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Conference Paper

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Beiträge zur Jahrestagung des Vereins für Socialpolitik 2019: 30 Jahre Mauerfall - Demokratie und Marktwirtschaft - Session: International Economics - Exchange Rates, No. A14-V1

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Rieth, Malte; Menkhoff, Lukas; Stöhr, Tobias (2019) : The dynamic impact of FX interventions on financial markets, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2019: 30 Jahre Mauerfall - Demokratie und Marktwirtschaft - Session: International Economics - Exchange Rates, No. A14-V1, ZBW - Leibniz-Informationszentrum Wirtschaft, Kiel, Hamburg

This Version is available at:

<https://hdl.handle.net/10419/203504>

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The dynamic impact of FX interventions on financial markets

Lukas Menkhoff, Malte Rieth and Tobias Stöhr

Abstract

Evidence on the effectiveness of FX interventions in the prevailing higher frequency approaches leaves a gap at horizons going beyond a few days. This is addressed by identifying a structural vector autoregressive model for the daily frequency with an external instrument. Using Japanese data, we find that FX interventions significantly affect exchange rates, although the effect is smaller than in emerging markets, and this impact persists for up to a year. There is no major effect on interest rates, but stock prices increase in line with currency devaluation, in particular those of large (exporting) firms. The results qualitatively hold for US and UK interventions.

JEL-Classification: F 31 (foreign exchange); F 33 (international monetary arrangements); E 58 (central banks and their policies)

Keywords: Foreign exchange intervention; structural VAR; exchange rates; interest rates; stock prices

February 14, 2019

We thank Dario Caldara, Georgios Georgiadis, Peter Karadi, Mathias Klein and Alexander Kriwoluzky for very helpful comments. We also gratefully acknowledge financial support by the German Research Foundation (DFG, ME 1070/12).

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1 Introduction

The case of foreign exchange (FX) interventions has gained prominence over the last years. Policy makers, in particular from the International Monetary Fund (IMF), seem to be much more open to the application of FX interventions as a policy tool than in the decades before (IMF, 2012; Blanchard et al., 2015; Ghosh et al., 2017). In line with this new appreciation of interventions, it is documented that central banks all over the world see this instrument as a regular part of their toolkit and apply it accordingly (Neely, 2008; Mohanty and Berger, 2013). This policy stance is complemented by a set of recent theoretical papers, adding to the earlier literature, such as Vitale (2003). They show that FX interventions can have positive effects for the economies applying them (Gabaix and Maggiori, 2015; Hassan et al., 2016; Fanelli and Straub, 2017; Chang, 2018; Basu et al., 2019; Cavallino, 2019).

In some contrast to these rather homogeneous positions of policy makers and theorists, there is less progress on the empirical front. While we take stock of this literature later on, we summarize that the most convincing evidence about the effectiveness of FX interventions is based on event studies (e.g., Fatum and Hutchison, 2003; Fratzscher et al., 2019). An attractive feature of this approach is the use of high frequency data, which reduces the risk of reverse causality and of confounding factors. However, it typically views the actual interventions as the true policy shocks, while it is likely that actual interventions measure such latent shocks with error. Important but difficult to capture aspects of interventions are central bank communication, the choice between spot and derivatives, and other related elements of a broader concept. Moreover, event studies, by definition, provide evidence over shorter horizons, such as a few days.

There are of course also studies addressing the longer-term impact of interventions by relying on lower frequency data (e.g., Blanchard et al., 2015, Adler et al., 2015). While this allows drawing conclusions about the macroeconomic effects of interventions, identification and measurement are more debatable when using monthly or quarterly data. Identification often relies on exclusion restrictions or tenuous instruments and data on the policy-induced foreign exchange position of the public sector are rarely available.

In this paper, we use a structural vector autoregression (VAR) for the daily frequency identified with an external instrument to study the dynamic effects of FX interventions on financial markets. This methodology, which is also called a Proxy-SVAR, was developed by Stock and Watson (2012) and Mertens and Ravn (2013) and is new to the FX intervention literature. It preserves the attractive features of the event study design and of models for lower

frequency data but addresses some of their key limitations. First, it views the actual interventions as a noisy measure, or instrument external to the VAR, for latent intervention shocks. By accounting for several forms of measurement error, it reduces the attenuation bias present in estimates from models treating the actual interventions as a one-to-one mapping to the intervention shocks. Second, it allows for quantifying the persistence of the effects of FX interventions, which is key for macroeconomists and policy makers. Third, by relying on high frequency data, it reduces the risk of confounding factors, reverse causality, and mismeasurement of policy-induced changes in reserves plaguing identification strategies for lower frequency data.

The study is mainly based data in the US-Dollar-Japanese Yen (USD/JPY) market. We select this case because it is a relatively rare flexible exchange rate regime (Ilzetzki et al., 2019), has many interventions, is a liquid market and is a relevant exchange rate for the world economy. While the use of daily data limits the set-up of the VAR largely to financial variables, this does not seem to be a problem from a macroeconomic viewpoint. Given the high number of observations in our sample we can include many lags of the endogenous variables without running into the curse of dimensionality and thereby estimate the impact of interventions reliably at macroeconomically relevant horizons of several quarters.

The crucial issue for our identification approach is the instrument. We propose using the first day of an intervention sequence as a proxy for latent intervention shocks. The central assumption is that news about the economy do not affect the decision to start a new sequence, which we argue is taken at least one day in advance. In a regime of largely floating exchange rates, there is no clear and communicated policy on exchange rate stabilization. So interventions are largely exogenous. Of course, interventions may be more or less probable but they are not anticipated with any certainty. As interventions often occur in sequences, this argument holds in particular for the first day, or the first intervention during a day, but less so for subsequent interventions. We provide detailed evidence on this argument in Section 2.2 and note that high-frequency studies reveal that most of an intervention impact comes from the first intervention (e.g. Fischer and Zurlinden, 1999; Payne and Vitale, 2003), indicating that these indeed surprise the market.

We have three main findings. First, a one standard deviation intervention shock by the Japanese authorities, equivalent to a purchase of 1.7 bn US-Dollar, depreciates the Yen significantly by about 0.2% relative to the US-Dollar, Pound and Euro. A comparison with previous findings (e.g., Kearns and Rigobon, 2005, Chen et al., 2012) shows that our estimate

(when considering the same sample) is at the upper end of the available estimates, consistent with the argument that accounting for measurement error reduces the attenuation bias and leads to more precise estimates of the efficacy of FX interventions. Qualitatively and in terms of statistical significance, we document similar effects on the exchange rate for the US and the UK. Second, the effect is highly persistent. The shock moves the exchange rate significantly for about four quarters. Third, we provide novel evidence on the dynamic impact of interventions on other asset prices. We find that Japanese interest rates remain largely unaffected, whereas the depreciation has significant and heterogeneous effects on stock prices of large vs. small firms. Equity valuations of the former (rather exporters) increase by about 0.1%, while those of the latter (rather importers) decrease by roughly the same amount.

Literature. Our study contributes to the literature about the effectiveness of FX interventions. One of the main challenges in this literature is the clean identification of an intervention impact in a macro environment where many forces interact. This seems easiest with very high frequency data which is where we start the short overview.

High frequency studies (e.g. Dominguez, 2003; Pasquariello, 2007; Melvin et al., 2009) can largely rule out interference by other influences than interventions due to the extremely short time interval of observation. However, their disadvantage is exactly this short-term concept. Although studies such as Payne and Vitale (2003) use the term of a “permanent” price impact of interventions, this permanence refers to high-frequency data. They cannot say anything about the impact over many days, weeks or longer. Still, these studies provide evidence of interventions’ effectiveness.

In particular event studies operate at lower frequencies. These typically use daily data and analyze horizons of days or a few weeks at most (e.g., Fatum and Hutchison, 2003; Fratzscher et al., 2019). Alternative approaches at this frequency include Kearns and Rigobon (2005) who exploit a policy change in Japan (and similarly in Australia), which is a country-specific event and thus this method cannot be generalized. Chen et al. (2012) use a Bayesian data interpolation method to infer intra-daily intervention pattern from observable daily data as a way to improve identification. All of these approaches find that interventions are highly effective (see also Dominguez et al., 2012, 2013). However, estimates may be more affected by confounding factors.

Another alternative approach is comparison to self-constructed counterfactuals. A prime example is Fischer und Zurlinden (1999) who, using transactions by the Swiss central bank, find that only interventions have an impact on exchange rates whereas transactions as fiscal

agent (which are transparently classified as such to the market) do not move the exchange rate. In order to generalize such an approach, counterfactuals can either be created by time-series forecasts (which are highly unreliable, Rossi, 2013) or by matching approaches (e.g., Fatum and Hutchison, 2003).

In relation to these approaches which rely on higher frequency data, conventional macro approaches seem to produce less reliable results. Still, there is a new and innovative literature in this direction. Blanchard et al. (2015) analyze a cross-country panel with quarterly data and basically use as an instrument for FX interventions the closeness of this country's reserves to an optimal level of reserves. Daude et al. (2016) take a similar route with monthly data, and use as instrument the ratio of reserves to M2. Finally, Adler et al. (2015) combine a set of instruments, which are similar to the mentioned ones. All studies find evidence for effective FX interventions and due to the lower frequency data their impact seems to persist for months or longer. The problem with these approaches is the weakness of their instruments which may be plausible to some extent but must be quite imprecise given the many reasons to intervene. Earlier papers in this direction include Dominguez and Frankel (1993) who use oral interventions as instrument for actual interventions, which would be not convincing in today's environment where communication is an explicit part of the policy concept.

