 0.41, respectively.

tend to be either in a situation of using this instrument, in which case they use it to a major degree, or they are not in this situation. If there is a change in the use of capital controls, this change is often a persistent regime change and less of a gradual change.

[Figure 4 about here]

4.2 Correlations between FX interventions and the regulatory instruments

Guided by the above results, we expect that the existence of a relevant degree of capital controls makes a decisive difference: FX interventions will be more often used if capital controls are important, while they change too frequently to be related to the infrequent changes in capital controls. These relations seem to be ex-ante less clear regarding the relation between FX interventions and macroprudential regulations. Table 3 provides a starting point for the analysis, highlighting that the correlation coefficients between tools are on average rather small, suggesting either an absence of a relationship or heterogeneity of relationships that differ by context.

[Table 3 about here]

General empirical setup. In order to test whether the policy instrument of interest in country/currency i at time t is systematically associated with FX intervention conditional on the regime and the year, we estimate:

$$Intervention_{it} = \alpha + \beta Instrument_{it} + regimeFE_i + yearFE_t + \epsilon_{it} \tag{1}$$

Intervention is included as a dummy variable. Controlling for the exchange rate regime and country differences is important because countries should see less need for capital controls as they develop (see, e.g., Korinek and Sandri, 2016) and are at the same time less likely to manage their exchange rate through intervention closely. In all of the following, we use "coarse" grid regime fixed effects as defined by Ilzetzki et al. (2019), i.e., a classification that results in four main exchange rate regimes. Standard errors are clustered at the country level.[16]

FX interventions and capital controls. Due to the annual frequency of capital control data, the monthly FX intervention proxy is aggregated accordingly when studying the correlation between changes in capital controls and changes in intervention incidence.[17] Both when using regime and year fixed effects as well as unconditionally (Table 4, Panel A, columns 1 and 2), we find that interventions occur significantly more often in countries that have higher levels of capital controls in place. This positive correlation becomes stronger when using actual intervention data instead of our news-based proxy. Most of this increase seems to be due to lower noise, as the comparison of columns 3 and 4 suggests, which are based on the same sample but use different outcome variables. In terms of the strength of the correlation, a one standard deviation increase in the standardized capital controls index is associated with an 8.3 percentage point higher probability of FX intervention in a given month.

[Table 4 about here]

Using a similar analysis at the yearly frequency to estimate the relationship between changes in FX intervention and changes in capital controls yields no systematic pattern (Table A12). That confirms that capital controls provide a stable background against which decisions about FX intervention are taken. Next, we disaggregate the data by country characteristics and policy characteristics.

As predicted by the theoretical literature (e.g., Korinek and Sandri, 2016), country characteristics indeed play a role: there is a strong negative correlation between capital controls and GDP per capita in our data. Accordingly, emerging economies not only far exceed advanced economies in their use of capital controls, they also intervene more often in the FX market. Related to this, there are strong positive correlations among narrow

[16] Results hold when we provide an alternative approach with detrended variables.

[17] In general, we choose that regime in which a country was for between six and twelve months in a given year. For the time being, countries that have spent less than six months in a regime or exactly six months in two regimes each are excluded from the analysis. In the case of 53 observations in our working sample, a country has spent less than six months in its longest regime setting in that year (e.g., three regimes in a year, each of them for four months).

and broad band regimes (dominating in emerging economies) between interventions and capital controls. By contrast, among free floaters, there is a negative relationship. That could be interpreted as tentative evidence that countries that do not normally intervene in the FX market and have capital controls in place need to intervene less frequently. The negative correlation is confirmed using actual intervention data (available only for a subset of countries) instead of the news-based proxy. Finally, distinguishing between inflow and outflow control levels across countries or regimes suggests that both kinds of capital controls are positively correlated with interventions – a consequence of many countries controlling both inflows and outflows (Table A14).

FX interventions and macroprudential policies. Studying the relationship of macroprudential policies and FX interventions, we reflect the quarterly frequency of the macroprudential policy data by conducting the analysis at the quarterly frequency. The empirical procedure mirrors the procedure on capital controls: a panel estimation including country and year fixed effects; however, the left-hand-side variable now refers to macroprudential policy. The estimates in Table 5 show a systematic positive relationship between quarterly changes in macroprudential policies and FX intervention. While the correlation retains its sign when reducing the sample size in column 2 to the countries with actual intervention data, the estimate becomes statistically insignificant in this smaller sample that overlaps with FGMSS. By contrast, the relationship remains weakly significant when using actual intervention data instead of the proxy.

[Table 5 about here]

In contrast to capital controls, several papers, such as Korinek and Sandri (2016), discuss that as economies become more advanced, countries should be in less need of capital controls, but their use of macroprudential policies should remain stable. We indeed observe this pattern within our data.[18] Macroprudential policies remain relevant, these authors argue, because they help mitigate boom and bust cycles. In the data, we find that emerging markets' macroprudential policies started increasing in the mid-2000s

[18]The pattern also holds when accounting for regimes, country characteristics, and time effects, each covered by adding dummy variables to the regression.

and that this trend accelerated in the early 2010s. In advanced economies there had been little change before 2010 but a similarly strong rise afterward (see also column 4 of Table 5). By contrast, for emerging economies (see column 5), the point estimate is more than twice that for advanced economies, i.e., this country group is driving the results. This is supported by the fact that the positive relationship between FX intervention and a higher level of prudential policies since the year 2000 is driven by one exchange rate regime in particular, namely broad bands (see Table A15 in the Appendix) and, among these, by emerging markets.

Regarding specific instruments, Cerutti et al. (2017a) distinguish ten different macroprudential policy instruments. Of these, only the two instruments of reserve requirements for foreign currency loans and locally denominated loans are both significantly and strongly related to FX intervention across countries, regimes, and time (see Table 5, columns 7 and 8). As reserve requirements for local loans are highly correlated with those for foreign currency loans, this may indicate that reserve requirements aim at reducing credit growth and are thus used as a counter-cyclical measure. Accordingly, the macro-environment also plays a role in understanding the use of instruments for capital account management.

4.3 The dynamic roles of FX intervention and macroprudential policies

As we have seen above that changes in FX interventions and macroprudential policies are positively related, we now analyze the potentially dynamic pattern between these two instruments. That analysis helps answer whether the two instruments are mainly used in combination or whether one instrument is systematically used before the other.

Results for all countries. To study how FX intervention and macroprudential regulation interact dynamically, we estimate a panel VAR model that includes the exchange rate as a third variable. Partly to reflect the nature of the relevant variables[19]

[19] The prudential policies data is defined in changes and does not have a proper levels variable (only cumulative changes from the start of the sample but no levels are available).

and to ensure stationarity, the whole model is defined in first differences. We thus consider changes in the exchange rate, intervention volumes as a share of GDP, and changes in the macroprudential policy index. Positive values for the exchange rate indicate an appreciation of the domestic currency. Positive FXI means purchases of foreign currency (intended to weaken the domestic currency) and positive values of the macroprudential policy variable indicate a more restrictive stance. The model is estimated at the quarterly frequency.[20] The results are not dependent on the ordering of the variables as different Choleski orderings give qualitatively identical results.

Our results for the panel of all countries[21] in Figure 5 show on the diagonal from the top left to the bottom right that both FX interventions and macroprudential policies are somewhat persistent over time, while the exchange rate is less so. Regarding the temporal relationship between the two instruments, increasing restrictions of prudential policies are followed by slightly more FX interventions in subsequent months (see the second IRF in the last row). This impact is only weakly statistically significant (at the 10 percent level). Thus the 95 percent confidence interval of the impact of an intervention on prudential policies covers the zero line. By contrast, FX interventions are not followed systematically by changes in prudential policies across the sample (see the third IRF in the second column).

That positive relationship flowing from prudential policy changes to foreign exchange interventions indicates a tendency to employ, in the stabilization policy of the economy, the more flexible tool of FX interventions as an additional step in the policy tool kit that can be used more intensively after macroprudential policies have been introduced. The direction of the interventions suggests that increasing macroprudential restrictions, which typically aim at decreasing excessive credit booms, tend to be followed by purchases of foreign currency, which are typically meant to counteract the appreciation of the local currency. Another take-away from Figure 5 that does not depend on fine distinctions of statistical significance levels is that both tools are combined to impact both financial

[20] The VAR is estimated using three lags for each variable, which maximizes the adjusted coefficient of determination.

[21] We exclude "freely falling" exchange rate regimes according to the Reinhart/Rogoff coarse classification.

stability and changes in the exchange rate value.

Moreover, the impulse response graph in Figure 5 shows the stylized fact that countries on average counteract the appreciation of their currency with purchases of foreign currency (second panel on top), i.e., they are leaning against the wind (see, e.g., FGMSS). This intervening against the trend is also why – at the quarterly frequency – FX interventions aiming at depreciation correlate with appreciations of the domestic currency. There is no such systematic relationship between exchange rate appreciation and changes to prudential policies. That suggests that medium-term (quarterly) fluctuations in the exchange rate are managed with the help of FX interventions.

[Figure 5 about here]

Results for a subsample of macroprudential policies. Going beyond Figure 5, we check the above results by referring not to all macroprudential policies but to the smaller subsample, where regulations directly address the FX market by changes in reserve requirements for foreign currency loans. These requirements are used to decrease the macroeconomic risks borrowers generate when taking foreign currency instead of domestic currency loans. Firms often prefer to borrow in foreign currency because it helps them finance their currency requirements for trade. However, this can also create currency mismatch (e.g., Gopinath and Stein, 2021). Furthermore, consumers and firms in higher interest environments sometimes take foreign currency loans that come with lower foreign interest rates while not fully accounting for the risks of currency depreciation (e.g., Verner and Gyögyösi, 2021). These behaviors and the resulting externalities can put the domestic currency under pressure, especially if unanticipated shocks cause instability. In this setting, macroprudential policies can be used to reduce risk and shift demand towards the local currency. Estimating the above patterns when focusing only on this tool, the general pattern of Figure 5 remains (see Appendix Figure A6).

Results for countries with and without capital controls. The reliance on capital controls is a fundamental decision about a country's stance on capital account liberalization. Thus, we expect that it makes a difference regarding the use of the two other instruments of capital account management, too. In particular, Korinek and Sandri (2016) argue that more volatile emerging markets should use both capital controls and macroprudential policies to mitigate fluctuations by reducing foreign credit and any credit, respectively. In more advanced economies with liberalized capital accounts, capital controls are often not permitted, but macroprudential policies still have a role to play (Erten et al, 2021).

Zooming into the subset of countries that have any capital controls in place and comparing these to the countries and time periods without any capital controls shows that the above patterns are found again (see Appendix Figure A7). Also, the tightening of macroprudential policies is related to later appreciation of the domestic currency, here to a significant extent. By contrast, countries without capital controls, i.e., basically advanced economies, that are often safe-haven currencies and intervene in the foreign exchange market more selectively, do not show this pattern (see Appendix Figure A8). In these countries, FX interventions are, on average, followed by an easing of macroprudential policies in subsequent quarters. That may indicate that intervention is a tool that is used at times of turmoil before macroprudential policies can be eased. The dynamics thus differ between these country groups. In sum, the overall results for all countries are dominated by countries with capital controls and these are largely emerging countries.

A pecking order of capital account management tools. The dynamic VAR analyses thus contribute to an emerging picture that looks akin to a pecking order in the use of capital account management tools. The most fundamental decision to be made is about the use of capital controls, which tend to be very persistent. If capital controls are in place, then FX interventions and macroprudential policies are used more often. A decision about using the macroprudential tools seems to be the next fundamental decision, while FX interventions are the most flexible tool. They are used to reinforce the effect of stricter macroprudential policies but they can also be independent of this function and used to lean against the wind in the FX market directly.

5 Conclusion

This paper contributes to the large literature on FX interventions by compiling a new database of FX interventions for a broad cross section of currencies. The new database relies on the news provided by a financial news platform to identify FX intervention episodes, which are extracted using a text classification approach. We train this algorithm using thousands of hand-coded documents. The results are then assessed using two sources of information: the performance of the news classification is compared to hand-coded data, and success in correctly identifying interventions is evaluated by comparison to the confidential, actual intervention data of Fratzscher et al. (2019).

We then use this new database to provide stylized facts about FX interventions, documenting that, for example, interventions are frequent, come in episodes, are generally characterized by purchases of foreign currency, and occur more often in turbulent times. These findings align with what we know from country studies and the cross-country evidence by Fratzscher et al. (2019), lending credibility to the new dataset. The advantage of the new database is its broader coverage and the fact that we can make it publicly available for use by other researchers.

Covering 49 countries over up to 22 years and available at the monthly frequency, our dataset will allow researchers to use it in many different forms of analyses. A particular strength of this dataset compared to other data is that this proxy has a lower noise-to-signal-ratio than existing intervention proxies, thus enabling researchers to more clearly distinguish between times with and without interventions. To highlight some of the strengths of the new dataset, we provide stylized facts about FX interventions and characterize the relationship between the main capital account management tools, i.e., FX interventions, capital controls, and macroprudential regulation.

Relating FX interventions to these two other policy tools of interest, i.e., capital controls and macroprudential regulation, we find that their use is positively correlated. This provides a clear motivation to avoid isolated analyses of capital account management tools. Capital controls are persistent, and hence changes in capital controls occur infrequently. FX interventions and macroprudential tools are used more often in countries with more capital controls. The relation between the latter instruments is that a change in regulation is followed (or strengthened) by increased FX interventions. These relations hold mainly for emerging economies but do not really exist for advanced economies. FX interventions seem to have a dual function: first, to support controlling the capital account as indicated above; second, FX interventions are used as a tool to stabilize the FX markets at a higher frequency.

References

Adler, Gustavo, Noëmie Lisack and Rui C. Mano. 2019. Unveiling the Effects of Foreign Exchange Intervention: A Panel Approach. *Emerging Markets Review*, 100620.

Adler, Gustavo, Kyun Suk Chang, Rui Mano and Yuting Shao. 2021. Foreign Exchange Intervention: A Dataset of Public Data and Proxies. *IMF Working Paper*, 2021/047.