The remaining paper is organized in five more sections. Section 2 describes the specific VAR model we employ, Section 3 shows results and Section adds extended results. Robustness checks are mentioned in Section 5 and Section 6 provides conclusions.

2 The Proxy-SVAR model

In this section, we first discuss the specification of the reduced form model, before we outline how we construct an instrument that captures the foreign exchange market intervention shock. Last, we show how the instrument is used to identify the structural model.

2.1 Reduced form model

The VAR model is

$$y_t = c + \Pi(L)y_{t-1} + \Gamma x_t + u_t, \quad (1)$$

and refers to variables at a daily frequency. The $k \times 1$ -vector c includes constant terms, the $k \times l$ matrix Γ collects the contemporaneous impact of l exogenous variables contained in the vector x_t , the matrix $\Pi(L)$ in lag polynomials captures the autoregressive part of the model,

and the vector u_t contains k serially uncorrelated innovations, or reduced form shocks, with $V(u_t) = \Sigma$ and $u_t \sim N(0, \Sigma)$.

We employ different specifications for the endogenous variables in y_t . The baseline specification includes the two variables that have been the focus of most of the previous literature: the size of the interventions and the nominal exchange. Specifically, we compute the cumulative daily interventions in million US-Dollars over the full sample. We use the level of this variable as our policy indicator to scale the size of the policy shock and to estimate its persistence. Moreover, we use the log of the bilateral nominal exchange rate of the intervening country to its reference currency. We define it as foreign currency to domestic currency such that an increase in the exchange rate implies an appreciation of the domestic currency. In extended specifications, y_t includes the two baseline variables plus additional variables, such as further bilateral exchange rates or interest rates and equity prices, which change across specifications.

Our sample depends on the data availability of the variables in y_t . In the bivariate model, it starts on April 1, 1991 and ends on January 4, 2017, for a total of 6723 observations. In some of the extended specifications, the sample starts later as data on one of the additional variables are unavailable before. The shortest sample starts on January 2, 1995 and contains 5743 observations. Given the large number of observations, we include 50 lags of the endogenous variables although Akaike's information criterion indicates only between 6 and 19 lags, depending on the specification. In this way, we carefully control for secular movements in exchange rates and can more reliably estimate the responses of the endogenous variables at longer horizons – of, say, 100 trading days. Finally, to control for potential institutional or seasonal patterns, the model contains day-of-the-week and monthly dummies in the vector of exogenous variables.

The VAR innovations are assumed to be linearly driven by an intervention policy shock ε_t^p , which we aim to identify, and other structural shocks ε_t^* , which are of no interest for the purpose of this paper. The VAR innovations u_t are related to the structural shocks as

$$u_t = b^p \varepsilon_t^p + B^* \varepsilon_t^* \quad (2)$$

The $k \times 1$ -vector b^p captures the impulse vector to an intervention shock of size 1 and is required to generate impulse responses to a one standard deviation shock. We use the identification approach with external instruments developed by Stock and Watson (2012) and Mertens and Ravn (2013). When a variable s_t is available such that

$$E(s_t \varepsilon_t^p) \neq 0 \quad \text{and} \quad E(s_t \varepsilon_t^*) = 0, \quad (3)$$

it can be used to consistently estimate the impulse vector b^p . We now discuss how we compute s_t in order to ensure that the conditions in (3) are satisfied and then outline how we use it to estimate b^p and to identify ε_t^p .

2.2 Data and instrument

Data. We use higher frequency data (i.e. daily) as is the event study literature on FX interventions. We refer mainly to the case of Japan, which publishes its daily intervention data in million USD. For the period covered, i.e. April 1991 to January 2017, there are 316 intervention days. They are shown in Figure 1, Panel A. Most of them are purchases of US-Dollars. They cluster in the 1990s, but there are also interventions in the 2000s. The average intervention amount per day is 1.7 bn US-Dollar. The Bank of Japan typically intervenes in sequences of several days or even weeks. Descriptive statistics are provided in Table 1.

<Table 1>

The procedure how decisions are made is, for example, illustrated in Ito and Yabu (2007). The central bank conducts the interventions but is not the prime authority to make these decisions. This authority lies with the Ministry of Finance (as in other advanced economies). Receiving the permission for interventions is a costly process which may be the reason why they occur in sequences. Officials have to convince the top authorities, which is a discretionary process. Given this permission, follow-up interventions do not need individual consent.

<Figure 1>

Instrument. The main idea of our identification strategy exactly exploits the described fact that the decision to start such a sequence is usually not based on new information on the specific intervention day, but is related to medium and longer-term trends as well as to general financial market and economic conditions. Hence, the first day of an intervention sequence can be considered as exogenous to contemporaneous exchange rates or other asset prices. By contrast, the subsequent decision after the first day of a new sequence and how long the sequence will last is taken on a day-by-day basis in response to current market conditions and the success of the initial intervention.

The largely exogenous character of the first intervention day is also apparent from intervention objectives of central banks. According to the survey by Mohanty and Berger (2013, Table 2), the objectives are to smooth trend path, limit pressure on exchange rates, limit volatility, etc. All these are longer-term developments, so that the decision to intervene

at a specific day is not predetermined but is the discretionary decision of the responsible authority; hence the intervention is not transparent to markets, similarly to the surprise component of a monetary policy decision. This becomes also clear when the policy process towards intervention is described, as it is assumed that the first intervention day is accompanied by effort to come to an intervention decision (yes or no) while later intervention days are then mainly covered by the first decision to intervene (e.g., Ito and Yabu, 2007). The longer-term basis for the first intervention decision is also reflected in event studies, such as Fatum and Hutchison (2003), who use averages over several days before the intervention as the basis to measure success. Finally, the most consistent empirical finding about intervention characteristics is that they “lean against the wind”, i.e. interventions are based on assessing the “longer-term” development of exchange rates which is clearly reaching beyond one or a few days (Sarno and Taylor, 2001; Kearns and Rigobon, 2005; Fratzscher et al., 2019).

As the first day of an intervention sequence is exogenous and in this respect different from other intervention days, the impact of interventions should also differ along this margin. Indeed, it is known from high-frequency studies (intra-daily data) that the first intervention contains almost all of the information and consequently moves the exchange rate while later interventions have much less impact (Zurlinden and Fischer, 1999; Payne and Vitale, 2003). We hypothesize that this pattern also holds at a daily level.

Sequences. The number of such sequences in our sample depends on the criterion used to define the start of a new sequence. We use the number of days without intervention before an intervention day to define a new sequence. Using a shorter window implies a larger number of non-zero observations for the proxy, while at the same time risks including interventions into the instrument that are the continuation of an earlier sequence and thus potentially not fully exogenous. Therefore, we use a 5 day window, i.e. one trading week, in the construction of our baseline proxy (as used in Fatum and Hutchison, 2003, or Fratzscher et al., 2019). This window yields 57 non-zero observations for the instrument. They are shown in the bottom Panel B of Figure 1. The average intervention on the first day of a sequence is 5.6 bn US-Dollar, implying that the central bank typically intervenes more than twice as strong on these than on the following days of a sequence. This is in line with the idea that the decision to start a sequence can be considered as exogenous while the decision to intervene and the quantity involved on the following days are more likely to depend on the success of the first day. In the sensitivity analysis, we show that our results are robust to using shorter windows and thereby increasing the number of non-zero observations.

The proxy is not required to be a correct measure of intervention shocks because several forms of measurement error can be accounted for (see Mertens and Ravn, 2013). This is important in our case as actual interventions are often accompanied by oral intervention such as communication of officials from the central bank or the Ministry of Finance (Fratzscher, 2008). The latter, however, are difficult – if not impossible – to perfectly measure as there are no official accounts of oral interventions. Consequently, models which treat the actual interventions as the true measure of interventions are likely to underestimate the effects of interventions due to the attenuation bias resulting from measurement error. In contrast, using an instrumental variable approach requires only that s_t correlates with ε_t^p to estimate the overall effect of interventions. Finally, our instrument contains purchases and sales of foreign currency and thus identifies both positive and negative intervention shocks.

2.3 Identification of the structural VAR

We now discuss how we use s_t for the identification of the structural VAR. The key step consists of estimating what we will refer to as the relative impulse vector. Call b_i^p the entry i of the $k \times 1$ impulse vector b^p from equation (2). We normalize the variance of the structural shocks to unity, so that b_i^p captures how variable i responds to a one standard deviation change in ε_t^p . The $k \times 1$ relative impulse vector is defined as $\tilde{b}^p = b^p/b_1^p = (1, b_2^p/b_1^p, \dots, b_k^p/b_1^p)'$ and captures the response of the last $k - 1$ variables relative to the first variable, which in our ordering is the policy indicator. \tilde{b}^p can be estimated as $(1, \hat{\beta}_2/\hat{\beta}_1, \dots, \hat{\beta}_k/\hat{\beta}_1)'$, with $\hat{\beta}_i$ the estimated coefficients in the regressions

$$\hat{u}_{it} = \alpha_i + \beta_i s_t + v_{it}, \quad i = 1, \dots, k, \quad (4)$$

with \hat{u}_{it} the estimated VAR residual corresponding to equation i of model (1).¹ The consistency of the estimate for \tilde{b}^p follows from the fact that $E(u_t s_t) = \gamma b^p$ with $\gamma = E(s_t \varepsilon_t^p)$, due to (2) and (3). As outlined in Mertens and Ravn (2013), once we have an estimate of \tilde{b}^p , we can combine it with the covariance restrictions $\Sigma = BB'$ with $B = [b^p, B^*]$ to estimate the impulse vector b^p .

We use (4) to assess the strength of our instrument. We compute the F -statistic for the null hypothesis $\beta_i = 0$, focusing on the equations of the VAR featuring the policy indicator

¹ An alternative approach consists of regressing \hat{u}_{it} for $i = 2, \dots, k$ on \hat{u}_{1t} , instrumented with s_t (Mertens and Ravn, 2013). The two procedures deliver the same estimate for \tilde{b}^p already in a finite sample, as can be verified analytically.

and the nominal exchange rate to the reference currency as dependent variables. The F -statistics are 729.83 and 57.9, respectively. This indicates that the instrument is strong.

3 Results

We present results in this section in several steps. We mainly discuss the effects of foreign exchange intervention policy using estimated impulse responses to a positive intervention shock of purchasing 1.7 bn US-Dollars. We assess the statistical significance of the responses by using 90% confidence bands based on bootstrap techniques.² Focusing on Japan, we show results of the bivariate baseline model (3.1) and a first extended model containing further exchange rates to assess the effect of interventions on the currency value (3.2). Then, we consider interest rates and stock prices and quantify the economic importance of interventions also for these financial markets (3.3) before we show variance decompositions (3.4).

3.1 Baseline model

Figure 1 reports the impulse responses of the cumulative interventions and the USD/JPY exchange rate from the baseline bivariate VAR. The solid line refers to the point estimate and the shaded area to the confidence bands. The top panel shows that a surprise intervention leads to an immediate and significant increase in the cumulated intervention series of 1.7 bn US-Dollars. The effect is highly significant and persistent. The latter observation is in line with the argument that interventions typically occur in sequences. Cumulative purchases of foreign currency reach roughly 2.5 bn US-Dollars after about 50 trading days before slowly returning back to trend.

<Figure 2>

The intervention is associated with a large, persistent, and highly significant devaluation of the domestic currency. The USD/JPY exchange rate depreciates upon impact by 0.2%. The impact is highly persistent as well. The exchange rate remains below the level where it would have been without the intervention shock over the full impulse horizon. Moreover, the impact

² We apply a fixed-design wild bootstrap, as in Mertens and Ravn (2013) and Gertler and Karadi (2015). For each bootstrap we recursively generate pseudo data after randomly selecting a subset of days and then changing sign of the estimated vectors of VAR innovations on those days. For identification within each bootstrap, in correspondence to the same day, we change the sign of s_t . Within each bootstrap we then apply the procedure discussed in Section 2. Confidence bands are constructed on 200 bootstrap replications.

is statistically significant for 250 trading days. The strong and long-lasting effects are consistent with the high persistence of the intervention. The baseline model suggests that a cumulative intervention of 2.5 bn US-Dollar leads to a nominal depreciation of the Yen of approximately 0.1% to 0.2% that lasts for about one year.

Qualitatively, our results are in line with existing evidence on the effect of FX intervention in the USD/JPY market. Kearns and Rigobon (2005) estimate the effect of a 1,000 bn Yen intervention on the exchange to be 1.49%, i.e. a 1 bn US-Dollar purchase depreciates the Yen by about 0.2%. Chen et al. (2012) estimate the impact of a 1 bn US-Dollar purchase at 0.18%. We show in Section 4.1 below that our immediate impact is even slightly larger than the one of the two studies, if we use the exactly same sample period.

Looking also at other currency markets, the results on USD/JPY is qualitatively confirmed by evidence on the DEM/USD market, where Dominguez (2003) estimates the maximum impact of a one billion US-Dollar intervention to be 0.29%; note, that this is the maximum impact under specific circumstances, so that the average is much smaller. In smaller (emerging) markets, however, the FX intervention impact is much larger, such as 1.8% on 100 million US-Dollar for the Australian Dollar (Kearns and Rigobon, 2005) or 0.8% on 60 million US-Dollar for the Colombian Peso (Kuersteiner et al., 2018).

At the same time our results reveal novel insights into the persistence of the effects. In high-frequency studies the “permanent” effect lasts for hours (e.g., Payne and Vitale, 2003). The horizon of event studies is a little longer, although this depends on the exact success criterion chosen. If we refer, for example, to Fatum and Hutchison (2003), their direction criterion measures the impact during a post-intervention period of 2 to 15 days. In robustness exercises they extend this period up to 30 days and find that the intervention effect becomes insignificant. It is only in a few recent macro-oriented studies, such as Blanchard et al. (2015), Adler et al. (2015) and Daude et al. (2016), that also consider effects over several months. However, their approach differs from ours in three respects: first, they cover mainly emerging markets and thus predominantly not floating exchange rates; second, their measure of FX intervention is necessarily quite imprecise as they cannot rely on true intervention data; third, while their IV-estimation is innovative in the field, the specific assumptions are at the same time debatable. Overall, according to our knowledge, the implementation of a well identified structural VAR is new to the literature on FX intervention. Our empirical result of a “persistent” (12 months) effect thus has a previously unmet level of credibility.

3.2 Effects on further exchange rates

While focusing on the direct impact of a Japanese intervention on the USD/JPY exchange rate, we extend this bivariate model also to two other important exchange rates relative to the Yen, i.e. the Euro (EUR/JPY) and the British Pound (GBP/JPY). It is expected that the intervention in the USD-JPY market, intended to weaken the Yen, will impact the two other exchange rates into the same direction due to the interrelations on foreign exchange markets. However, as these additional currencies are only indirectly affected, we expect a somewhat weaker impact on them. Results are shown in Figure 3.

<Figure 3>

The graphs on cumulated interventions and their impact on the USD/JPY remain largely the same, although the impact on the exchange rates is slightly weaker. Interestingly, also the impacts on EUR/JPY and GBP/JPY mirror qualitatively those of the targeted US-Dollar, and – as expected – these impacts are not as strong as for the US-Dollar. The initial effects are similar for all three currencies. The most relevant difference compared to the bivariate model is that impact on the EUR/JPY turns insignificant after about 30 to 40 trading days; this may be partially caused by the fact that the USD/EUR rate is the most important exchange rate and dominates any impacts from the Yen and respective interventions. Overall, these results support the impression of a significant impact of FX intervention on exchange rates.

3.3 Effects on interest rates and stock prices

The two models presented so far provide a first impression of interventions on exchange rates. However, the concern of omitted variables may be raised, so that we now consider further financial markets in an extended model. In detail, we extend the bivariate model, presented in Section 3.1, by also considering four interest rates and two stock market indices, i.e. large and small firms listed on the Tokyo Stock Exchange.³

To see whether the augmented structural VAR model is invertible, we follow Stock and Watson (2018) and test the null hypothesis that lags of the instrument are jointly equal to zero in each of the VAR equations. We consider up to six lags. Table 2 indicates that there is no statistically significant evidence against the hypothesis of invertibility. This finding is consistent with the notion that exchange rates, interest rates, and equity prices summarize a potentially large set of information such that there are no omitted factors.

³ We use the MSCI Japan Large (Small) Cap Index, which contain 139 (979) constituents and covers approximately 70% (14%) and of the free float-adjusted market capitalization in Japan.

<Table 2>

Regarding interest rates, we consider four rates. First, in order to capture potential monetary policy shocks, we consider the short –term (three months) interest rate differential of Japanese rate minus US rate. Accordingly, if the Japanese interest rate goes up, the differential becomes positive (relative to the period before the intervention shock). In addition, we consider the 2-year, 5-year and 10-year risk-free interest rates in Japan. The impact of a FX intervention on interest rates, by purchasing 1.7 bn US-Dollar, is generally only marginally statistically significant as shown in Figure 4. Coming specifically to the short-term rates, it is comforting that there is no instantaneous impact of intervention on interest rates; this confirms that we indeed observe an FX intervention shock and not contemporaneous monetary policy effects.

<Figure 4>

Turning to the longer-term interest rates, their reaction follows the same pattern, although basically being always insignificant, except for the slight decrease of the two-year rate (by 0.1 basis points) for the first 10 to 20 days. During the first 20 days these interest rates tend to fall by about 0.1 to 0.2 basis points and from thereon they tend to rise for another 20 days, overshoot the starting level by about 0.1 to 0.2 basis points and then move towards the level before the shock. An explanation might be that monetary policy tends to slightly support the intervention-intended weakening of the Yen by rather lowering than increasing the policy rate. While this may shortly spillover to the longer-term rates, potential effects of a Yen depreciation on inflation and growth would induce higher interest rates before the overall limited effects level off.