Ahnert, Toni, Kristin Forbes, Christian Friedrich and Dennis Reinhardt. 2021. Macroprudential FX Regulations: Shifting the Snowbanks of FX Vulnerability? *Journal of Financial Economics*, 140(1), 145-174.

Alfaro, Laura, Anusha Chari and Fabio Kanczuk. 2017. The Real Effects of Capital Controls: Firm-Level Evidence from a Policy Experiment. *Journal of International Economics*, 108, 191-210.

Bank of International Settlement (BIS). 2017. Turnover of OTC foreign exchange instruments, by country. Available at http://stats.bis.org/statx/srs/table/d11.2.

Basu, Suman, Emine Boz, Gita Gopinath, Francisco Roch and Filiz Unsal. 2020. A Conceptual Model for the Integrated Policy Framework. *IMF Working Paper*, 2020/121.

Benigno, Gianluca, Huigang Chen, Christopher Otrok, Alessandro Rebucci and Eric R. Young. 2016. Optimal Capital Controls and Real Exchange Rate Policies: A Pecuniary Externality Perspective. *Journal of Monetary Economics*, 84, 147-165.

Bianchi, Javier and Enrique G. Mendoza, 2018. Optimal Time-Consistent Macroprudential Policy. *Journal of Political Economy*, 126(2), 588-634.

Blanchard, Olivier, Gustavo Adler and Irineude Carvalho Filho. 2015. Can FX Intervention Stem Exchange Rate Pressures from Global Capital Flow Shocks? NBER Working Paper No. 21427.

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

Cerutti, Eugenio, Ricardo Correa, Elisabetta Fiorentino and Esther Segalla. 2017a. Changes in Prudential Policy Instruments – A New Cross-Country Database. *International Journal of Central Banking*, 13(1), 477-503.

Cerutti, Eugenio, Stijn Claessens and Luc Laeven. 2017b. The Use and Effectiveness of Macroprudential Policies: New Evidence. *Journal of Financial Stability*, 28(2), 203-224.

Chamon, Marcos, Garcia Márcio and Laura Souza. 2017. FX Interventions in Brazil: A Synthetic Control Approach, *Journal of International Economics*, 108, 157-168.

Chinn, Menzie and Hiro Ito. 2008. A New Measure of Financial Openness. *Journal of Comparative Policy Analysis*, 10(3), 307-320.

Costinot, Arnaud, Guido Lorenzoni and Ivan Werning. 2014. A Theory of Capital Controls as Dynamic Terms-of-Trade Manipulation. *Journal of Political Economy*, 122 (1), 77-128.

Daude, Christian, Eduardo Levy Yeyati and Arne Nagengast. 2016. On the Effectiveness of Exchange Rate Intervention in Emerging Markets. *Journal of International Money and Finance*, 64(5), 239-261.

Dominguez, Kathryn M.E. 2003. The Market Microstructure of Central Bank Intervention. *Journal of International Economics*, 59(1), 25-45.

Dominguez, Kathryn M.E. 2020. Revisiting Exchange Rate Rules. *IMF Economic Review*, 68, 693-719.

Dominguez, Kathryn M.E. and Jeffrey A. Frankel. 1993. Does FX Intervention Matter? The Portfolio Effect. *American Economic Review*, 83(5), 1356-1369.

Dominguez, Kathryn M.E., Yuko Hashimoto and Takatoshi Ito. 2012. International Reserves and the Global Financial Crisis. *Journal of International Economics*, 88, 388-406.

Dominguez, Kathryn M.E. and Freyan Panthaki. 2007. The Influence of Actual and Unrequited Interventions. *International Journal of Finance and Economics*, 12, 171-200.

Eichengreen, Barry. 2019. Globalizing Capital: A History of the International Monetary System. Princeton University Press, Third edition, Princeton University Press.

Erten, Bilge, Anton Korinek and José Antonio Ocampo. 2021. Capital Controls: Theory and Evidence. *Journal of Economic Literature*, 59(1), 45-89.

Farhi, Emmanuel and Ivan Werning. 2016. A Theory of Macroprudential Policies in the Presence of Nominal Rigidities. *Econometrica*, 84(5), 1645-1704.

Fatum, Rasmus and Michael M. Hutchison. 2003. Is Sterilized FX Intervention Effective after All? An Event Study Approach. *Economic Journal*, 113(487), 390-411.

Fernández, Andrés, Allesandro Rebucci and Martín Uribe. 2015. Are Capital Controls Countercyclical? *Journal of Monetray Economics*, 76, 1-14.

Fernández, Andrés, Michael W. Klein, Allesandro Rebucci, Martin Schindler and Martín Uribe. 2016. Capital Control Measures: A New Dataset. *IMF Economic Review*, 64, 548-574

Fischer, Andreas M. 2006. On the Inadequacy of Newswire Reports for Empirical Research on FX Interventions. *Journal of International Money and Finance*, 25(8), 1226-1240.

Fischer, Andreas M. and Mathias Zurlinden. 1999. Exchange Rate Effects of Central

Bank Interventions: An Analysis of Transaction Prices. *Economic Journal*, 109(459), 662-676.

Forbes, Kristin J. and Francis E. Warnock. 2012. Capital Flow Waves: Surges, Stops, Flight, and Retrenchment. *Journal of International Economics*, 88(2), 235-251.

Forbes, Kristin J., Marcel Fratzscher and Roland Straub. 2015. Capital-flow Management Measures: What Are They Good for? *Journal of International Economics*, 96, S76-S97.

Frankel, Jeffrey A. 2019. Systematic Managed Floating. *Open Economies Review*, 30, 255–295.

Fratzscher, Marcel, Oliver Gloede, Lukas Menkhoff, Lucio Sarno, Tobias Stöhr. 2019. When Is Foreign Exchange Intervention Effective? Evidence from 33 Countries. *American Economic Journal: Macroeconomics*, 11(1), 132-156.

Ghosh, Atish R. 1992. Is it Signalling? Exchange Intervention and the Dollar-Deutschemark Rate. *Journal of International Economics*, 32(3–4), 201-220.

Ghosh, Atish R., Jonathan D. Ostry and Mahvash S. Qureshi. 2017. Managing the Tide: How Do Emerging Markets Respond to Capital Flows? IMF Working Paper 17/69.

Hansen, Stephen, Michael McMahon, Andrea Prat. 2018. Transparency and Deliberation Within the FOMC: A Computational Linguistics Approach. *Quarterly Journal of Economics*, 133(2), 801–870.

Hassan, Tarek A., Thomas M. Mertens, Tony Zhang. 2022. A Risk-Based Theory of Exchange Rate Stabilization. *Review of Economic Studies*, forthcoming.

Ilzetzki, Ethan, Carmen M. Reinhart and Kenneth S. Rogoff. 2019. Exchange Arrangements Entering the 21st Century: Which Anchor Will Hold? *Quarterly Journal of Economics*, 134(2), 599-646.

Ilzetzki, Ethan, Carmen M. Reinhart and Kenneth S. Rogoff. 2017. The Country Chronologies to Exchange Rate Arrangements into the 21st Century: Will the Anchor Currency Hold?

International Monetary Fund (IMF). 2012. The Liberalization and Management of Capital Flows: An Institutional View. International Monetary Fund, Washington, D.C.

International Monetary Fund (IMF). 2019. Macroprudential Policy Survey. Available at https://www.elibrary-areaer.imf.org/Macroprudential/Pages/Home.aspx.

International Monetary Fund (IMF). 2022. Review of the Institutional View on the Liberalization and Management of Capital Flows. International Monetary Fund, Washington, D.C.

Jeanne, Olivier. 2012. Capital Flow Management. *American Economic Review: Papers and Proceedings*, 102(3), 203-206.

Jeanne, Olivier and Anton Korinek. 2010. Excessive Volatility in Capital Flows: A Pigouvian Taxation Approach. *American Economic Review: Papers and Proceedings*, 403-407.

Kaminsky, Graciela, Saul Lizondo and Carmen M. Reinhart. 1998. Leading Indicators of Currency Crises. *IMF Staff Papers*, 45(1), 1-48.

Klein, Michael W. 1993. The Accuracy of Reports of Foreign Exchange Intervention. *Journal of International Money and Finance*, 12, 644-653.

Klein, Michael W. 2012. Capital Controls: Gates Versus Walls. *Brookings Papers on Economic Activity*, 43(2), 317-367.

Klein, Michael W. and Jay C. Shambaugh. 2015. Rounding the Corners of the Policy Trilemma: Sources of Monetary Policy Autonomy. *American Economic Journal: Macroeconomics*, 7(4), 33-66.

Korinek, Anton and Damiano Sandri. 2016. Capital Controls or Macroprudential Regulation? *Journal of International Economics*, 99, S27-S42.

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

Kuersteiner, Guido M., David C. Phillips, and Mauricio Villamizar-Villegas, 2018. Effective Sterilized Foreign Exchange Intervention? Evidence from a Rule-Based Policy. *Journal of International Economics*, 113, 118-138.

Melvin, Michael, Lukas Menkhoff and Maik Schmeling. 2009. Exchange Rate Management in Emerging Markets: Intervention via an Electronic Limit Order Book. *Journal of International Economics*, 79(1), 54-63.

Menkhoff, Lukas. 2013. Foreign Exchange Intervention in Emerging Markets: A Survey of Empirical Studies. *The World Economy*, 36(9), 1187-1208.

Menkhoff, Lukas, Malte Rieth and Tobias Stöhr. 2021. The Dynamic Impact of FX Interventions on Financial Markets. *The Review of Economics and Statistics*, 103(5), 939-953.

Neely, Christopher J. 2000. Are Changes in Foreign Exchange Reserves Well Correlated with Official Intervention? *Federal Reserve Bank of St. Louis Review*, 82(5), 17-32.

Ostry, Jonathan D., R. Atish Ghosh, and Chamon, Marcos. 2012. Two Targets, Two Instruments: Monetary and Exchange Rate Policies in Emerging Market Economies. IMF Staff Position Note 12/01.

Roberts, Margaret E., Brandon M. Stewart, Dustin Tingley, Christopher Lucas, Jetson Leder-Luis, Shana Kushner Gadarian, Bethany Albertson, and David G. Rand. 2014. Structural Topic Models for Open-Ended Survey Responses. *American Journal of Political Science* 58(4), 1064–82.

Roberts, Margaret E., Brandon M. Stewart, and Eduardo M. Airoldi. 2016. A Model of Text for Experimentation in the Social Sciences. *Journal of the American Statistical Association*, 111(515), 988-1003.

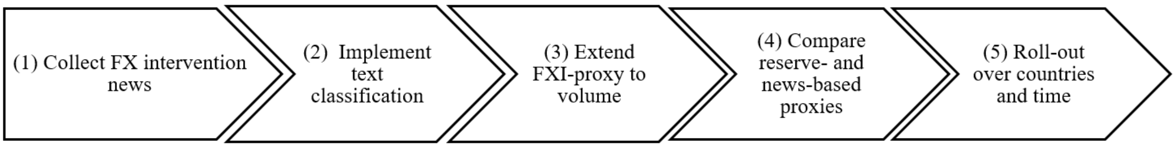
Sarno, Lucio and Mark P. Taylor. 2001. Official Intervention in the FX Markets: Is It Effective and, If So, How Does It Work? *Journal of Economic Literature*, 34(3), 839-868.

Vapnik, Vladimir. 2000. The Nature of Statistical Learning Theory. Second Edition. Springer, New York.

Figures and Tables

Figure 1: Creating a new database of FX interventions

This figure explains the workflow used to create the new foreign exchange intervention proxy database.



Hand-coding of headline news from database mentioning FXI etc. (33 countries – 6 with few news) → training dataset	SVM approach: crossfold-validation to identify FX intervention news according to FGMSS: 94% success, 99% at monthly frequency → monthly binary indicator of news-based FXI proxy	Complement FXI proxy dummy by FX proxy volume: if FXI, then take reserve change for volume and apply adjustment factor (per ER regime) → FXI proxy	Reserve-based proxy and news-based proxy to capture actual FXI at monthly frequency: Our proxy succeeds → in-sample assessment of quality	Roll-out of our proxy: A. collect news for more countries and longer time periods B. apply the SVM approach C. take adjusted reserve changes for volumes → our new database on FX interventions

Figure 2: Illustration of a support vector machine in two dimensional space

The graph shows how two groups of observations (blue, red) can be distinguished with the help of a support vector machine approach. The algorithm chooses the dividing line (solid) that best separates the blue and red points. The algorithm maximizes the margin between the support vectors as in the top panel.

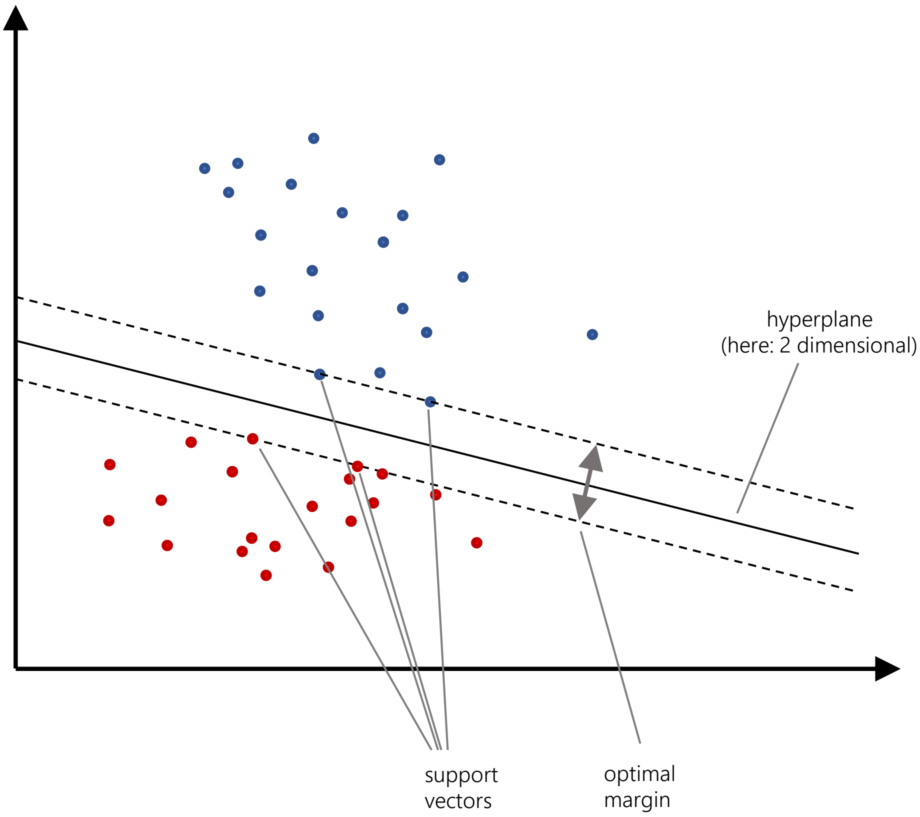


Figure 3: Precision and reserve change cutoffs

The figure shows the performance of an intervention proxy based solely on reserve changes for different levels of filtering. Filtering is done by using the relative size of the absolute monthly reserve change for a given country relative to its GDP. The horizontal axis provides the percentiles used as cutoff. The solid line is the share of true positive intervention months (i.e., precision) and the dashed line the number of true positives. The number of correctly classified intervention months (dashed line) refers to the second vertical axis. As the cutoff increases, precision increases slowly while the number of true positive interventions decreases linearly. These statistics refer to all countries and times covered in the data.