The situation is completely different for stock prices. Large firms' prices are immediately positively impacted by the intervention as expected: the Yen-depreciation alleviates exports which are mainly conducted by larger firms and thus supports their business which is reflected in higher stock prices; these remain significant at a level of about 0.1% gain for 10 days and keep their level thereafter. By contrast, the immediate impact of a FX intervention on the stock prices of small firms is negative by about 0.1% for 10 days, before stock prices return to the level before the shock. In interpretation, the small firm effect seems reasonable, as this segment of the economy does not directly profit from depreciation.

3.4 Variance and historical decomposition

To estimate the average economic importance of intervention shocks for exchange rate and other asset price fluctuations Table 3 documents the contribution of FX interventions to the forecast error variance of the respective time-series at various horizons.

<Table 3>

Turning to cumulated interventions, the high explained variance is a rather mechanical effect as intervention is itself the driving force. Turning to asset prices, the largest effect is observed on the USD/JPY exchange rate. Here the explained variance starts at remarkable 11.5% and decreases to 5.2% for longer horizons. This indicates that FX intervention has quite some relevance for understanding the USD/JPY exchange rate (although its influence on the exchange rate is not dominating). By contrast all 20 effects on interest rates – regarding the four measures and five horizons – remain below 0.4% and thus quite negligible. Finally, the explained variance of stock prices increases is larger than on interest rates but still small. The share of explained variance is larger for large firms than for small firms, and is between 0.5 and 0.7% over the horizons covered, reflecting the lasting effects on exports and growth.

To assess the economic importance of intervention shocks during certain times in our sample, we compute a historical decomposition of the exchange rate. The top panel of Figure 5 shows that the contribution of intervention shocks to the bilateral USD/JPY exchange rate is limited throughout most of the sample. There are, however, two noteworthy episodes - in 2003 and 2011 - where interventions seem to have curbed the appreciation of the Yen. According to the estimated intervention shocks in the bottom panel, Japanese authorities massively purchased foreign currency to stem the appreciation of the domestic currency, consistent with the implicit aim of smoothing the exchange rate.

<Figure 5>

4 Results in perspective

In this section we put our main results in perspective. First, we compare them with those of earlier papers by adjusting the sample periods (4.1). Second, we compare our identification strategy to an alternative identification scheme (4.2), third, we address the concern of interventions being forecasted by applying a reaction function (4.3) and, fourth, we compare our results for Japan to those of the most recent FX interventions in the US and UK (4.4).

4.1 Comparison with the literature

In order to more exactly compare the intervention impact with those measured in more recent studies about USD/JPY interventions, we use our full model from Section 3.1 and adjust the observed sample period to those of earlier studies, i.e. Kearns and Rigobon (2005) and Chen et al. (2012). In particular, we take out the few huge interventions during the year 2011. Moreover, we adjust the intervention volume to the one trillion Yen as taken in the mentioned papers. The result is shown in Figure 6. Relative to the full period, intervention impact increases remarkably to about 0.2%. This impact is larger than the comparable impacts estimated by Kearns and Rigobon (1.49%) and Chen et al. (1.8%). Moreover, it is about 60% larger than for the full sample (1991-2017), indicating that FX intervention impact may change over time.

<Figure 6>

As, for example, Kearns and Rigobon (2005) emphasize the policy change in June 1995, we also test whether a start of the analysis after this point in time has a major influence on our results. This is not the case as can be seen from Figure 6, and the immediate impacts are the same as for the longer samples, but the shorter samples show a smaller degree of persistency.

4.2 Comparison to identification via timing restriction

So far, the literature tends to shy away from conventional VARs due to the endogeneity of FX intervention in relation to exchange rates. Let us conduct a kind of thought experiment: What would be the outcome of a conventional VAR where identification is assumed via timing restrictions. Such an approach means that FX intervention is assumed to impact the exchange rate and the other asset prices in the model, but not the other way round. Due to the intended more precise estimation via the Proxy-SVAR compared to the conventional VAR, we expect that identification via timing restrictions leads to shocks with smaller impacts. We show the impacts of such a conventional Cholesky ordering of variables, and our modeling approach (from Section 3.3) in Figure 7.

<Figure 7>

As the impulse responses are always plotted for both methods in the same figure, it becomes obvious that our identification indeed leads to much larger impacts of FX intervention. Regarding the exchange rate, for example, the effect size estimated via Cholesky decomposition is half as large and significant for 10 days only instead of more than 100 days otherwise. Interest rates show the same pattern as before, but effect sizes are even smaller and consistently insignificant. Regarding stock prices, there is no effect on large firms anymore

and a short-lived effect (5 days) on small firms' stock prices. Thus it may be reassuring that a different method leads to the same qualitative findings but if one believes in the superiority of the Proxy-SVAR, this method is crucial to get relatively large and persistent effects on exchange rates and stock prices.

4.3 Reaction function approach

We argue that the first day of any intervention sequence is largely exogenous. This implies that it would be difficult to forecast these days, although we acknowledge that market participants form expectations about future interventions. In order to capture this reasoning we use the reaction function for Japanese FX interventions proposed by Ito and Yabu (2008). Assuming that interventions being explained by this approach can be expected, we take the (unexplained) residual as instrument in our Proxy-SVAR. These values deviate at most $\pm 7\%$ from the indicator, i.e. the value of 1. Thus it does not come as surprise that the estimated intervention impact, as shown in Figure 8, is graphically difficult to distinguish from the impact relying on our specification from Section 3.1. We conclude that the exact intervention can indeed hardly be anticipated.

<Figure 8>

4.4 Evidence for the US and UK

In order to alleviate concerns that above results may be driven by unknown specifics of the Japanese case, we also apply our new method to the few FX interventions that are known for two other countries with floating exchange rates over the last 15 years. We refer to the US first, and then to the UK. Due to limitations of observations, we expect less significant results and have to reduce lag length of the VARs.

Regarding the US, we moreover expect that intervention impacts are smaller than in the Japanese case because interventions volumes are smaller, they do not continue over time and occur in an even larger market, i.e. EUR/USD. Indeed, results presented in Figure 8 show that the effect on the exchange rate is small (0.03%) and persists only over a few days. The effects on interest rates are rather unexpected: while there is no recognizable contemporaneous effect from monetary policy, the longer-term rates appear to increase by about 0.1 basis points for a few days. This may reflect a specificity of the US bond market during the intervention times. Finally, stock prices of larger firms move as expected but to a much smaller and less persistent extent; somewhat surprisingly stock price of small firms move in the same pattern,

overall indicating that the smaller impact of FX interventions does not really feed through to stock prices.

<Figure 9>

Regarding the UK, we analyze the EUR/GBP exchange rate because the intervention occurred here. Overall effects are closer to the Japanese case, possibly because the exchange rate is also more important than for the US. The exchange rate effect is about 0.1%, despite much smaller intervention volumes, and persists for more than ten days (see Figure 9). Shorter-term interest rates may decline a bit in the beginning, however, hardly to a significant extent, and move back to the initial level. This pattern can be also seen with longer-term interest rates. Stock prices increase, both of large and small firms, indicating that the stimulus of a depreciation may dominate potential distributional effects across firm size.

<Figure 10>

In summary, despite serious data limitations, we find that the cases of US and UK interventions in the FX market tend to support the experience of the Japanese case. While the pattern of observations is qualitatively similar, the extent is smaller for the UK, and much smaller for the US.

5 Robustness

In this section, we summarize the results from an extensive sensitivity analysis. The Appendix contains the corresponding figures. They demonstrate that our main results are robust and tend to provide a conservative, that is, lower bound of the estimate of the effect of FX interventions. In detail, we exclude either the weekday or month dummies from the set of exogenous variables, or include either a linear trend or year dummies. The differences are so small that they are graphically not visible, so we do not report them in a separate figure in the Appendix. Furthermore, we use the following different numbers of lags of the endogenous variables: 10, 20, 30, 40, 60, and 70. Outcomes presented in [Figure A1](#) show that there no major qualitative modifications to the benchmark results.

Next, we consider alternative definitions of our instrument. On the one hand, we change the definition of an intervention sequences by shortening the time-window before the start of a new sequence without interventions from 5 days in the baseline specification of the instrument to 4, 3, 2, 1, and 0 days. This increases the number of non-zero observation of the proxy up to 327 actual intervention days. But the corresponding [Figure A2](#) shows that the impact decreases in the size of the disconnection window since the risk of defining

continuation days of an earlier sequence as a new sequence increases. On the other hand, we use the actual intervention size, instead of a categorical variable indicating the direction of the intervention, which we winsorize at the 10% level to remove outliers. The estimated impact decreases slightly in absolute size but remains significant for about 100 trading day (see [Figure A3](#)).

Finally, we consider alternative samples. We cut 1, 2, 3, 4, and 5 years of observations both at the beginning and at the end of the sample, and estimate the model on all 25 different subsamples. The results shown in [Figure A4](#) indicate that the estimated impact is larger when excluding more recent years, but that the effect is of similar order of magnitudes across subsamples.

6 Conclusions

FX intervention is in many respects a macro issue. Still, the literature hesitates to apply VAR-approaches which are a common method in other areas of macroeconomic research, such as examining the impact of monetary policy. The empirical problem is the partial endogeneity of FX intervention which responds to exchange rate developments. So, how can we properly identify FX interventions and still get results that fit into macro-oriented research?

While some recent macro-oriented papers have to make major assumptions for identification, we remain closer to the convention of working with higher frequency data and apply an approach that is to the field of FX intervention: the external instrument VAR in a sense combines a regular VAR with an event study identification strategy. The identifying assumption is based on the fact that FX interventions typically occur in sequences. Each first FX intervention then differs from subsequent ones because the first intervention is typically not driven by events on the specific day but by exchange rate developments over a longer period, in particular in floating exchange rate regimes. This assumption is well documented in the intervention objectives of central banks and reflected in the empirical literature.

With this identification strategy we set up the Proxy-SVAR which has three appealing consequences: first, this method provides a more precise estimate of intervention impact than conventional VARs, second, by way of the VAR we can better assess potential persistence of intervention than in event studies, and, third, by extending the VAR to further asset prices beyond exchange rates we get a fuller picture of its broader impact.

We apply this approach to Japanese data because the Yen has a flexible exchange rate, is a relevant market, and there are many public FX interventions. Our main findings are threefold: (i) interventions have a sizable impact on the exchange rate. A 1.7 bn US-Dollar intervention has a contemporaneous impact on the USD/JPY of 0.2%. This shock is of similar scale but somewhat higher than many previous estimates, fitting the expectation that the method we employ reduces attenuation bias. We provide similar evidence for the US and the UK. (ii) This impact on the exchange rate remains significant over four quarters. (iii) There is hardly any impact on interest rates. However, stock prices change, increasing due to depreciation. Valuations of larger firms increase whereas those of smaller firms which are typically less export-oriented decrease to a similar extent. Robustness checks show that these main findings hold in various settings and extensions, including applying the approach to a small set of US and UK FX interventions.

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Figure 1: Interventions and instrument

The figure shows the purchases and sales of billion USD by of the Bank of Japan. The top panel contains all 327 intervention days in the sample. The bottom panel shows the 57 starts of an intervention sequence, which we use as instrumental variable for the identification of intervention shocks.

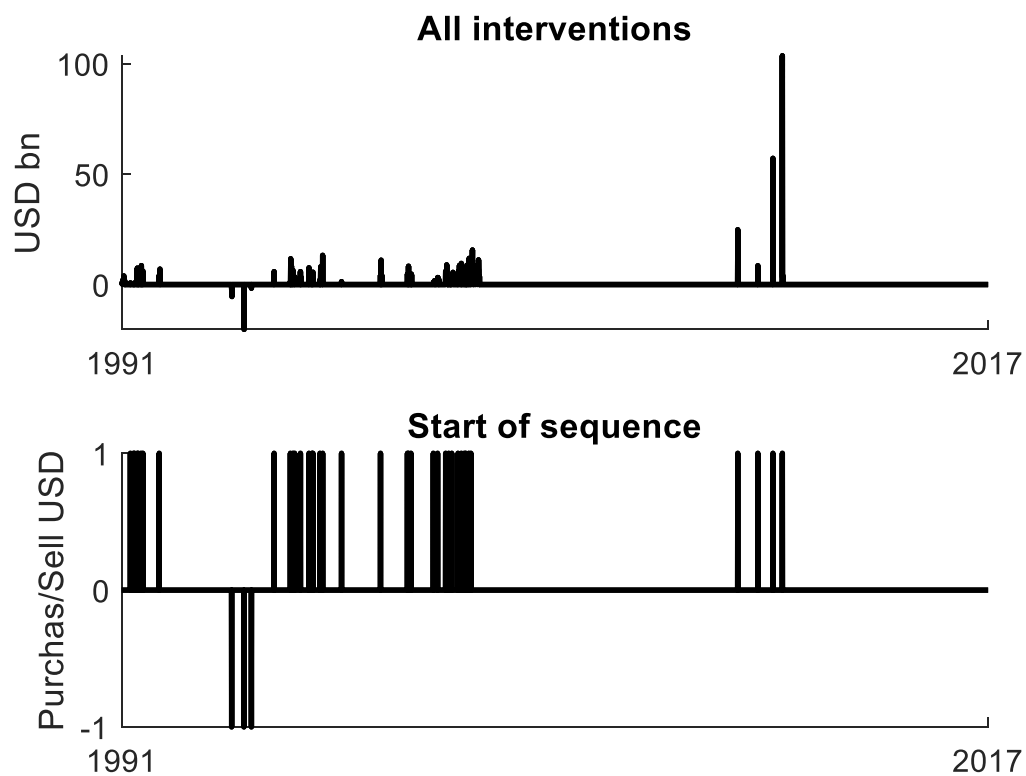


Table 1: Descriptive statistics for Japan

	All interventions	Instrument (start of sequence)
<i>Number of interventions</i>		
Number of interventions	327	57
Purchases of foreign currency	321	54
Sales of foreign currency	6	3
Unconditional probability	0.05	0.01
Conditional on previous intervention	0.65	0
<i>In billion USD</i>		
Average intervention	2.33	5.60
Average purchase	2.47	6.01
Average sale	-5.29	-1.80
Maximum purchase	103.53	103.53
Maximum sale	-20.32	-2.21

Figure 2: The dynamic effects of foreign exchange market intervention in Japan

The figure shows the response of cumulated interventions (in billion USD) and the USD/JPY exchange rate (in %) to an intervention shock of one standard deviation over a horizon of 250 trading days, along with 90-percent confidence bands from 200 bootstrap replications, based on a SVAR(50) identified with an external instrument (five days criterion).

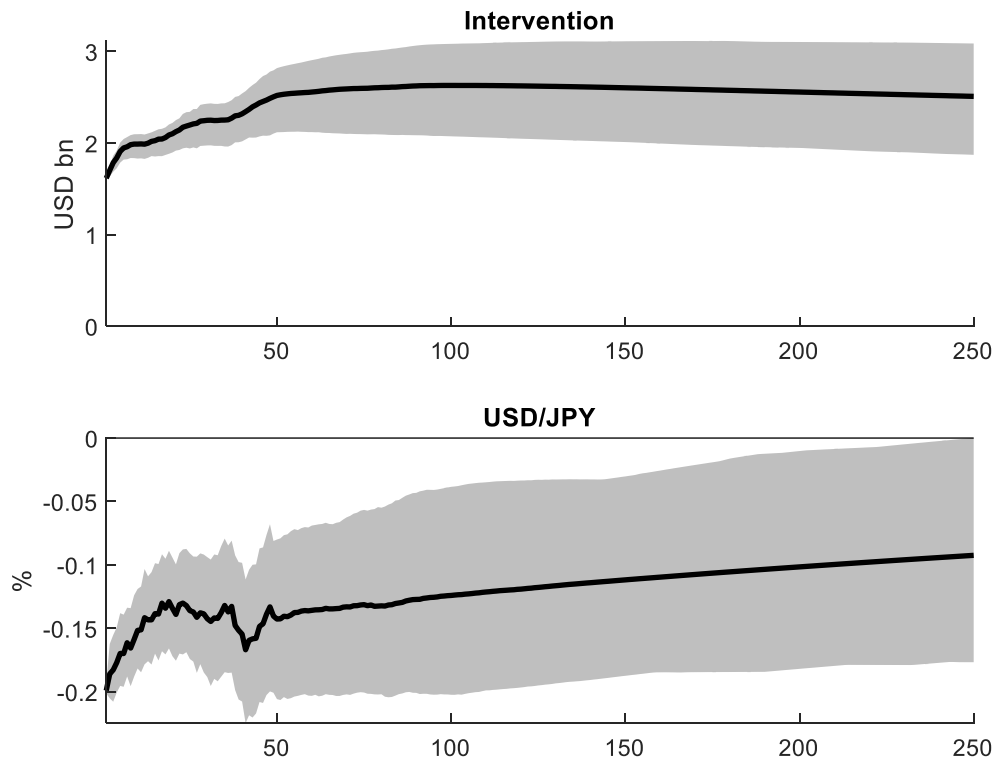


Figure 3: Dynamic effects of JPY intervention on other currencies

The figure shows the responses of cumulated interventions and nominal exchange rates of the Japanese Yen to a one standard deviation intervention shock over a horizon of 100 trading days, along with their 90-percent confidence bands from 200 bootstrap replications, based on a SVAR(50) identified with an external instrument (five days criterion).