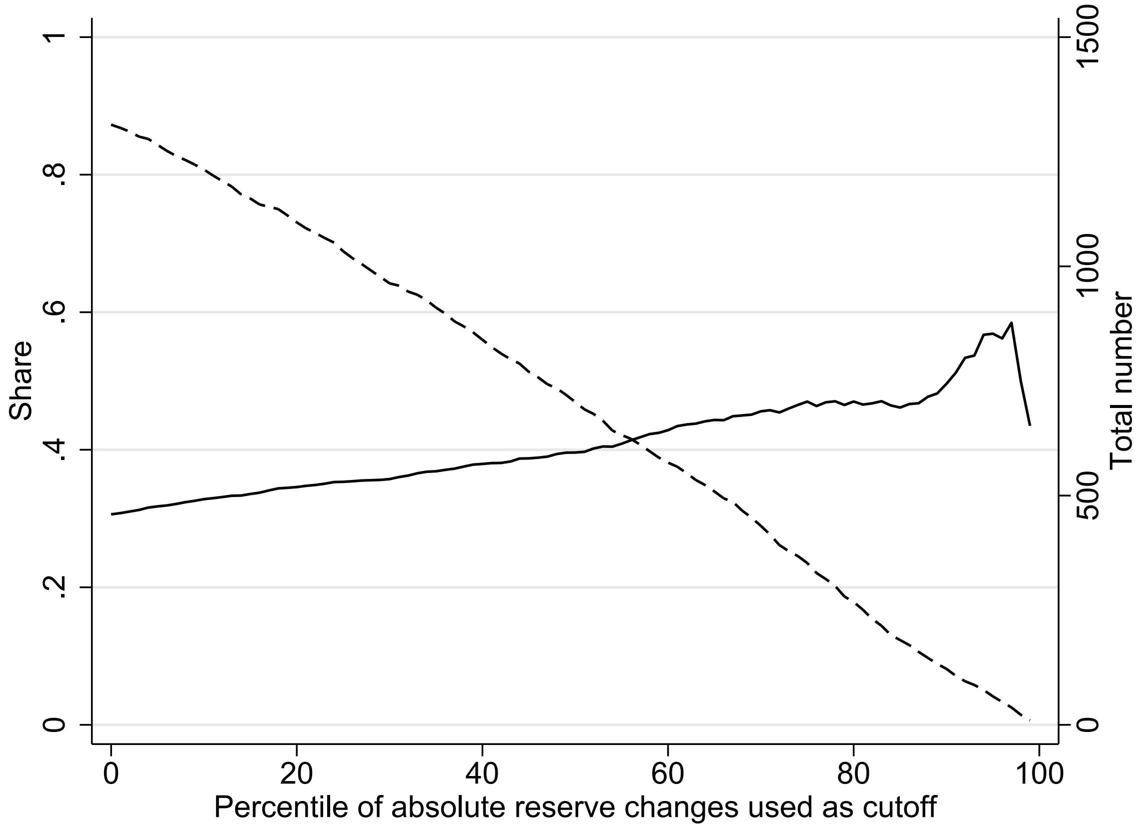


Figure 4: Frequency and intensity of changes in foreign exchange intervention, capital controls, and macroprudential policies over time

This figure compares estimates for the use of foreign exchange interventions, the capital controls and macroprudential policies indices. The reported net total intervention volume as a share of GDP is estimated using the news-based proxy created in this paper and then aggregated across countries. Capital controls and cumulative macroprudential policy index come from Fernández et al. (2016) and Cerutti et al. (2017a), respectively. These are rescaled as described in the text to yield changes relative to the existing level of these policies. These statistics refer to all countries and times covered in the data for which all three data series are available.

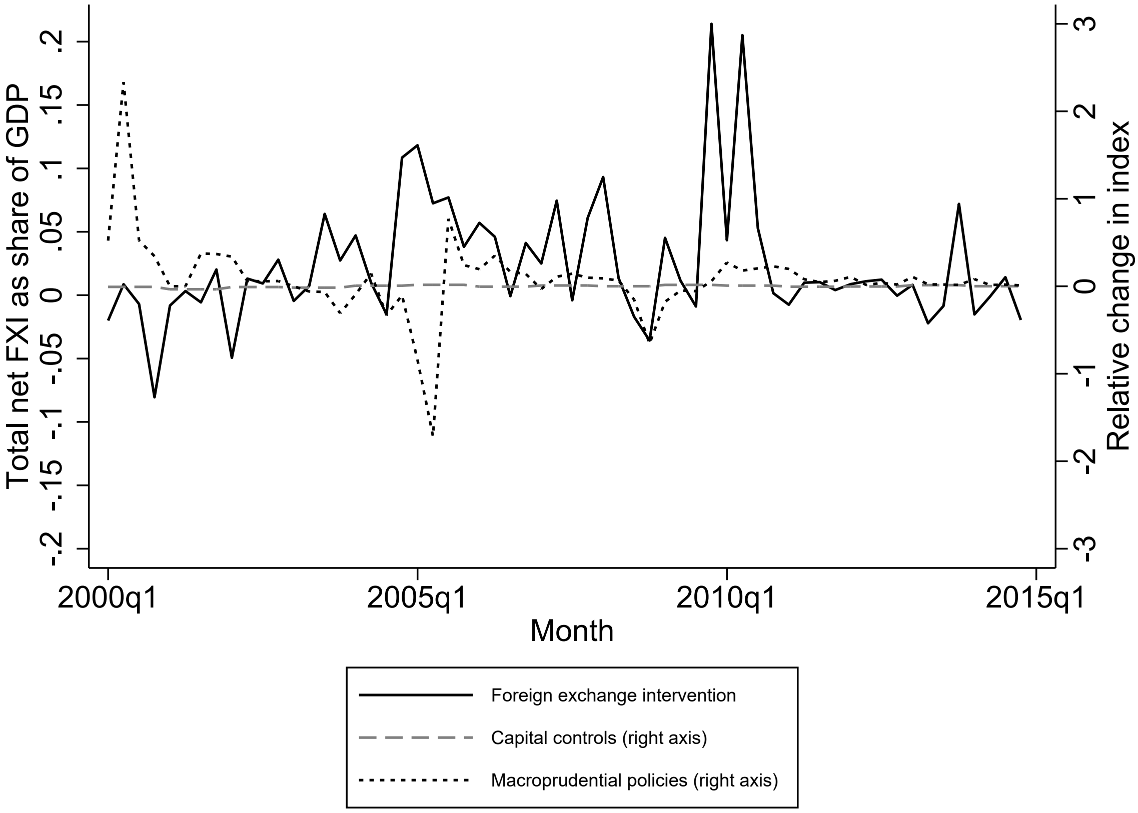


Figure 5: Dynamic relationships of foreign exchange intervention and macroprudential regulation

This figure reports cumulative impulse responses estimated using a panel VAR model. The shaded areas indicate 95% confidence intervals, calculated based on 500 Monte Carlo draws. The model is estimated at the quarterly frequency. All variables are included with three lags and there are no exogenous restrictions to the structure of the model imposed. Intervention volumes as a share of GDP based on our intervention proxy. The macroprudential policy index comes from Cerutti et al. (2017a). Quarter-on-quarter changes in exchange rates (exrate) are based on end-of-month spot rates.

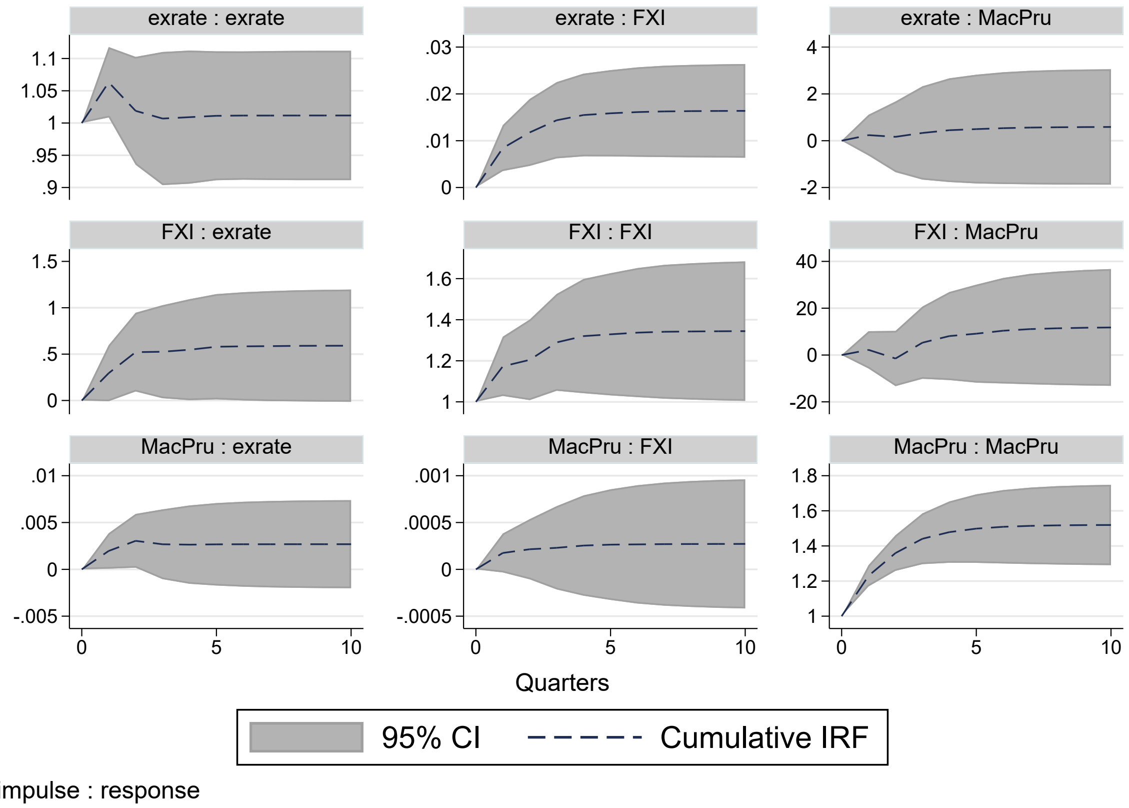


Table 1: Performance of proxies

Panel A: Frequency tables of classifications by proxy

Panel A plots the distributions of true and false positives (cf. Table A1 for three intervention proxies). The first is an intervention proxy that is solely based on reserve changes. The second is a reserve change based proxy calibrated to yield the same percentage of intervention months as the true intervention data. The third is the news-based intervention that we develop in this paper. These statistics refer to all countries and times covered in the data from Fratzscher et al. (2019) for which we can compare the performance of our proxies with actual intervention data.

Reserve proxy

		Actual intervention No	Yes	Total
Classified as intervention	No	6	0	6
	Yes	2,961	1,309	4,270
	Total	2,967	1,309	4,276

Reserve proxy with cutoff

		Actual intervention No	Yes	Total
Classified as intervention	No	2,224	744	2,968
	Yes	743	565	1,308
	Total	2,967	1,309	4,276

News proxy

		Actual intervention No	Yes	Total
Classified as intervention	No	2,840	952	2,792
	Yes	127	357	484
	Total	2,967	1,309	4,276

Panel B: Measures of predictive quality by proxy and explained variance of actual intervention explained by proxy

This panel provides additional estimates of the predictive quality of the reserves-based and the news-based proxies. The "Adjusted News Proxy" in the rightmost column is the main intervention proxy developed in this paper. The R^2 is calculated using a regression of actual intervention (dummy or volume) on the respective proxy (dummy or volume). The R^2 for intervention incidence is calculated using the respective intervention dummy of a proxy as explanatory variable for a dummy measuring actual intervention from true intervention data. The overall R^2 at the bottom indicates the R^2 in the full sample. The R^2 above only includes those cases when the proxy indicates an intervention. The news proxy thus dominates the reserve proxy both regarding its performance on incidence and regarding the level conditional on predicted incidence. These statistics refer to all countries and times covered in the data.

Name of Proxy	Reserve Changes	Reserve Cutoff	Reserve News	Adjusted Reserve	Adjusted Cutoff	Adjusted News
Incidence provided by	Reserve	Cutoff	News	Reserve	Cutoff	News
Volumes provided by	Standard reserve data			Adler et al. spot proxy		
Incidence						
Accuracy	0.308	0.652	0.748	0.302	0.485	0.748
Probability of detection	1.000	0.432	0.273	1.000	0.529	0.273
Probability of false alarm	0.998	0.250	0.043	1.000	0.535	0.043
Noise-to-signal-ratio	0.998	0.580	0.157	1.000	1.010	0.157
Volume						
R^2 for volume	0.536	0.630	0.554	0.243	0.197	0.745
Overall						
Correlation coefficient	0.732	0.739	0.512	0.493	0.428	0.765
R^2 overall	0.536	0.546	0.262	0.243	0.183	0.585

Table 2: Summary of interventions using our intervention proxy

This table provides summary statistics of intervention characteristics according to our news-based proxy for the aggregate sample and by exchange regime. Country-regime refers to unique combinations of country and exchange regime. * assuming 20 trading days per month and using interpolated data from the BIS triennial survey. Reading example: net intervention volume of 100% indicates monthly intervention volume is as large as 1/20th of daily FX turnover in the respective market. Mean absolute size where indicated.