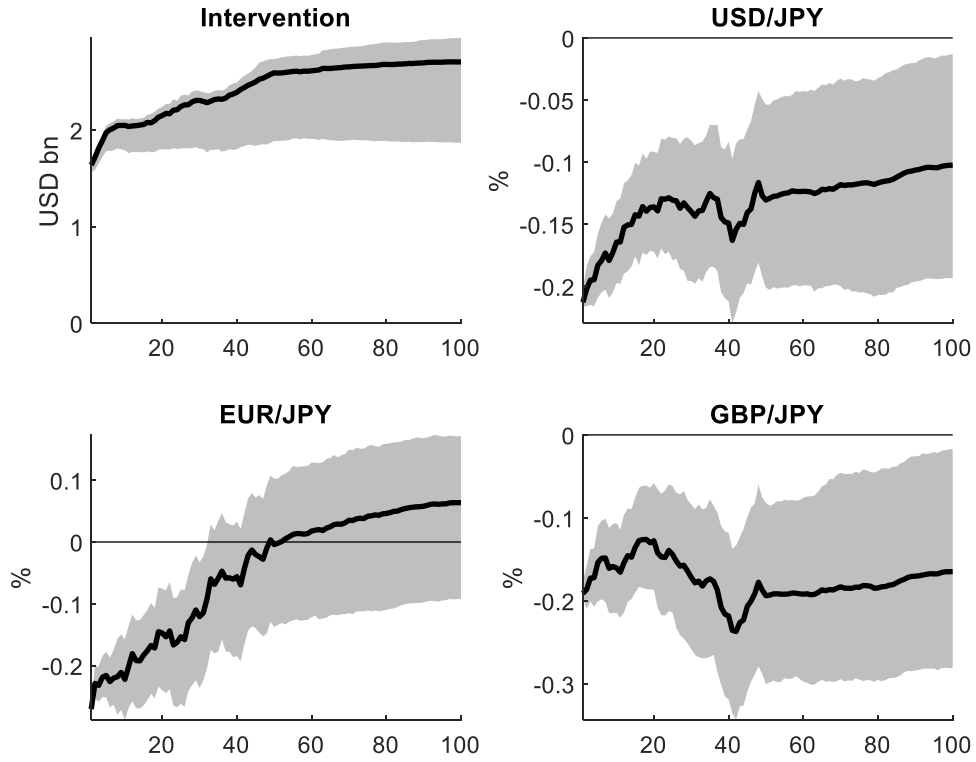


Figure 4: Responses of interest rates and equity prices to JPY-intervention

The figure shows the responses of different asset prices to intervention shock of one standard deviation over a horizon of 100 trading days, along with their 90-percent confidence bands from 200 bootstrap replications, based on a SVAR(50) identified with an external instrument (5-day criterion).

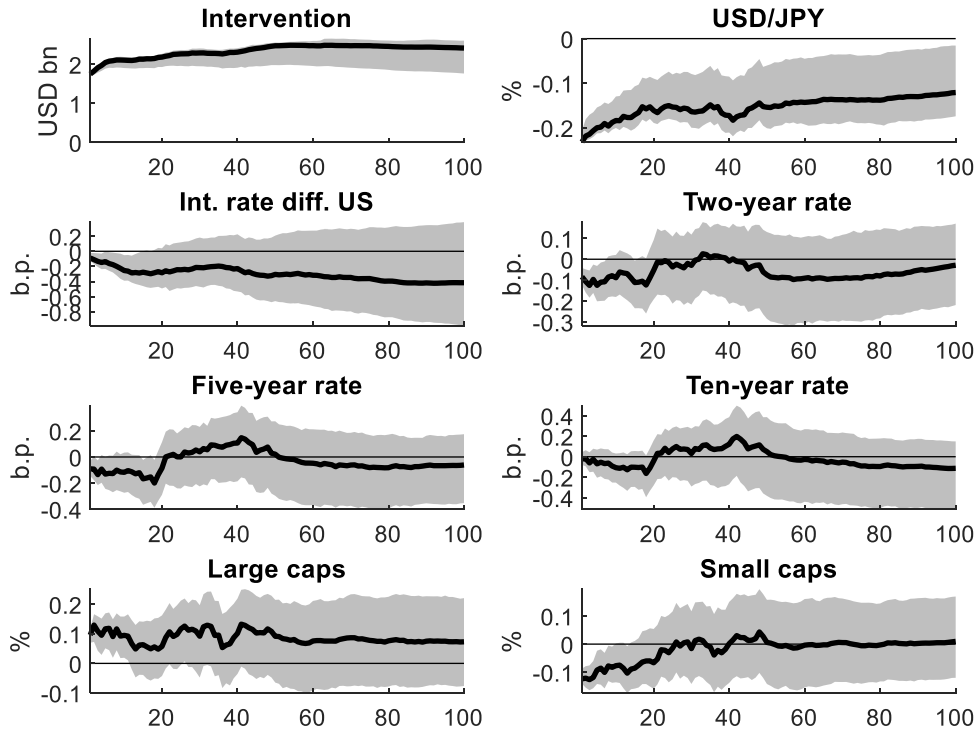


Table 2: Test for invertibility of SVAR identified with external instrument.

The table shows p -values for a robust F -statistic testing the null hypothesis that the coefficients on 1 to 1-6 lags of the instrument are jointly equal to zero in each of the VAR equations of the extended model.

Lags	Equation Interv- ention	Exch. rate (FC/DC)	Int. rate diff.	Two-year rate	Five-year rate	Ten-year rate	Large caps	Small caps
1	0.91	0.24	0.31	0.35	0.66	0.38	0.37	0.68
2	0.36	0.32	0.59	0.63	0.17	0.07	0.08	0.20
3	0.32	0.39	0.25	0.23	0.14	0.11	0.16	0.26
4	0.47	0.46	0.30	0.18	0.07	0.05	0.13	0.20
5	0.59	0.61	0.40	0.23	0.08	0.07	0.21	0.30
6	0.71	0.70	0.51	0.32	0.11	0.08	0.30	0.41

Table 3: Forecast error variance decomposition.

Horizon	Inter- vention	USD/JPY	Int. rate diff.	Two-year rate	Five-year rate	Ten-year rate	Large caps	Small caps
1	94.9	11.5	0.1	0.2	0.1	0.0	0.5	0.8
5	92.2	10.3	0.1	0.3	0.1	0.0	0.7	0.7
10	89.9	9.4	0.2	0.2	0.2	0.0	0.7	0.5
50	82.2	6.4	0.3	0.1	0.1	0.1	0.6	0.2
100	78.3	5.2	0.4	0.2	0.1	0.1	0.5	0.1

Figure 5: Historical decomposition of USD/JPY exchange rate and estimated intervention shocks

The upper panel shows the historical decomposition of the observed USD/JPY nominal exchange rate (solid line) and the exchange rate without the contribution of the intervention shocks (dashed line). The lower panel contains the estimated (thin line) and the cumulated (thick line) structural intervention shocks.

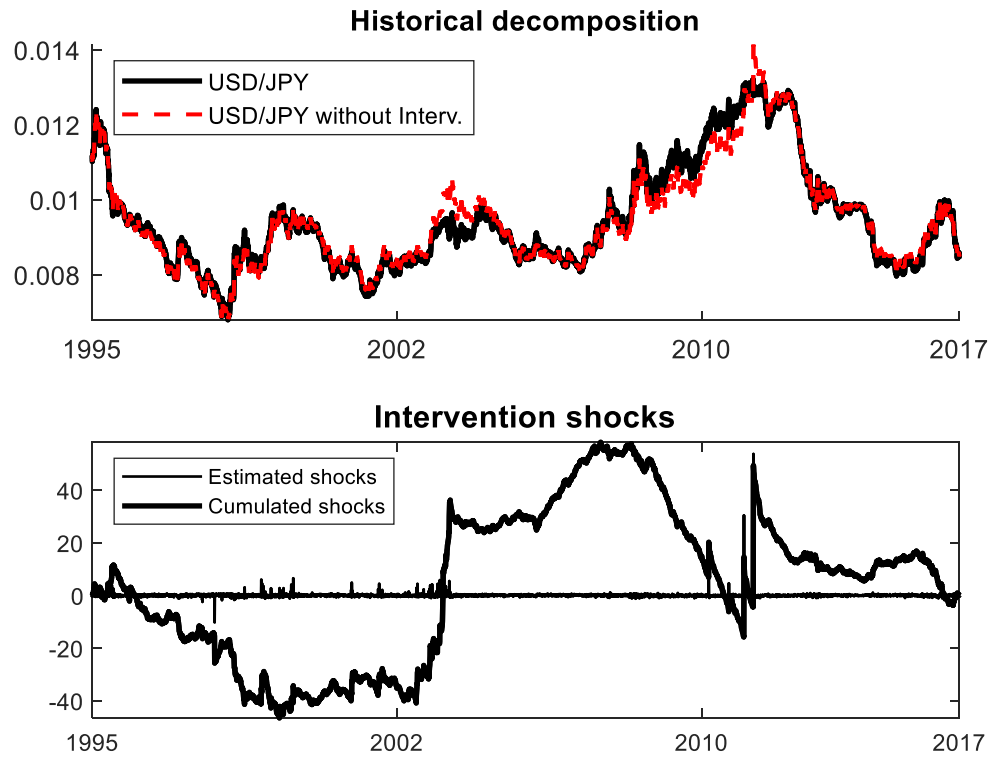


Figure 6: Subsample estimates

The figure shows the responses of the endogenous variables to an intervention shock of one standard deviation over a horizon of 250 trading days based on a SVAR(50) identified with external instrument estimated over the full sample (solid line), along with 90% confidence bands, and the point estimates for different subsamples.

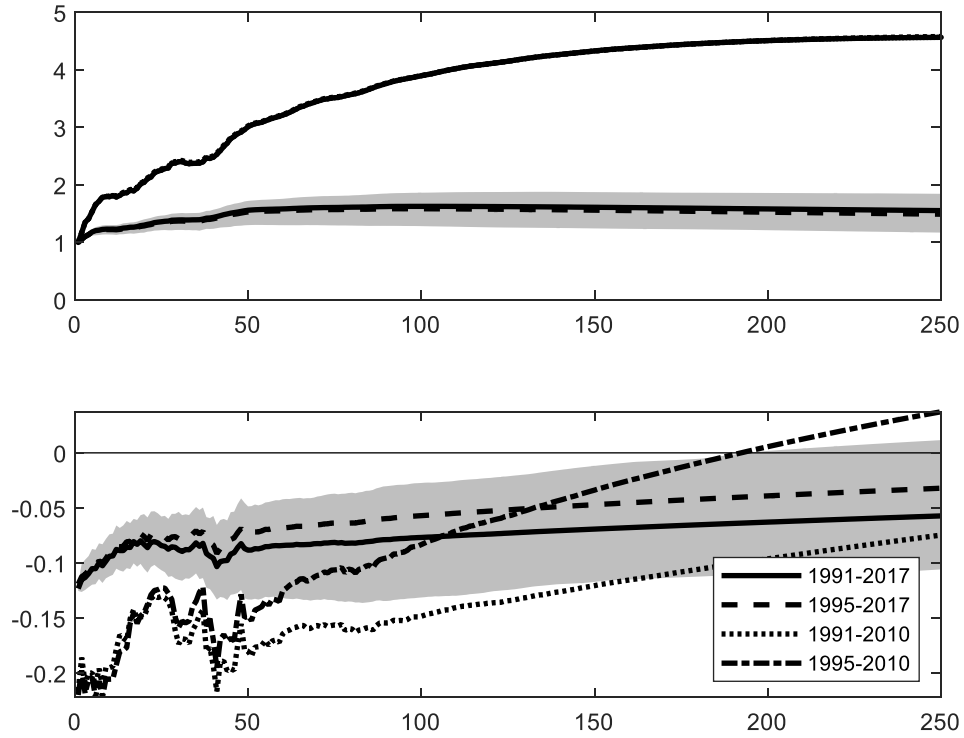


Figure 7: Comparison of Proxy-SVAR and recursive identification

The figure shows the responses of different asset prices to an intervention shock of one standard deviation over a horizon of 100 trading days based on a SVAR(50) identified with an external instrument (solid line) and based on a SVAR(50) identified recursively with the cumulated interventions ordered first (dashed line), along with their 90% confidence bands.

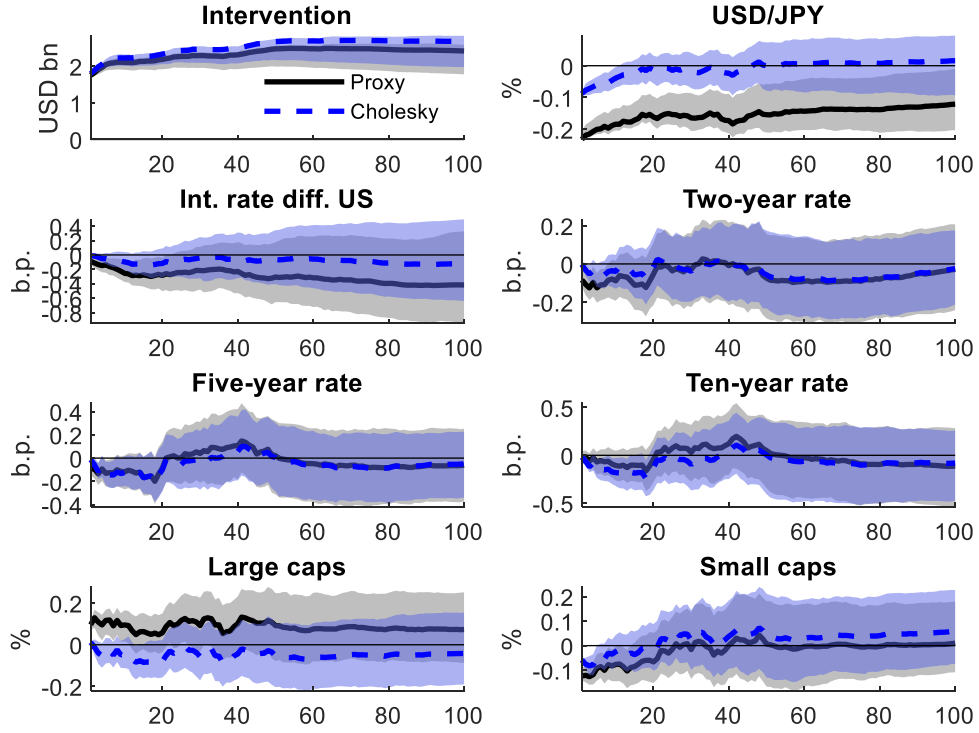


Figure 8: Impulse responses for cleaned instrument

The figure shows the responses of the endogenous variables to an intervention shock of one standard deviation over a horizon of 250 trading days based on a SVAR(50) identified with an external instrument which is cleaned through a policy function approach, along with 90-percent confidence bands using 200 bootstrap replications.

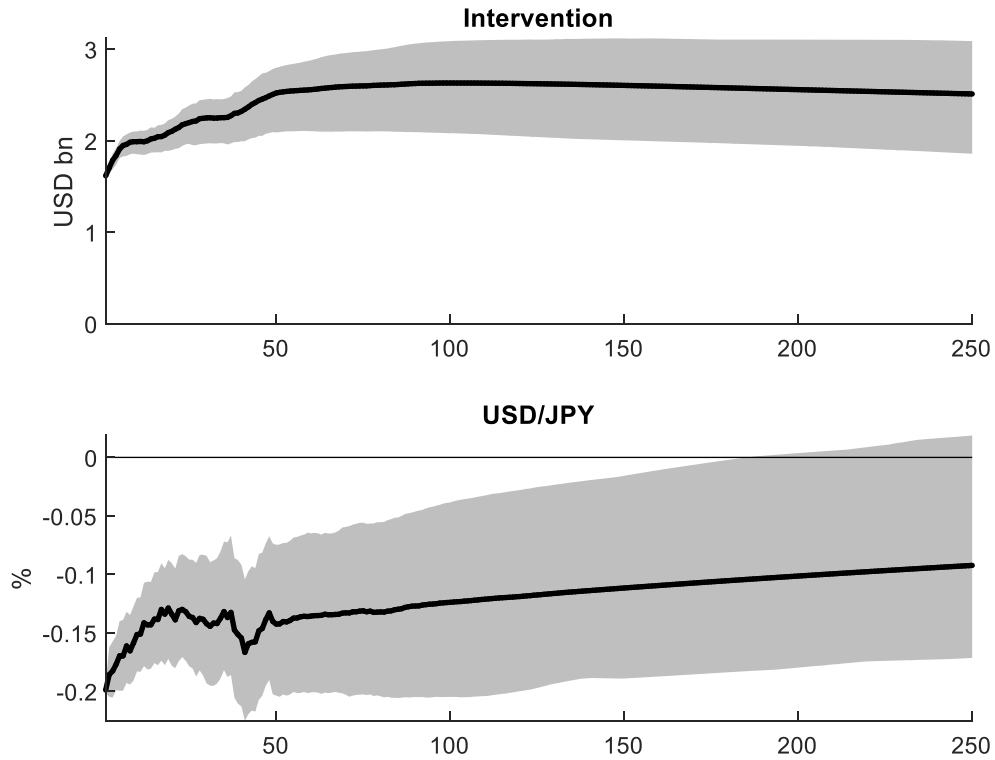


Figure 9: The dynamic effects of foreign exchange market intervention in the US

The figure shows the responses of the endogenous variables to an intervention shock of one standard deviation over a horizon of 25 trading days based on a SVAR(25) identified with an external instrument, along with 90-percent confidence bands using 200 bootstrap replications.