	Total	Free Floaters	Broad Bands	Narrow Bands	Rigid Regimes	Other regimes
Number of country-regime observations	104	6	33	28	20	19
Months covered	12648	1092	5406	3058	2594	498
Size of reserve changes in mill USD (mean abs)	1839	3073	1289	2669	1652	975
Size of reserve changes (mean abs %/GDP)	0.52	0.12	0.47	0.47	0.84	0.50
Months with intervention (%)	10.7	8.0	12.5	12.0	4.9	19.5
Months with net FX purchase intervention (%)	6.5	5.8	8.1	6.7	2.8	8.4
Months with net FX sale interventions (%)	4.3	2.2	4.4	5.3	2.1	11.0
Size in mill USD (mean abs)	2729	8557	2112	3257	1762	1080
Size in % of GDP (mean abs)	0.53	0.19	0.53	0.49	0.94	0.45
Size in % of FX turnover (mean abs)	46	1.9	38.3	49.8	160	62.5
Months in turbulent times (%)	7.3	7.5	7.9	6.8	7.5	3.4
Months in turbulent times with intervention (%)	15.0	15.9	15.8	15.3	9.8	47.1

Table 3: Correlation matrix for different instruments

This table provides pairwise correlation coefficients for foreign exchange interventions (relative to GDP, monthly variable), the capital controls index (yearly variable), the changes prudential policy index (quarterly), and the cumulative changes in the macroprudential policy index. The dagger indicates significance at the 1 percent level.

	FXI	CControls	PruC	PruC (cum)
FXI	1.0000			
CControls	-0.0328†	1.0000		
PruC	0.0379†	0.0307†	1.0000	
PruC (cum)	-0.0027	0.1045†	0.2112†	1.0000

Table 4: FX intervention and the level of capital controls

The table reports estimates of the relationship between FX interventions and capital controls. Interventions are included as dummy variables. We either use our proxy or actual intervention data in different columns. Capital controls data from Fernández et al. (2016) and included as levels. Intervention data are monthly while capital controls data are yearly, hence we do not use changes in capital controls and treat capital controls as background level. The sample period is from 1995-2015. All estimates are based on OLS models. These include year and regime fixed effects where indicated. Heteroskedasticity-robust standard errors throughout. *** p<0.01, ** p<0.05, * p<0.1. Panel A provides a comparison of intervention proxy and true data. Panel B provides estimates of the relationship for advanced and emerging countries, respectively, as well as differentiating between inflow and outflow controls.

Panel A: Comparison of proxy and actual data

	(1)	(2)	(3)	(4)
Outcome variable	Intervention proxy	Intervention proxy	Intervention proxy	Actual intervention
Subgroup	All	All	Sample of column 4	If actual data available
Covariate of interest				
Capital controls	0.0533***	0.0581***	0.0763***	0.265***
(levels)	(0.00889)	(0.00885)	(0.0211)	(0.0296)
Year FE	yes	no	yes	yes
Regime FE	yes	no	yes	yes
Observations	11,731	11,731	3,971	3,971
R-squared	0.030	0.004	0.022	0.110

Panel B: Subgroup analysis for the intervention proxy

	(5)	(6)	(7)	(8)
Covariate of interest	All controls	All controls	Outflow controls	Inflow controls
Subgroup	Advanced economies	Emerging markets	All	All
Covariate of interest				
Capital controls	0.124***	0.0312**	0.0540***	0.0423***
(levels)	(0.0217)	(0.0129)	(0.00787)	(0.00954)
Year FE	yes	yes	yes	yes
Regime FE	yes	yes	yes	yes
Observations	5,214	6,517	11,731	11,742
R-squared	0.030	0.037	0.031	0.029

Table 5: FX intervention and the changes in prudential policies

The table reports estimates of the relationship between FX interventions and macroprudential policies. Interventions are included as dummy variables. We either use our proxy or actual intervention data in different columns. Macroprudential instruments are from Cerutti et al. (2017a). Since these data are quarterly, intervention data are aggregated up to quarterly data. The sample period is from 2000-2014. All estimates are based on OLS models. These include year and regime fixed effects where indicated. Heteroskedasticity-robust standard errors throughout. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome	Intervention proxy		Actual intervention data	Intervention proxy			
Subgroup	All	Sample as in column 3	Countries where actual data available	Advanced Economies	Emerging Markets	All	All
Covariate of interest							
Prudential Policies	0.0462**	0.0585	0.0823*	0.0219	0.0486*		
	(0.0203)	(0.0480)	(0.0468)	(0.0326)	(0.0258)		
Reserve requirements (foreign)						0.0734**	
						(0.0331)	
Reserve requirements (local)							0.0465*
							(0.0246)
Regime FE	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes
Observations	2,815	991	991	1,319	1,496	2,815	2,815
R-squared	0.043	0.031	0.135	0.044	0.054	0.043	0.042

INTERNET APPENDIX

(not for publication)

Foreign exchange intervention: A new database

Appendix A: News data

The source of our news data on foreign exchange intervention is Factiva. We structured a search query which is able to provide coverage of known intervention episodes that were public while omitting highly irrelevant news. This reduction in search outcomes is required because it is not legally possible to download the full Factiva news database on a specific topic. Using our search query (see box for exact formulation), we identify all news items in which foreign currency and interventions are mentioned in combination with a relevant body such as the central bank and the country name.

Factiva Search Query:
"(foreign exchange or fx or forex or currenc*) and (intervene* or operation?) and (countrystub near10 interven*) and (rst=trtw or rst=tprw or rst=tdjw) and (central bank or ministry of finance or treasury ministry or monetary authority)", where countrystub is, for example, "australia*"
Other settings: language=English, Region=respective country, all dates, all sources, all authors, etc.

Examples of news items that are thus found are:

AUD/USD Softer After RBA's Kent's Comment on Intervention – Market Talk
Dow Jones Institutional News, 04:23 GMT, 13 November 2014, 1507 words, (Englisch)
0423 GMT [Dow Jones] The Australian dollar is displaying a softer tone against the greenback Thursday after Reserve Bank of Australia Assistant Governor Christopher Kent said intervention on the Aussie has not been ruled out. The spot ...
Document DJDN000020141113eabd000i3

RBA Keeps Currency Intervention as Option
Dow Jones Institutional News, 02:15 GMT, 20 August 2014, 480 words, (Englisch)
SYDNEY–Australia's central bank Gov. Glenn Stevens said intervention in currency markets to help drive the Aussie dollar lower remained a real option.
Document DJDN000020140820ea8k000mo

For each of these news items, the full summary (see above) is then downloaded for each country which reports reserve data in the IFS.

These news items can then be used to code each article. Manual coding was done based on the article summaries for countries for which we have actual intervention data. A standardized codebook and double-entry by separate research assistants was used to standardize coding. Research assistants were asked to identify separate categories of news, including rumors about intervention and confirmations of interventions by central banks or the treasury that we use as indication of relevant news.

Rumors are defined as immediate rumors of market participants of central bank interventions on the same day. Reports are defined as ex-post reports about previous intervention activity, for example, reporting net intervention amount or simply activity at the end of a month. Confirmations are defined as announcements by central bank or government authorities that confirm an intervention has taken place.

Appendix B: Brief summary of the machine learning algorithm

We use a standard text classification algorithm from the python library scikit-learn (link), which is open-source and includes a large variety of different machine learning and classification approaches. The algorithm is used to classify individual Factiva news items, i.e., short pieces of text such as the following:

> "UPDATE 1-Bank of Israel buys $200 mln of forex -dealers
> Reuters News, 11:25 GMT, 6 October 2009, 337 words, (English) (Adds details, dealer comment) JERUSALEM, Oct 6 (Reuters) - The Bank of Israel bought as much as $200 million of foreign currency in its first intervention in the forex market in three weeks, dealers said."

These data include both relevant ("Bank of Israel buys $200 mln", "intervention in the forex market") and irrelevant information (such as "UPDATE", "Oct 6", "Reuters"). Hence the algorithm needs to be trained to distinguish relevant from irrelevant information and to make a classification based on the relevant substrings.

For this hand-coded data (see Appendix A) are used. The algorithm thus receives several thousand text items and the hand-coded information, for example which news reports include "rumors."

The algorithm then extracts features from the text files, which involves turning text into numerical vectors. These vectors can be a simple count of the number of occurrences of each word in a text file, leading to typically hundreds of thousands of features for each news item. This yields a high-dimensional, very sparse (mostly zeros) dataset.

The next step is text preprocessing, filtering and some automatized editing to aid the classification. This means cutting words or N-gram (combinations of e.g. 15 consecutive characters like "foreign currenc"). An important part is furthermore the elimination of stopwords. These are words that occur often in language but do not carry any predictive quality, so we would not want to make the algorithm use this information in prediction. Examples of stopwords are "of", "as" and "is".

Next, the classifier is trained to distinguish relevant from irrelevant news. For this, we use a random sample of 90 percent of the hand-coded data. The remaining 10 percent of news items are held back as a test dataset. The methods we use in prediction are regularized linear models such as Support Vector Machines (SVM).

SVMs classifies observations into different classes based on the hyperplane that best separates the observations into those classes (Vapnik, 2000). In their most basic form in two-dimensional space and with two classes of observations to distinguish, a linear SVM draws the line that best separates both groups of observations. The criterion for this is maximizing the margin between the "support vectors", i.e., the observations closest to the dividing line. This is also illustrated in Figure 2. As can be seen in the graph, an important assumption of the approach is that groups can be distinguished based on the observations that are closest to those of the other group. The remaining observations, e.g. top-right and bottom-left in the illustration, do not contribute the optimal choice of the dividing line.

Prediction then works by determining on which side of the separating line an observation lies. The approach can easily be generalized to higher dimensional cases, which in fact typically makes distinguishing groups of observations much easier because there are more dimensions in which to draw the separating hyperplane. Also, by using polynomials instead of assuming a linear functional form for the hyperplane, a group of observations that at first seem "surrounded'' by the other group can be distinguished with this method. SVMs have the advantage of being able to learn independent of the dimensionality of the data. Hence, contrary to a simple regression model, it is possible to have more potentially relevant dimensions (here, for example, counts of 1 million different words, i.e., 1 million potential regressors) than observations (here: news items). Furthermore, they can work with extremely sparse data (data containing many zeros as known for example from bilateral trade statistics). To implement the SVM, we use sklearn's linear model SGDClassifier (see the following link for formulae and more explanation: link), which implements regularized linear models with stochastic gradient descent learning. Excellent results are achieved using a "modified Huber" loss function and the standard l2 penalty setting.

Finally, the model that is selected on the basis of the training is used to predict other data. To check the quality of the prediction, news items in the test data are classified. To create the working sample, we however automatically code ALL data. That means no matter whether the data were hand-coded or not, their labels are based on the algorithm. This means there will be no systematic difference in quality of labels between training data and out-of-sample data as long as we use the predicted labels. Since the algorithm is excellent but not perfect, there are some small deviations from the hand-coded data. Predicted labels are then matched to the data first on a day-by-day level. These data are then aggregated to the monthly level and matched with all the other datasets we use.

Appendix C: Determinants of news on FX intervention

We analyze publicly available news headlines about foreign exchange interventions to understand the context of FX interventions systematically. For this, we use topic models (LDA (Latent Dirichlet Allocation) and structural topic model). Topic models can classify large corpora of text into a specified number of topics. Each text, in our case headlines of news articles, is expressed as a mixture of topics while topics are distributions over words. Topic models reduce the dimensionality of the raw data consisting of thousands of words and allow assessing the data's structure and detecting hidden patterns.

We aim to discover topics that can be interpreted as underlying themes for foreign exchange interventions, for instance, such as "exports," "financial uncertainty," or "labor markets."

Before applying a topic model to the corpus of news items, we preprocess/clean the individual items. For example, after discarding duplicate news, we extract unigrams (single words) and bigrams (word pairs like "central bank" or "forex market") from the news. Figure A1 shows a word cloud displaying the most common words in the corpus.

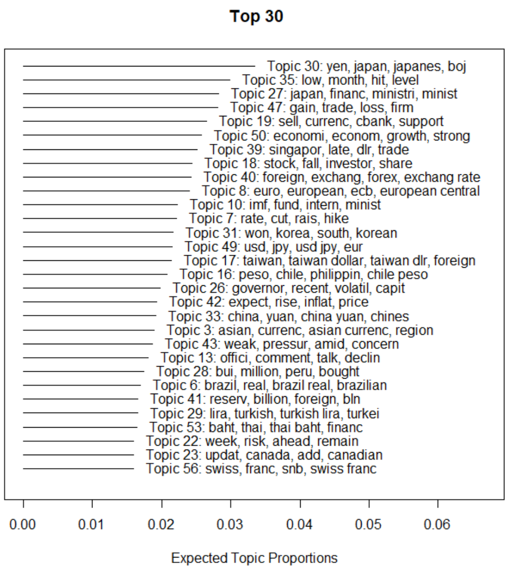
Figure A1: Word cloud of the most frequent words in the corpus

The larger a word, the more frequent it is.

For the preprocessed news items, we run the structural topic model from Roberts, Stewart, and Airoldi (2016) with the associated R-package stm (Roberts et al., 2014). After preprocessing, we are left with around 24,500 items that, on average, contain 20 individual words. Based on four diagnostic criteria we choose a topic number of 60.

Figure A2 shows the 30 topics that are most prevalent in the corpus measured on the x-axis by a topics proportion. Next to each topic, the four tokens with the highest proportion for that topic are displayed. It becomes evident that many topics pertain to countries. Topic 30 and 27 for Japan, 39 for Singapore, 38 for the Euro area, topic 17 for Taiwan etc. Topics that might represent motives or themes are, for instance, topic 50 on the economy and growth, topic 18 on stocks or topic 42 on inflation.

Figure A2: 30 most prevalent topics in the FXI news corpus



However, when we look at the news items that consist of the highest fraction of these topics, we realize that those items do not speak about interventions. Even though the news items are extracted such that they should incorporate FX interventions somewhere, the headline and the first sentence that we obtained often do not include information on interventions. These are thus news items that do not feed into the intervention proxy, making these two separate sets of news items.

Hence, we continue to work with subsamples of the data that should only talk about interventions in the news snippet part that we obtained. Again, the topics we receive do not yield interpretable word groups that would give any information on underlying intervention motives.

In a further attempt, we try to focus just on the country with the largest number of news items referring to it, Japan. With those 4,666 news items, we ran an LDA, but the topics were again not interpretable or did not identify any relevant motives.

We conjecture that using the full news body, i.e., the complete news items and not merely the first few lines that we exploit for the intervention proxy, would be required to assess the circumstances of intervention from the news more successfully. The short headlines that we have to rely on in this paper reasons of database access let one mostly merely infer information whether there had been an intervention or not but do not yield any further information.

Appendix D: Determinants of news on FX intervention

To provide a basis for assessing the performance of the news-based proxy and comparing it to the one based on reserve changes, we systematically analyze whether there are any determinants of news data that may create systematic biases when using such data in the construction of a proxy. We hypothesize that (i) economies with larger GDP, (ii) larger currency markets, or (iii) freer press have greater news coverage. We also test whether there are systematic differences (iv) during crisis times or (v) in different exchange rate regimes.

In Table A2 we estimate regressions that explain the number of or incidence of news in months with and without intervention. These are identified using our confidential actual intervention data. Columns 1 and 2 use the log number of news yielded by our search query and an indicator of whether any of these are classified as rumors or confirmations of intervention by our machine learning algorithm in a given month. Columns 3 and 4 are restricted to months with and without intervention, respectively. They thus help assess the probability of detection and precision. Column 5 measures the volume dimension of the indicator from column 3. Results suggest that news will not introduce large systematic biases along most of the dimensions considered above. Specifically, (i) The procedure we use to identify relevant news items does not generate a systematically greater number for larger economies. Still, in larger countries, an intervention is more likely to be covered by rumors or confirmations as a doubling of a country's GDP means approximately 0.5 additional news items per intervention month. The rather low level of statistical significance indicates that this pattern is not as strong as one might expect.

(ii) Unconditionally, the estimated FX trading volume of the respective currency is positively correlated with more news but, after controlling for GDP, no systematic association remains. The size of the economy thus matters more for overall news coverage and the coverage of interventions than a currency's trading volume. (iii) Countries that have a freer press, approximated by having a lower Freedom House score, are covered by more news, but FX interventions are not more likely to be covered. (iv) Furthermore, there is no evidence of systematic differences in reporting during times of crisis, captured by the VIX. (v) While exchange rate regimes do not generally explain differences in news coverage of intervention, the case of ERM-II membership seems to be important as we observe significantly less news if a country is an ERM-II member. This result should be treated with caution though, because among the countries from FGMSS that we can use there are only two ERM-II-countries: Denmark and Slovakia. This may therefore result from pure chance or unobserved characteristics of these countries. However, we rather suspect that ERM-II countries are expected to intervene frequently, thus rendering intervention not very newsworthy. This finding would suggest caution is needed when applying our proxy to ERM-II countries. (vi) In Table A3 we study whether adding covariates helps explain the probability that news is triggered at times of actual interventions. These regressions highlight that larger reserve changes or larger intervention volumes increase the probability of any relevant news. The news-based intervention proxy will thus typically detect the larger interventions, which are also the ones that are more likely to affect outcomes such as the level of the exchange rate. In additional tests, we study persistence of news reports. Contrary to what might be expected, interventions that come after a month without intervention do not have a higher likelihood of resulting in news, even after controlling for country and regime fixed effects. The basic results from above thus can be generalized. Also, during episodes of ongoing intervention, those that have been covered by news during previous months are more likely to receive coverage even after controlling for many country characteristics.

Correction of sample mean intervention series. Our intervention proxy sometimes misses interventions if these are not covered in the news reports. As discussed above, reporting behavior differs by how common interventions are in a given exchange rate regime. To account for these differences, we estimate the degree of underreporting by using separate linear regression models by regime r for each currency c in month t. Using no intercept, a model of the form

$$\text{Actual intervention dummy}_{it} = \beta \text{News-based intervention dummy}_{it} + \epsilon_{it}$$

yields an inflator β that we can then use to correct for the expected amount of underreporting. Assuming that this coefficient is stable over time, we can then calculate a corrected aggregate intervention proxy for each regime my multiplying β_r with the average intervention proxy for exchange rate regime r at time t.

We plot the underlying actual data, the uncorrected proxy and the corrected proxy for in Figure A4. Note that the solid line is the "corrected" number for the full sample, not the subsample for which we have actual intervention data. The corrected proxy series is used in Figure A9 where we aggregate countries that belong to different regimes by emerging market status.

Figure A3: Reserve proxy and actual intervention for the case of Japan

This figure reports the performance of an intervention proxy that is solely based on reserve changes for the case of Japan, where intervention data are public and results can thus be shown. Each bar provides monthly information. The top panel reports all months where the reserve proxy correctly predicts any intervention. The shading allows comparing the true and predicted size of the respective intervention. All volumes in billion USD. Actual intervention amounts (black) and predicted intervention amounts that are based on reserve changes (white). Each bar in the top panel thus consists of a white and a black part. A black bar without a clearly visible white bar indicates excellent fit of the proxy. A white bar on top of a black bar indicates that the proxy overestimated the true intervention. A white bar smaller than a black bar indicates an underestimated true intervention. The middle panel shows erroneously predicted intervention months (false positives) and the reserve changes during those months which would be interpreted as intervention volumes under such a proxy. In all of the cases in this panel, there is thus no actual intervention but a predicted volume based on the reserve change (grey). The bottom panel shows false negatively predicted interventions, which hardly exist for any country (and not at all in the case of Japan) because reserves change every month. Figure based on publicly available data for Japan. The probability of detection is 1, the probability of false alarm is 1. The coefficient of correlation between the actual and predicted volumes is 0.78.

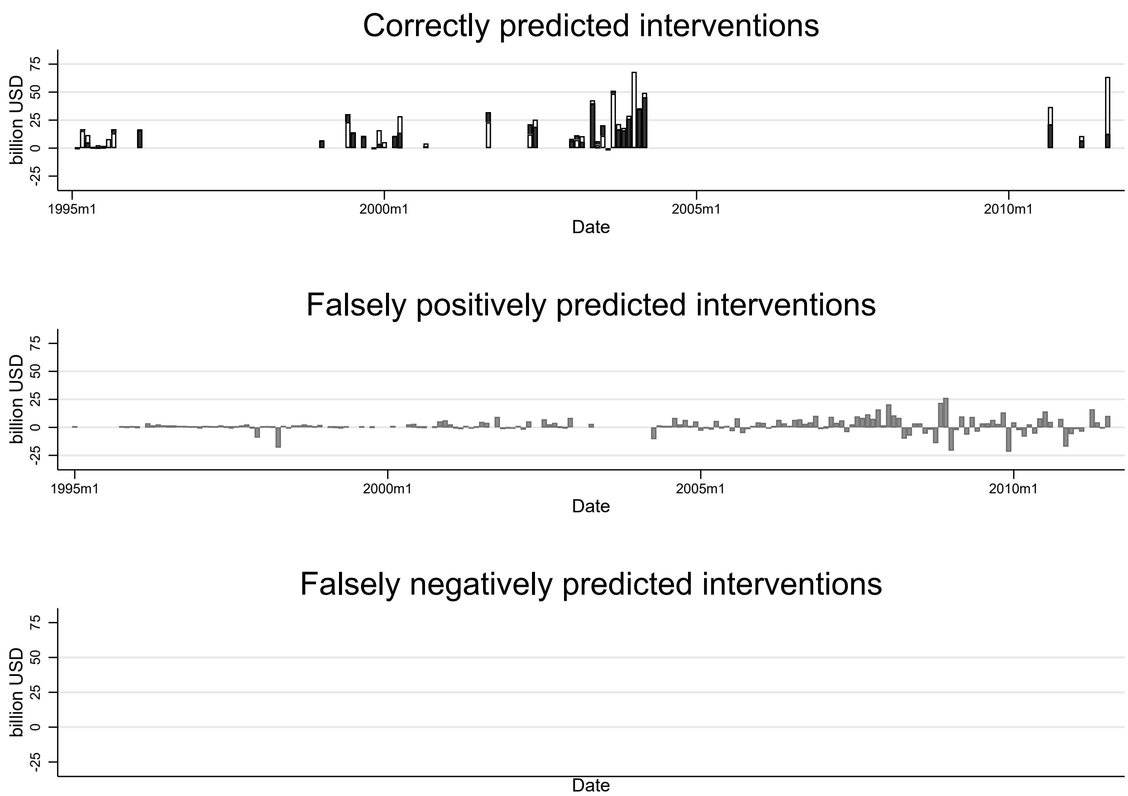


Figure A4: Intervention incidence over time according to the proxy in comparison to actual data

The graph indicates the shares of intervening central banks according to the actual data and the proxy for the same subsample. The time series are smoothed using a rolling 6 month window around each point in time. The underlying data are monthly and the sample is restricted to the 1995-2011 time period used by Fratzscher et al. (2019) to be able to compare an identical set of countries. The "corrected" number is calculated by scaling up the proxy time series with a correction factor as described in Appendix D.

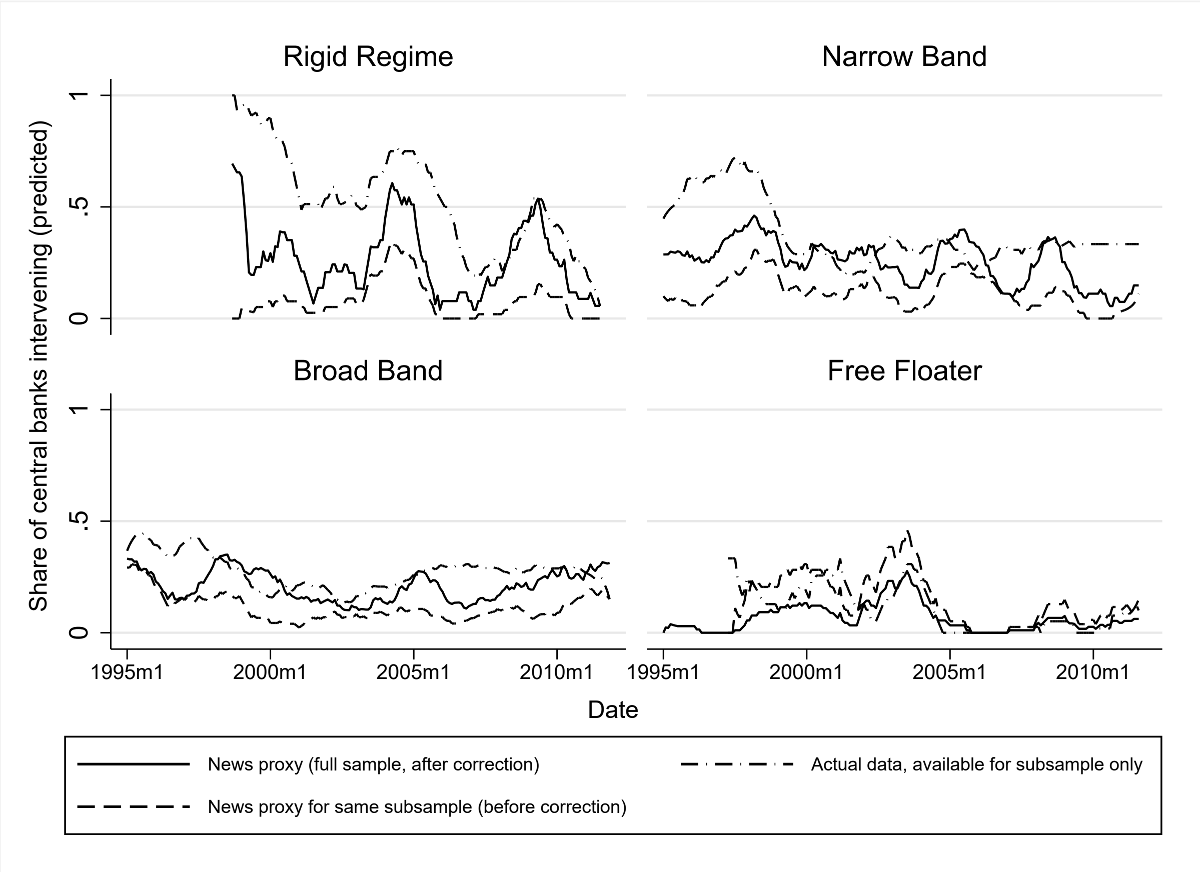


Figure A5: Quality of proxies by intervention size relative to turnover

The graph plots the rate of share of true positives and false positives for the reserve proxy and news-based proxy, respectively. The horizontal axis is a cutoff value that is defined by intervention size relative to FX turnover. FX turnover from the BIS triennial survey. True and false positives are differentiated using the actual intervention data from Fratzscher et al. (2019). The sample is therefore restricted to their 1995-2011 time period. The statistics are calculated for each cutoff and the graph is then automatically smoothed using an epanechnikov kernel of degree 0 and a 0.1 bandwith.

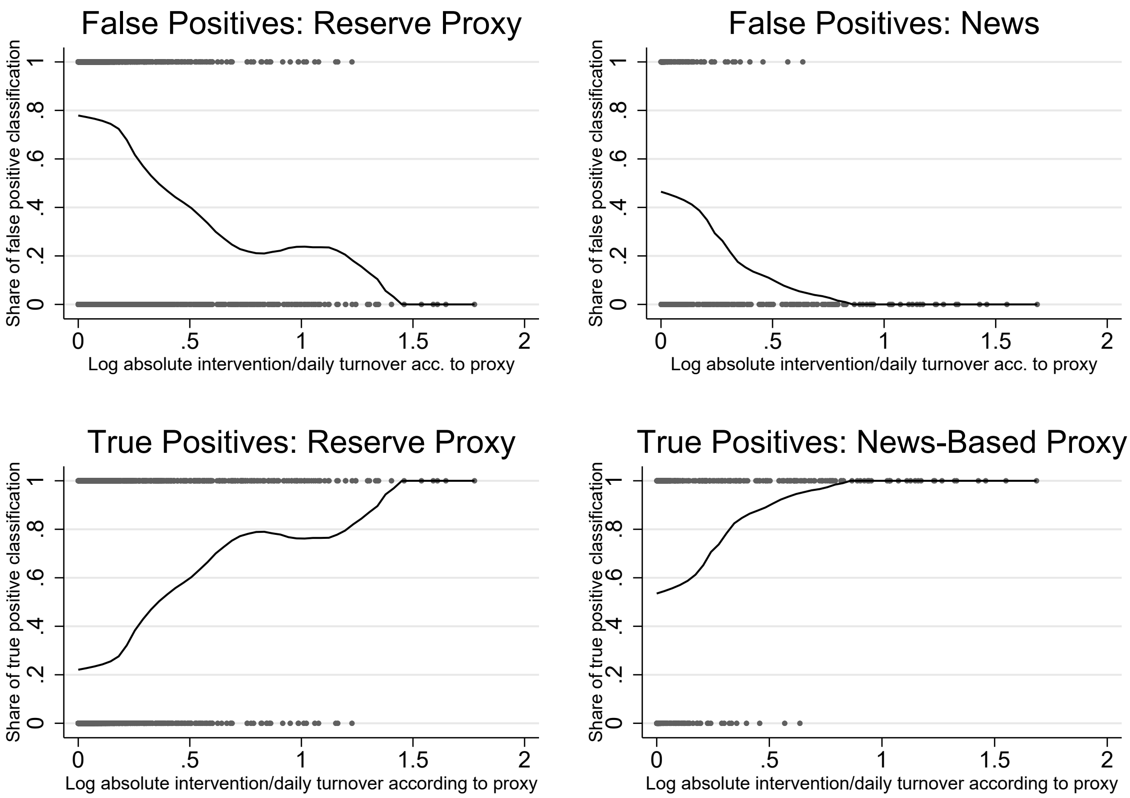


Figure A6: Dynamic relationships of foreign exchange intervention and reserve requirements for foreign currency

This figure reports cumulative impulse responses estimated using a panel VAR model. Compared to Table 5 we do not use the aggregate macroprudential policy index and only focus on reserve requirements for foreign currency loans (rr_foreign) here. The shaded areas indicate 95% confidence intervals, calculated based on 500 Monte Carlo draws. The model is estimated at the quarterly frequency. All variables are included with three lags and there are no exogenous restrictions to the structure of the model imposed. Intervention volumes as a share of GDP based on our intervention proxy. The macroprudential policy index comes from Cerutti et al. (2017a). Quarter-on-quarter changes in exchange rates (d_exrate) are based on end-of-month spot rates.

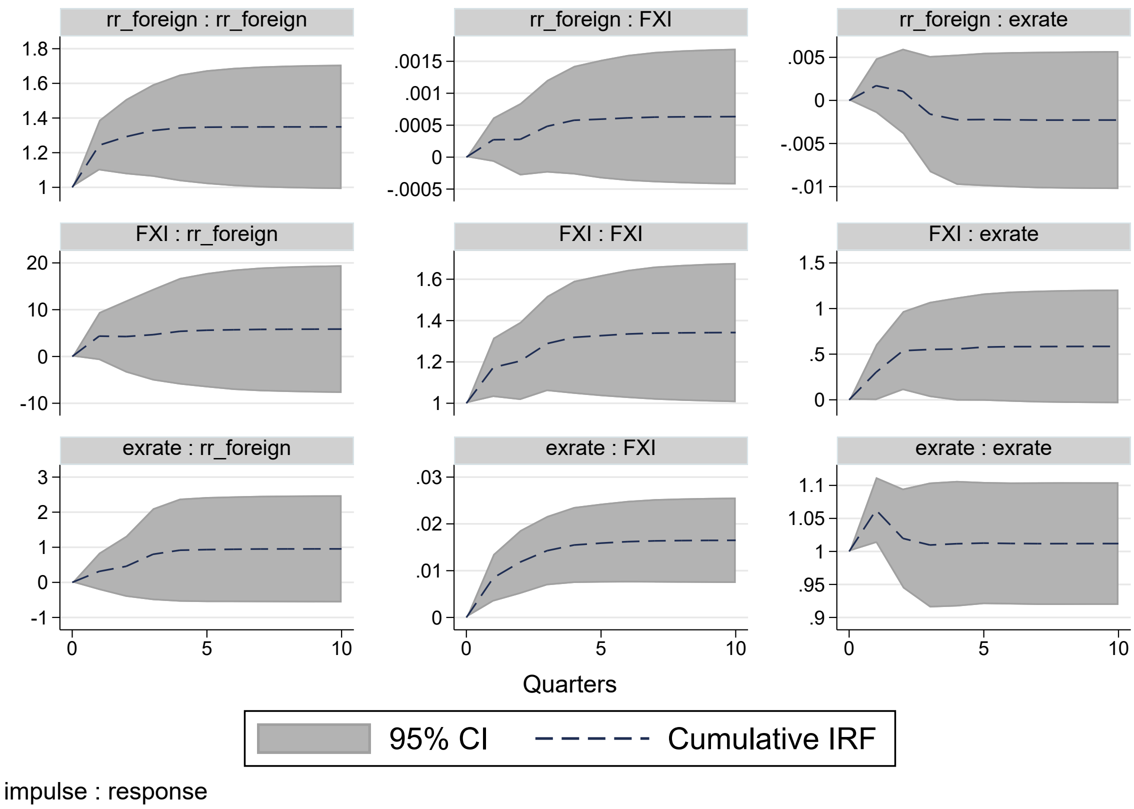


Figure A7: Dynamic relationships of foreign exchange intervention and macroprudential regulation for countries with capital controls

This figure reports cumulative impulse responses estimated using a panel VAR model for the subset of countries that have any capital controls in place. The shaded areas indicate 95% confidence intervals, calculated based on 500 Monte Carlo draws. The model is estimated at the quarterly frequency. All variables are included with three lags and there are no exogenous restrictions to the structure of the model imposed. Intervention volumes as a share of GDP based on our intervention proxy. The macroprudential policy index comes from Cerutti et al. (2017a). Quarter-on-quarter changes in exchange rates (d_exrate) are based on end-of-month spot rates.

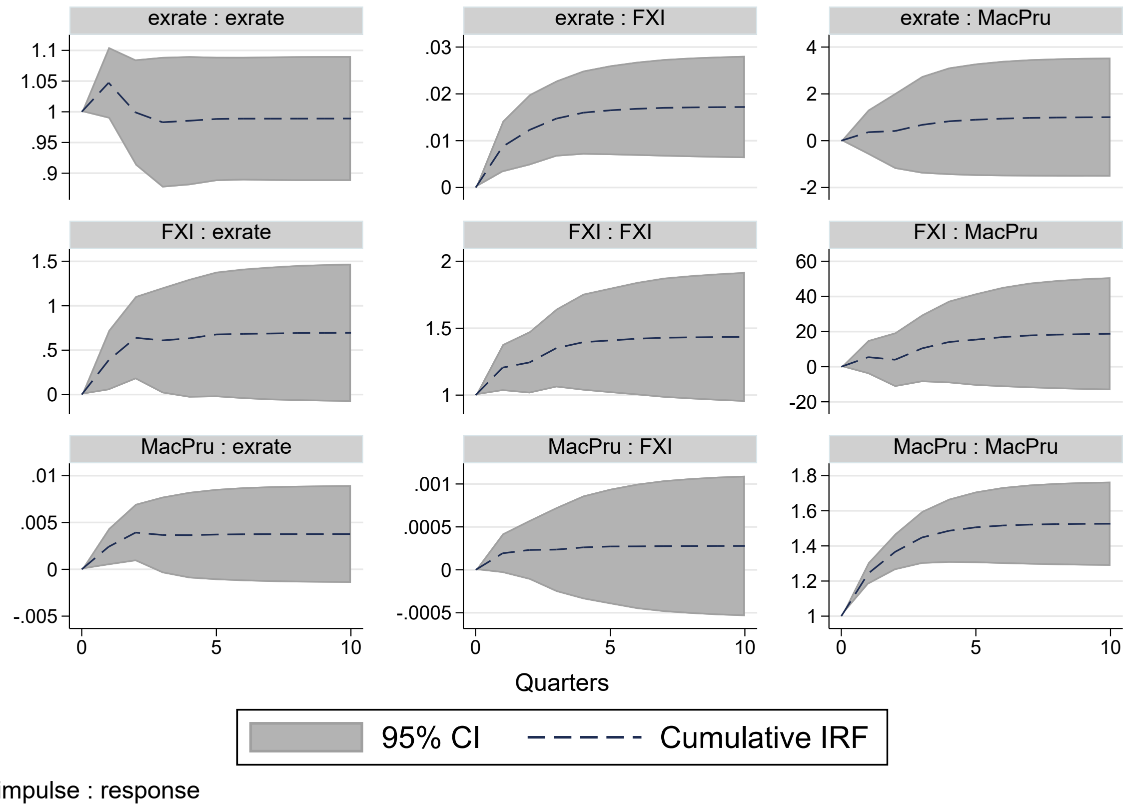


Figure A8: Dynamic relationships of foreign exchange intervention and macroprudential regulation for countries without capital controls

This figure reports cumulative impulse responses estimated using a panel VAR model for the subset of countries that have no capital controls in place. The shaded areas indicate 95% confidence intervals, calculated based on 500 Monte Carlo draws. The model is estimated at the quarterly frequency. All variables are included with three lags and there are no exogenous restrictions to the structure of the model imposed. Intervention volumes as a share of GDP based on our intervention proxy. The macroprudential policy index comes from Cerutti et al. (2017a). Quarter-on-quarter changes in exchange rates (d_exrate) are based on end-of-month spot rates.

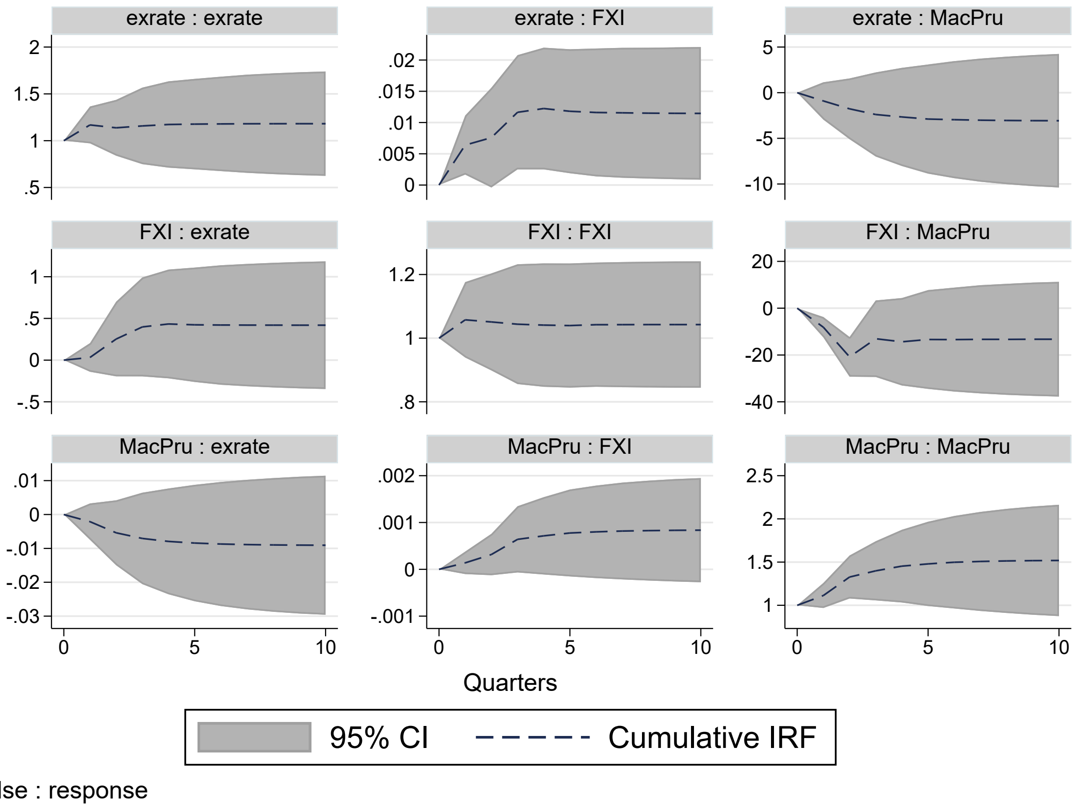


Figure A9: Foreign exchange intervention, capital controls, and changes in macroprudential policies over time

This figure compares estimates for the use of foreign exchange interventions, capital controls and macroprudential policies. The reported share of intervening central banks is estimated using the news-based proxy created in this paper. Capital controls and cumulative macroprudential policy index come from Fernández et al. (2016) and Cerutti et al. (2017a), respectively. These are rescaled as described in the text. Average FX intervention data from our new database are scaled up to reflect estimated underreporting (cf. Figure A4) and smoothed using a rolling 6 month window around each point in time. These statistics refer to all countries and times covered in the data for which all three data series are available.

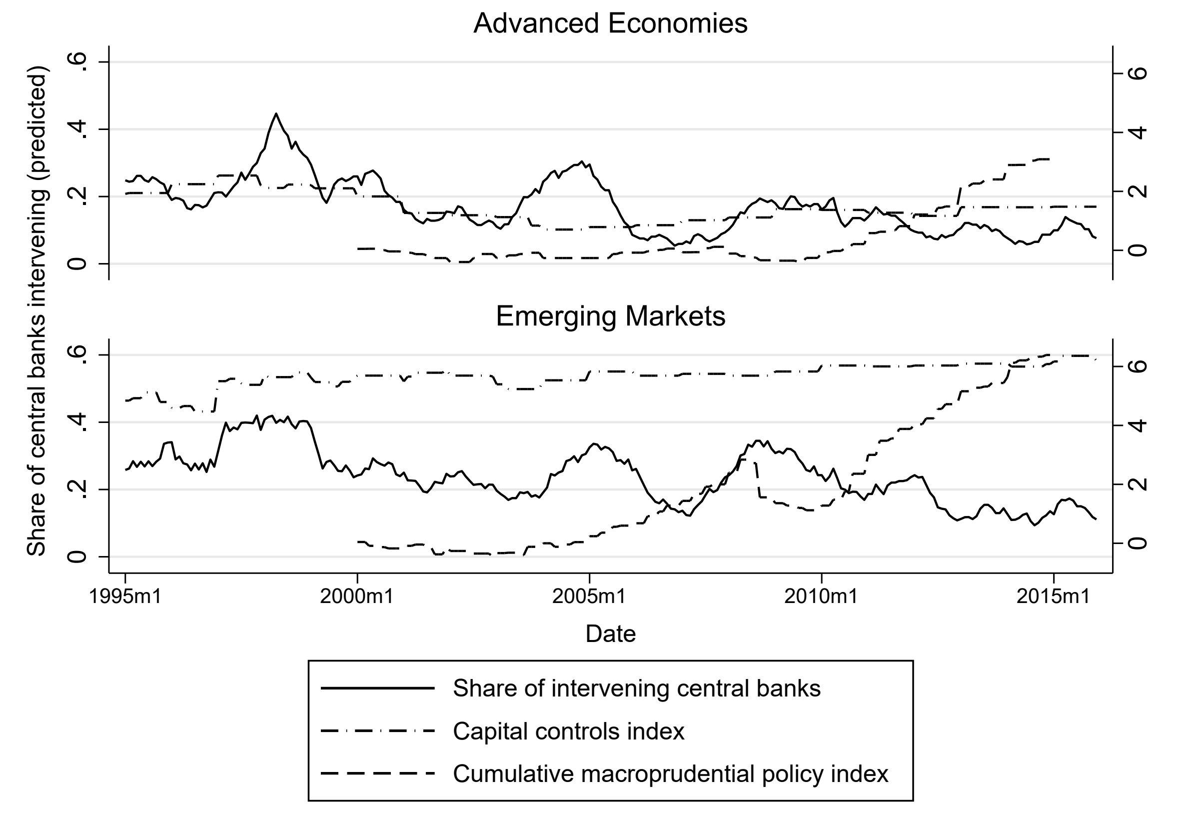


Table A1: Prediction quality measures

		Actual intervention: Yes	Actual intervention: No
Classified as intervention	Yes	True positive (A)	False positive (B)
	No	False Negative (C)	True negative (D)

Table A2: Determinants of observing relevant news items

The table provides estimates of the determinants of observing relevant news items about foreign exchange intervention on Factiva in a given month and country. The dependent variable is given at the top of the column. Column 1 uses the total number of news items yielded by our search query for a country in a given month. Columns 2 to 5 use the number of news items among these that were classified as "rumor" or "confirmation" by our text classification algorithm. Standard errors that cluster at the country level in parentheses.

	(1)	(2)	(3)	(4)	(5)
Outcome	Log number of news per month	Any rumor or confirmation in given month	Any rumor or confirmation in given month	Any rumor or confirmation in given month	Log news items per month with actual intervention
Covariate of interest					
log(GDP)	0.111	0.0710	0.0316	0.00132	0.0647
	(0.179)	(0.0435)	(0.0878)	(0.0579)	(0.159)
log(BIS FX turnover)	-0.147*	-0.112***	-0.0622	-0.0267	-0.0401
	(0.0835)	(0.0291)	(0.0371)	(0.0436)	(0.0732)
Freedom house score	-0.00638	0.000167	0.000494	0.00104	-0.00761**
	(0.00395)	(0.00261)	(0.00214)	(0.00328)	(0.00358)
Vix (rolling, 6 months)	-0.00443	0.000223	-0.00300	0.00292*	-0.00190
	(0.00517)	(0.00181)	(0.00273)	(0.00155)	(0.00622)
ERM II Member	-0.531*	-0.337**	-0.464***	0.0663	-0.351
	(0.256)	(0.140)	(0.120)	(0.135)	(0.216)
Absolute log reserve change	0.130**	0.00917	0.0108	-0.0253*	0.117***
	(0.0551)	(0.0160)	(0.0251)	(0.0129)	(0.0334)
Absolute log exchange rate change	2.113	-1.065	-0.724	-0.882	-1.907
	(1.973)	(0.812)	(1.215)	(0.759)	(2.098)
Regime fixed effects	yes	yes	yes	yes	yes
Observations	1,101	1,101	433	668	433
R-squared	0.152	0.110	0.133	0.033	0.424

Table A3: Determinants of observing relevant news items during intervention months

This table provides estimates for an OLS regression without fixed effects that predicts whether, for a given country, a month has rumors about intervention or confirmation of these on Factiva news according to our text classification algorithm. Heteroskedasticity-robust standard errors used throughout.

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	Any rumor or confirmation in month					
Covariate of interest						
Log(GDP)	0.0500	0.0301	-0.0185	0.0212	-0.00673	-0.122
	(0.0663)	(0.0816)	(0.0808)	(0.0875)	(0.0866)	(0.128)
Log (BIS FX turnover)	-0.0642	-0.0624	-0.0465	-0.0534	-0.0504	-0.0104
	(0.0374)	(0.0372)	(0.0388)	(0.0389)	(0.0392)	(0.0597)
VIX (rolling 6 months)	-0.00360	-0.00372	-0.00367	-0.00478	-0.00353	-0.00357
	(0.00249)	(0.00253)	(0.00277)	(0.00299)	(0.00250)	(0.00284)
Narrow band (0/1)	0.0615	0.0900	0.144	0.151	-0.0514	0.129
	(0.124)	(0.122)	(0.123)	(0.120)	(0.163)	(0.123)
Broad band (0/1)	-0.150	-0.125	-0.0708	-0.0686	-0.278	-0.106
	(0.108)	(0.117)	(0.124)	(0.119)	(0.175)	(0.119)
Free floater (0/1)	0.303*	0.327*	0.362**	0.375**	0.184	0.306*
	(0.162)	(0.176)	(0.170)	(0.167)	(0.224)	(0.151)
Other regime (0/1)	0.295**	0.313**	0.628***	0.569***	0.374	0.529***
	(0.141)	(0.145)	(0.196)	(0.194)	(0.229)	(0.179)
ERM II member	-0.355***	-0.358***	-0.376***	-0.361***	-0.492***	-0.276***
	(0.0424)	(0.0397)	(0.0403)	(0.0391)	(0.104)	(0.0947)
Log(absolute reserve change)		0.0203	-0.00129	-0.00888	-0.00737	0.0113
		(0.0230)	(0.0255)	(0.0267)	(0.0282)	(0.0247)
Log(absolute intervention volume)			0.0515***	0.0291	0.0437**	0.0480***
			(0.0157)	(0.0176)	(0.0156)	(0.0165)
Log(absolute intervention volume/GDP)				8.185***		
				(2.686)		
Freedom house score					0.000515	
					(0.00217)	
Log(population size)						0.107
						(0.0781)
Constant	0.647	0.729	0.969	0.705	1.125	1.565*
	(0.663)	(0.722)	(0.719)	(0.747)	(0.726)	(0.896)
Observations	457	457	457	457	433	457
R-squared	0.119	0.123	0.142	0.149	0.146	0.155

Table A4: Relationship between news reports and absolute intervention volumes

This table provides estimates for an OLS regression without fixed effects that estimates the relationship between the share of a country's intervention volume (in absolute value) and the share of intervention related news, both for the given month and standardized as a percentage within the sample period. For example, if a country intervened using 10 million out of a total of 1 billion in given month and 2 out of 200 news items for the countries occurred in that month, the relationship would be 0.72% of the intervention volume to 1% of the country's news. Actual intervention volumes from Fratzscher et al. (2019). Heteroskedasticity-robust standard errors used throughout.

	(1)	(2)	(3)	(4)
Subgroup	All regimes	Narrow bands	Managed floaters	Free floaters
Share of news in country	0.720***	0.805***	0.486***	1.537***
	(0.0328)	(0.0462)	(0.0507)	(0.107)
Constant	0.00332***	0.00257***	0.00435***	-0.000625
	(0.000441)	(0.000665)	(0.000685)	(0.00157)
Observations	4,276	1,052	2,102	568
R-squared	0.101	0.224	0.042	0.266

Table A5: Relationship between intervention volumes, reserve changes, and news reports

This table provides estimates for an OLS regression without fixed effects that estimates the relationship actual log intervention volumes (in absolute value) and log reserve changes, both as a percentage of GDP, and the log number of news. The regression is estimated at the monthly level. Actual intervention volumes from Fratzscher et al. (2019). Heteroskedasticity-robust standard errors used throughout.

Panel A: Using only reserves

	(1)	(2)	(3)	(4)	(5)
Subset	All regimes	Narrow bands	Managed floaters	Free floaters	Remaining regimes
Log (abs reserve change / GDP)	0.572***	0.635***	0.395***	0.702***	0.618***
	(0.0509)	(0.126)	(0.0991)	(0.145)	(0.0558)
Constant	0.000863***	0.000842*	0.00140***	0.000345	0.000469
	(0.000215)	(0.000484)	(0.000325)	(0.000282)	(0.000414)
Observations	1,309	402	566	62	279
R-squared	0.506	0.509	0.203	0.606	0.685

Panel B: Including the log number of news

	(6)	(7)	(8)	(9)	(10)
Subset	All regimes	Narrow bands	Managed floaters	Free floaters	Remaining regimes
Log (abs reserve change / GDP)	0.555***	0.620***	0.312***	0.649***	0.607***
	(0.0500)	(0.124)	(0.0812)	(0.162)	(0.0554)
log__number__news	0.000764***	0.000448*	0.00191***	0.000229*	0.000548*
	(0.000127)	(0.000251)	(0.000266)	(0.000131)	(0.000290)
Constant	0.000383*	0.000624	0.000363	-9.68e-05	0.000284
	(0.000230)	(0.000527)	(0.000326)	(0.000262)	(0.000423)
Observations	1,309	402	566	62	279
R-squared	0.525	0.514	0.348	0.623	0.688

Table A6: Performance of different intervention proxies

This table provides performance measures regarding incidence and volumes for different intervention dummies. Column 1 reports results for the reserve proxy, i.e., using reserve changes as a proxy for intervention. The proxy in column 2 counts only the largest 19.1 percent of reserve changes (relative to GDP) as interventions. This cutoff is based on the stylized fact that in Fratzscher et al. (2019) there are on average interventions on 19.1 percent of days. Column 3 uses a proxy based on the actual monthly share of intervention months in the Fratzscher et al. (2019) sample, 30.6 of months. Column 4 reports results for the news-based intervention proxy introduced in this paper. Column 5 through 7 implement the proxies from columns 1, 3, and 4 but instead use the Adler et al. (2021) cleaned reserve changes as the cutoff. The benchmark in this figure is the overlap between the actual intervention data from Fratzscher et al. (2019) and the Adler et al. (2021) cleaned reserve change sample. This sample covers 2859 monthly observations from 23 countries.

Name of Proxy	Reserve Changes	Reserve Cutoff	Raw News	Adjusted Reserve	Adjusted Cutoff	Adjusted News
Incidence provided by	Reserve	Cutoff	News	Reserve	Cutoff	News
Volumes provided by	Standard reserve data			Adler et al. spot proxy		
Incidence Accuracy	0.304	0.621	0.748	0.302	0.569	0.748
Probability of detection	1	0.447	0.241	1	0.286	0.241
Probability of false alarm	0.997	0.304	0.033	1	0.309	0.033
Noise-to-signal-ratio	0.997	0.679	0.135	1	1.078	0.135
Volume						
R^2 for volume	0.221	0.261	0.554	0.243	0.197	0.554
Overall						
Correlation coefficient	0.47	0.498	0.512	0.493	0.428	0.512
R^2 overall	0.221	0.248	0.262	0.243	0.183	0.262

Table A7: Performance of different intervention proxies

This table provides performance measures for our news proxy by exchange rate regime using the exchange rate regime classifications by Reinhart and Rogoff.

Regime type	All regimes	Free floaters	Broad bands	Narrow Bands	Others
Incidence					
Accuracy	0.75	0.89	0.77	0.71	0.58
Probabability of detection	0.27	0.60	0.27	0.29	0.17
Probabability of false alarm	0.04	0.08	0.04	0.03	0.01
Noise-to-signal-ratio	0.16	0.13	0.16	0.10	0.06
Volume					
R^2 for volume	0.74	0.71	0.27	0.35	0.75
Overall					
Correlation coefficient	0.76	0.78	0.39	0.41	0.59
R^2 overall	0.58	0.61	0.15	0.17	0.35
Sample size	4276	568	2102	1052	554

Table A8: Summary table: Distribution of key policy instruments

The table provides summary statistics of the frequency of use of foreign exchange intervention, capital controls, and macroprudential policies for different country groups. Capital controls from Fernández et al. (2016) and macroprudential policies from Cerutti et al. (2017). The sample is restricted to the lowest common denominator in terms of time frame, which is 2000-2014 from the Cerutti et al. database. Data are included at the monthly level. Quarter-on-quarter changes counted in column 4 to reflect the structure of the macroprudential policy data. Capital control indices scaled between 0 and 1 as described in Section 4. Changes in policy index can take values between 1 and -1. Cumulative index takes values between -8 and 25.

	Any intervention according to proxy	Inflow controls index	Outflow controls index	Changes in macroprud. policy index	Cumulative macroprud. policy index
All countries	0.107	0.337	0.411	0.057	1.134
Advanced Economies	0.098	0.140	0.193	0.044	0.387
Emerging Markets	0.118	0.494	0.584	0.069	1.787
Narrow bands	0.120	0.438	0.477	0.041	1.253
Broad bands	0.125	0.311	0.417	0.069	1.666
Free floaters	0.080	0.081	0.165	0.045	0.470
Other regimes	0.072	0.382	0.427	0.051	0.196

Table A9: Summary statistic of main working sample

This table provides summary statistics of the intervention database that is used in most parts of the text. Exchange rate regimes based on annual coarse classification by Ilzetzki et al. (2017a, 2017b). 1 represents rigid regimes, 2 narrow bands, 3 broad bands, 4 free floaters, 5 and 6 other regimes. FX turnover is based on the BIS triennial survey (e.g. BIS, 2017) thus not always available.

Country	First year covered	Last year covered	Average GDP in billion USD	Average daily FX turnover in billion USD	Regimes
Argentina	1995	2016	349	1.5	1,2,5,
Australia	1995	2016	848	193	4
Brazil	1995	2016	1315	23	2,3,5
Bulgaria	1995	2015	33	0.74	1,5
Canada	1995	2016	1173	135	2,3
Chile	1995	2016	148	6.2	3
China	1995	2016	4011	50	1,2
Colombia	1995	2016	196	3.2	3
Croatia	1995	2016	43		1,2
Czech Republic	1995	2016	139	8.0	2,3
Denmark	1995	2016	258	22	1,2
EMU	1999	2016		1226	4
Hong Kong	1997	2016	210	60	1
Hungary	1995	2016	97	9.6	2,3
Iceland	1995	2016	13		2,3
India	1995	2016	1029	25	1,2,3
Indonesia	1995	2016	458	4.4	2,3,5
Israel	1995	2016	179	6.1	3
Japan	1995	2016	4875	612	4
Kenya	1995	2016	29		2,3
Latvia	1995	2015	18	0.28	1,2,3
Lebanon	1995	2016	27		1
Malaysia	1995	2016	177	7.8	1,2,3,4
Malta	1995	2016	6.7		1,2,3
Mexico	1995	2016	841	51	3,5
New Zealand	1995	2016	112	45	3
Nigeria	1995	2016	232		2,3,5
Norway	1995	2016	313	41	3
Peru	1995	2016	103	1.5	2,3
Philippines	1995	2016	146	3.7	1,2,3,5
Poland	1995	2016	331	20	2,3,6
Romania	1995	2016	110	3.9	1,2,3,5
Russia	1995	2015	995	28	2,3,5,6
Saudi Arabia	1995	2016	379	3.8	1
Singapore	1995	2016	166	38	3
Slovak Republic	1995	2016	57		1,2
Slovenia	1995	2015	36		1,2
South Africa	1995	2016	245	25	3,6
South Korea	1995	2016	870	39	2,3,5
Sweden	1995	2016	396	57	2,3
Switzerland	1995	2016	455	170	1,3
Thailand	1995	2016	239	7.8	1,3,5
Turkey	1995	2016	489	29	3,5
Ukraine	1995	2016	97		1,3,5,6
United Kingdom	1995	2016	2224	375	3,4
United States	1995	2016	12767	2515	4
Uruguay	1995	2016	30		2,3,5
Venezuela	1995	2016	206		1,2,5
Vietnam	1995	2015	85		2

Table A10: Overview of overlap between actual intervention data and main working sample

This table provides an overview of the overlap between the new proxy sample and Actual intervention data as in Fratzscher et al. (2019). Exchange rate regimes based on annual coarse classification by Ilzelzki et al. (2017a, 2017b). 1 represents rigid regimes, 2 narrow bands, 3 broad bands, 4 free floaters, 5 and 6 other regimes. FX turnover is based on the BIS triennial survey (e.g. BIS, 2017) thus not always available.

Country	First year covered	Last year covered	Average GDP in billion USD	Average daily FX turnover in billion USD	Regimes
Argentina	2003	2011	282	1.1	2
Australia	1997	2011	731	148	4
Canada	1995	2011	1016	98	2,3
Chile	2001	2011	145	3.9	3
Colombia	1999	2011	167	1.7	3
Croatia	1996	2011	40		1,2
Czech Republic	1995	2011	122	4.8	2,3
Denmark	1995	2011	238	15	1,2
EMU	1999	2016		1226	4
Hong Kong	1998	2009	184	47	1
Iceland	1995	2011	12		2,3
Israel	1995	2011	150	3.6	3
Japan	1995	2011	4784	441	4
Kenya	1999	2011	25		2
Mexico	1997	2011	798	26	3
New Zealand	1995	2010	90	27	3
Norway	1995	2011	268	29	3
Peru	1995	2011	79	0.58	2,3
Poland	1995	2010	277	14	3
Slovak Republic	1999	2008	45		2
South Africa	1999	2011	233	21	3
Sweden	1995	2006	300	21	2,3
Switzerland	1995	2001	301	93	3
Turkey	2002	2011	534	12	3,5
United Kingdom	1995	2011	2071	294	3,4
United States	1997	2011	12179	2072	4
Venezuela	1997	2011	177		1,2

Table A11: Logit Estimates on capital controls and intervention corresponding to Table 4

This table provides logit estimates of the relationship between foreign exchange intervention and capital controls. Panel A provides a comparison of intervention proxy and true data. Panel B provides estimates of the relationship for advanced and emerging countries, respectively, as well as differentiating between inflow and outflow controls. The dependent variable is the foreign exchange intervention proxy or actual intervention data from Fratzscher et al. (2019). Capital controls data from Fernández et al. (2016) and included as levels. Intervention data are monthly while capital controls data are yearly. Hence, we do not use changes in capital controls here and treat capital controls as a background variable. The sample period is from 1995-2015. The logit models include year and regime fixed effects where indicated. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Comparison of proxy and actual data

	(1)	(2)	(3)	(4)
Outcome variable	Intervention proxy	Intervention proxy	Intervention proxy	Actual intervention
Subgroup	All	All	Sample of column 4	If actual data available
Covariate of interest				
Capital controls	0.593***	0.577***	0.779***	1.361***
(levels)	(0.0920)	(0.0858)	(0.206)	(0.153)
Year FE	yes	no	yes	yes
Regime FE	yes	no	yes	yes
Observations	11,731	11,731	3,971	3,971

Panel B: Subgroup analysis for the intervention proxy

	(5)	(6)	(7)	(8)
Covariate of interest	All controls	All controls	Outflow controls	Inflow controls
Subgroup	Advanced economies	Emerging markets	All	All
Estimate	1.094***	0.321**	0.580***	0.445***
	(0.171)	(0.136)	(0.0825)	(0.0958)
Year FE	yes	yes	yes	yes
Regime FE	yes	yes	yes	yes
Observations	5,214	6,503	11,731	11,742

Table A12: FX intervention and the changes of capital controls

The table reports estimates of the relationship between FX interventions and changes in capital controls. Interventions are included as dummy variables. We either use our proxy or actual intervention data in different columns. Capital controls data from Fernández et al. (2016) and included as changes. Intervention data are monthly while capital controls data are yearly, hence aggregate intervention variables up to the yearly level. To reflect that monthly intervention data are aggregated up, Panel A and B use different outcome variables. Panel A uses a dummy variable that takes the value 1 if there was any intervention during the respective year (i.e., the maximum of the intervention series per country-year). Panel B uses the number of months with interventions (i.e., the sum of the intervention series per country-year). The sample period is from 1995-2015. All estimates are based on OLS models. These include year and regime fixed effects where indicated. Heteroskedasticity-robust standard errors throughout. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: FXI proxy measuring whether any FX intervention during the year

	(1)	(2)	(3)	(4)
Outcome variable	Intervention proxy	Intervention proxy	Intervention proxy	Actual intervention
Subgroup	All	All	Sample of column 4	If actual data available
Estimate	-0.0007	0.0000	0.0020	0.0005
	(0.0018)	(0.0017)	(0.0028)	(0.0011)
Year FE	yes	no	yes	yes
Regime FE	yes	no	yes	yes
Observations	922	931	305	305
R-squared	0.073	0.000	0.052	0.050

Panel B: FXI proxy measuring number of months with any FX intervention during year

	(5)	(6)	(7)	(8)
Outcome variable	Intervention proxy	Intervention proxy	Intervention proxy	Actual intervention
Subgroup	All	All	Sample of column 4	If actual data available
Estimate	-0.0007	0.0000	0.0020	0.0005
	(0.0018)	(0.0017)	(0.0028)	(0.0011)
Year FE	yes	no	yes	yes
Regime FE	yes	no	yes	yes
Observations	922	931	305	305
R-squared	0.073	0.000	0.052	0.050

Table A13: Capital controls and FX intervention by exchange rate regime

This table provides estimates of the relationship between foreign exchange intervention and capital controls. Panel A uses inflow controls, Panel B uses outflow controls. The dependent variable is the foreign exchange intervention proxy or actual intervention data from Fratzscher et al. (2019). Capital controls data from Fernández et al. (2016) and included as levels. Intervention data are monthly while capital controls data are yearly. Hence, we do not use changes in capital controls here and treat capital controls as a background variable. The sample period is from 1995-2015. The OLS models include year and regime fixed effects where indicated. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Levels of inflow controls

	(1)	(2)	(3)	(4)
Covariate of interest	Inflow controls			
Subgroup	Narrow Bands	Broad Bands	Free Floaters	Other regimes
Covariate of interest				
Inflow controls	0.100***	0.0341**	-0.354***	-0.000
(levels)	(0.0183)	(0.0152)	(0.0744)	(0.0153)
Year FE	yes	yes	yes	yes
Observations	2,779	5,209	1,057	2,697
R-squared	0.033	0.020	0.149	0.065

Panel B: Levels of outflow controls

	(5)	(6)	(7)	(8)
Covariate of interest	Outflow controls			
Subgroup	Narrow Bands	Broad Bands	Free Floaters	Other regimes
Covariate of interest				
Outflow controls	0.110***	0.0434***	-0.222***	0.0326**
(levels)	(0.0169)	(0.0115)	(0.0534)	(0.0144)
Year FE	yes	yes	yes	yes
Observations	2,768	5,209	1,057	2,697
R-squared	0.037	0.021	0.149	0.067

Table A14: Capital controls and FX intervention by direction of flow

This table provides estimates of the relationship between foreign exchange intervention and capital controls. Panel A uses levels of controls by direction and development level of the economy. Panel B uses changes (here at the monthly level, cf. Table A12). The dependent variable is the foreign exchange intervention proxy or actual intervention data from Fratzscher et al. (2019). Capital controls data from Fernández et al. (2016) and included as levels. Intervention data are monthly while capital controls data are yearly. Hence, we do not use changes in capital controls here and treat capital controls as a background variable. The sample period is from 1995-2015. The OLS models include year and regime fixed effects where indicated. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Levels of capital controls

	(1)	(2)	(3)	(4)
Subgroup	All	All	Advanced Economies	Emerging Markets
Covariate of interest				
Inflow controls	0.0423***		0.0853***	0.0243*
	(0.00954)		(0.0231)	(0.0133)
Outflow controls		0.0542***		
		(0.00787)		
Year FE	yes	yes	yes	yes
Regime FE	yes	yes	yes	yes
Observations	11,742	11,731	5,214	6,528
R-squared	0.029	0.031	0.025	0.037

Panel B: Changes in capital controls

	(1)	(2)	(3)	(4)
Subgroup	All	All	Advanced Economies	Emerging Markets
Covariate of interest				
Inflow controls	-0.00853		-0.0919	0.0146
	(0.0356)		(0.0696)	(0.0425)
Outflow controls		-0.00584		
		(0.0301)		
Year FE	yes	yes	yes	yes
Regime FE	yes	yes	yes	yes
Observations	11,196	11,184	4,977	6,219
R-squared	0.028	0.028	0.023	0.038

Table A15: Prudential policies and FX intervention by exchange rate regime

This table provides estimates of the relationship between foreign exchange intervention and prudential policies by exchange regime. Panel A uses levels of prudential policies. Panel B uses quarterly changes for reserve requirements for foreign currency, which we expect to be more closely linked with foreign exchange intervention than others macroprudential policies. The dependent variable is the foreign exchange intervention proxy or actual intervention data from Fratzscher et al. (2019). Capital controls data from Cerutti et al. (2016). Intervention data are monthly. Macroprudential policy data are quarterly, hence we aggregate intervention data up accordingly.The sample period is from 2000-2014. The OLS models include year . *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Panel A: Levels of prudential policy index

	(1)	(2)	(3)	(4)
Covariate of interest	Level of macroprudential policies			
Subgroup	Narrow Bands	Broad Bands	Free Floaters	Other regimes
MacPrus	0.00547*	0.0291***	-0.0317	-0.0185***
(levels)	(0.00304)	(0.00435)	(0.0231)	(0.00409)
Year FE	yes	yes	yes	yes
Observations	596	1,315	264	700
R-squared	0.044	0.057	0.217	0.094

Panel B: Changes in reserve requirements for foreign currency

	(5)	(6)	(7)	(8)
Covariate of interest	Level of macroprudential policies			
Subgroup	Narrow Bands	Broad Bands	Free Floaters	Other regimes
ResReq	0.0439	0.130**	*No changes*	0.0132
(changes)	(0.0588)	(0.0624)	*to exploit*	(0.0701)
Year FE	yes	yes	yes	yes
Observations	596	1,315	264	700
R-squared	0.040	0.022	0.212	0.060

Table A16: FX intervention and the levels of prudential policies

The table reports estimates of the relationship between FX interventions and the macroprudential policy level. The table provides the equivalent to Table 5. Interventions are included as dummy variables. We either use our proxy or actual intervention data in different columns. Macroprudential policies are from Cerutti et al. (2017a). Since macroprudential policy data quarterly, intervention data are aggregated up to quarterly data. The Cerutti et al. database is based on changes and does not have a start level, so we use the cumulative changes variable they provide. This should be interpreted not as a level of intensity but as a level in addition to the policies that were already in place in the end of 1999 in the given country. The sample period is from 2000-2014. All estimates are based on OLS models. These include year and regime fixed effects where indicated. Heteroskedasticity-robust standard errors throughout. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)
Outcome	Intervention proxy		Actual intervention data	Intervention proxy	
Subgroup	All	Sample of column 3	Countries where actual data available	Advanced Economies	Emerging Markets
Covariate of interest					
Cumulative PruC	0.00523***	-0.00370	-0.00401	0.00992***	0.00280**
	(0.000978)	(0.00315)	(0.00403)	(0.00197)	(0.00116)
Regime FE	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
Observations	8,445	2,997	2,997	3,957	4,488
R-squared	0.024	0.015	0.069	0.030	0.026