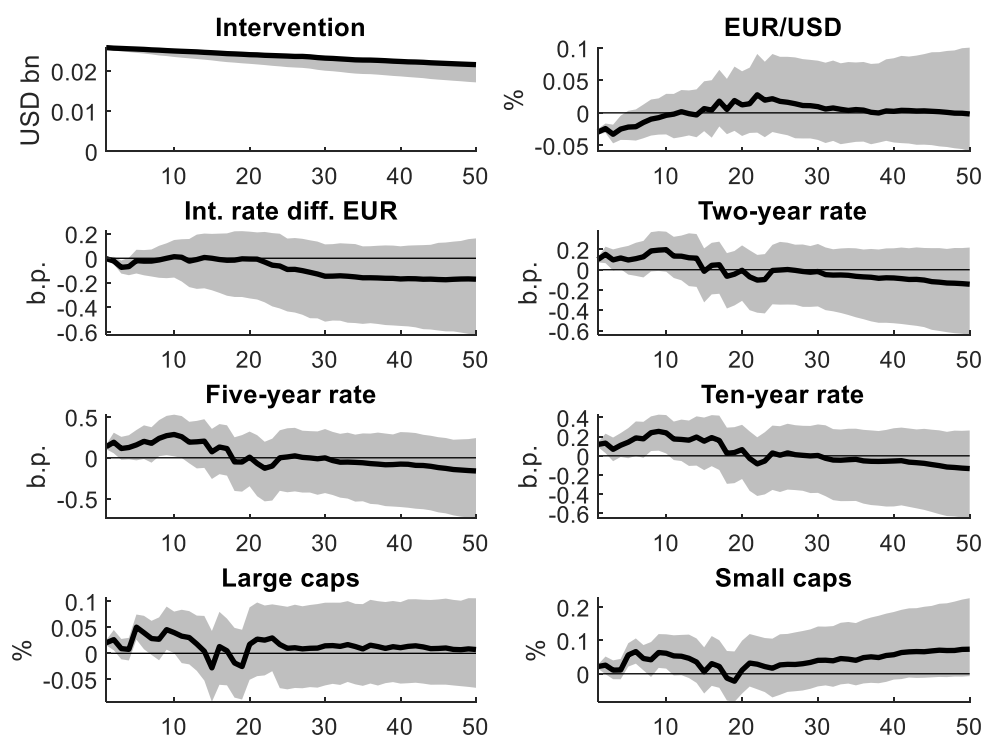
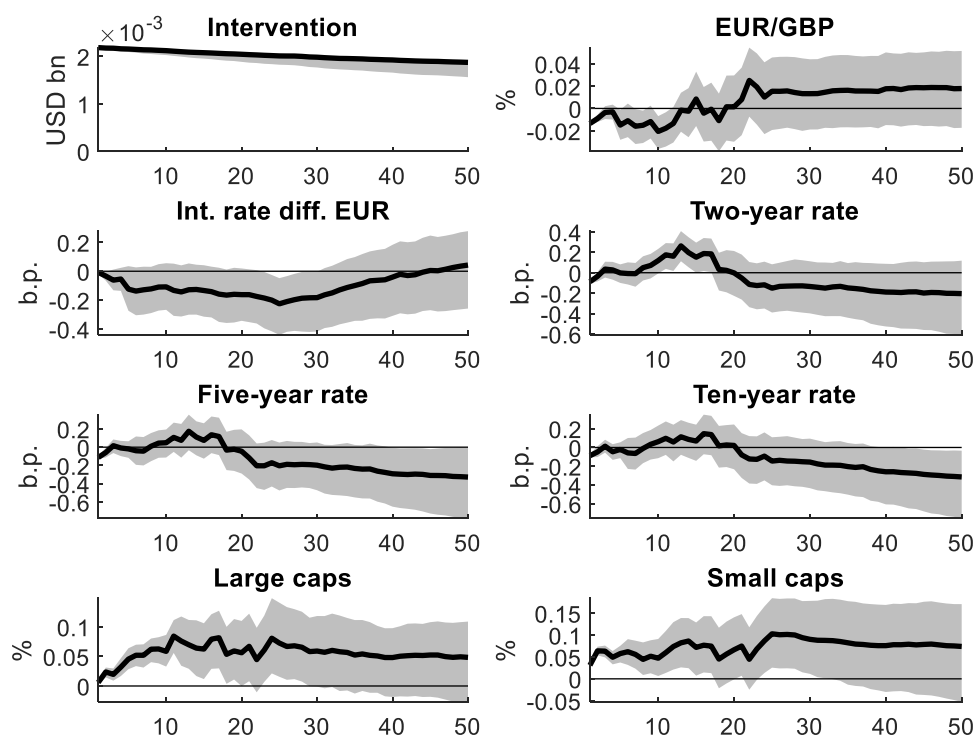


Figure 10: The dynamic effects of foreign exchange market intervention in the UK

The figure shows the responses of the endogenous variables to an intervention shock of one standard deviation over a horizon of 25 trading days based on a SVAR(25) identified with an external instrument, along with 90-percent confidence bands using 200 bootstrap replications.



APPENDIX

Figure A1: Robustness to using alternative lag length

The figure shows the responses of the endogenous variables to an intervention shock of one standard deviation over a horizon of 100 trading days based on a $SVAR(p)$, for $p=10,20,30,40,60,70$ identified with an external instrument, along with 90-percent confidence bands using 200 bootstrap replications for the baseline specification with $p=50$.

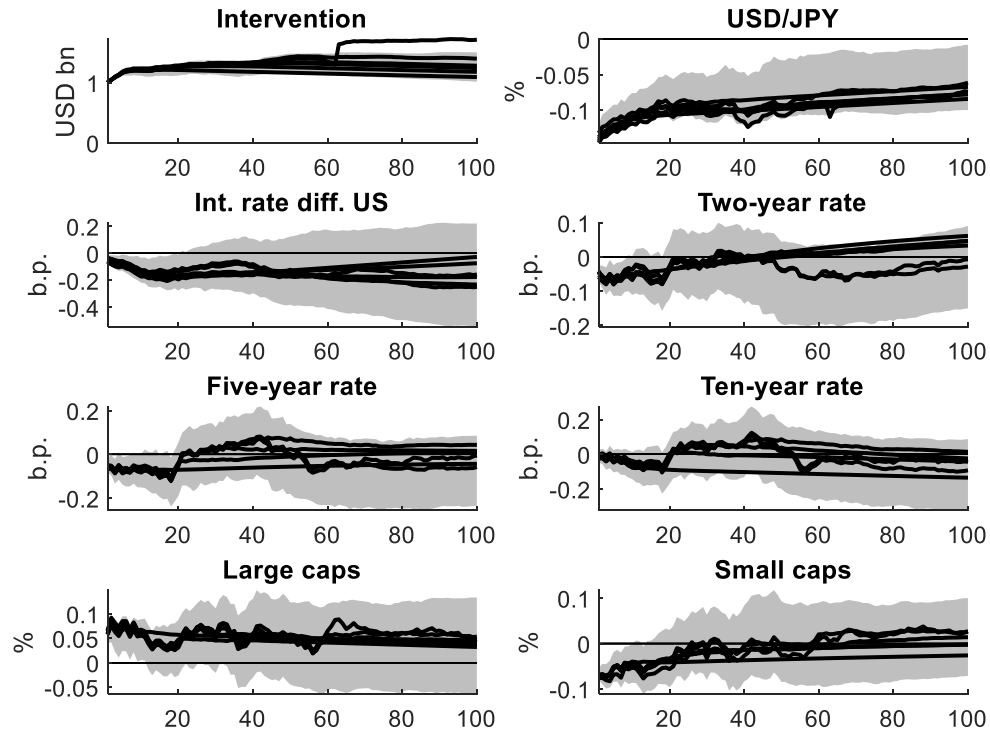


Figure A2: Robustness to alternative definition of intervention sequence

The figure shows the responses of the endogenous variables to an intervention shock of one standard deviation over a horizon of 100 trading days based on a SVAR(50) identified with an external instrument using a 1, 2, 3, and 4 day disconnect between actual interventions to define a new intervention sequence, along with 90-percent confidence bands using 200 bootstrap replications for the baseline specification using a 5-day disconnect.

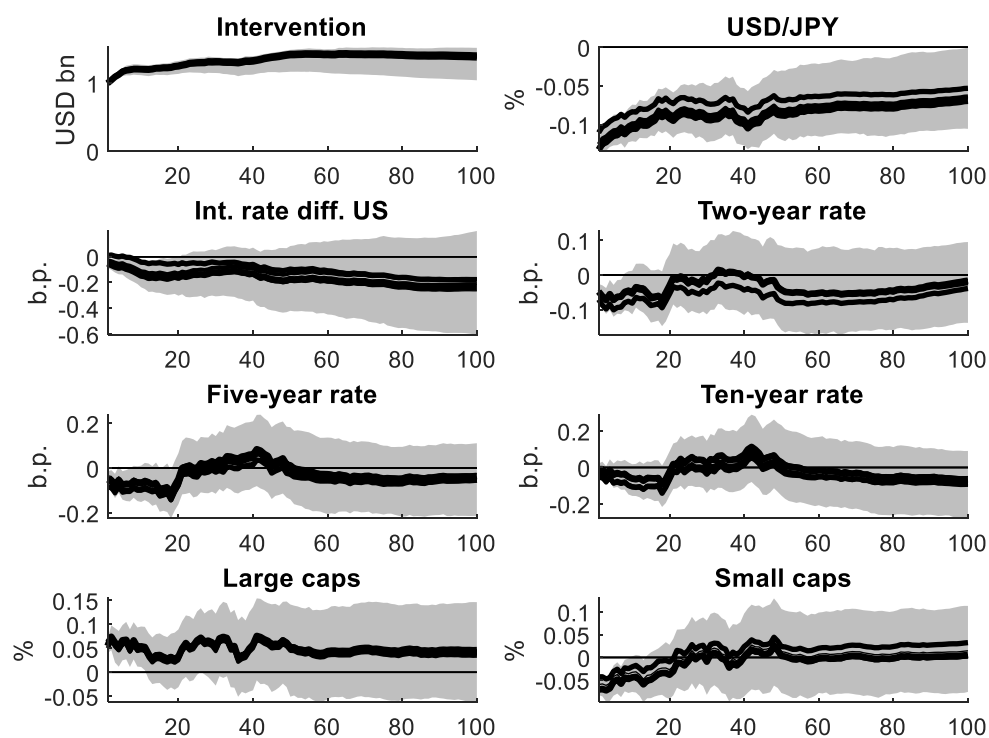


Figure A3: Robustness to using intervention volume as instrument

The figure shows the responses of the endogenous variables to an intervention shock of one standard deviation over a horizon of 100 trading days from an SVAR(50) identified with an external instrument, which is based on the 10%-Winsorized intervention volume on the first day of an intervention sequence, along with 90-percent confidence bands using 200 bootstrap replications.

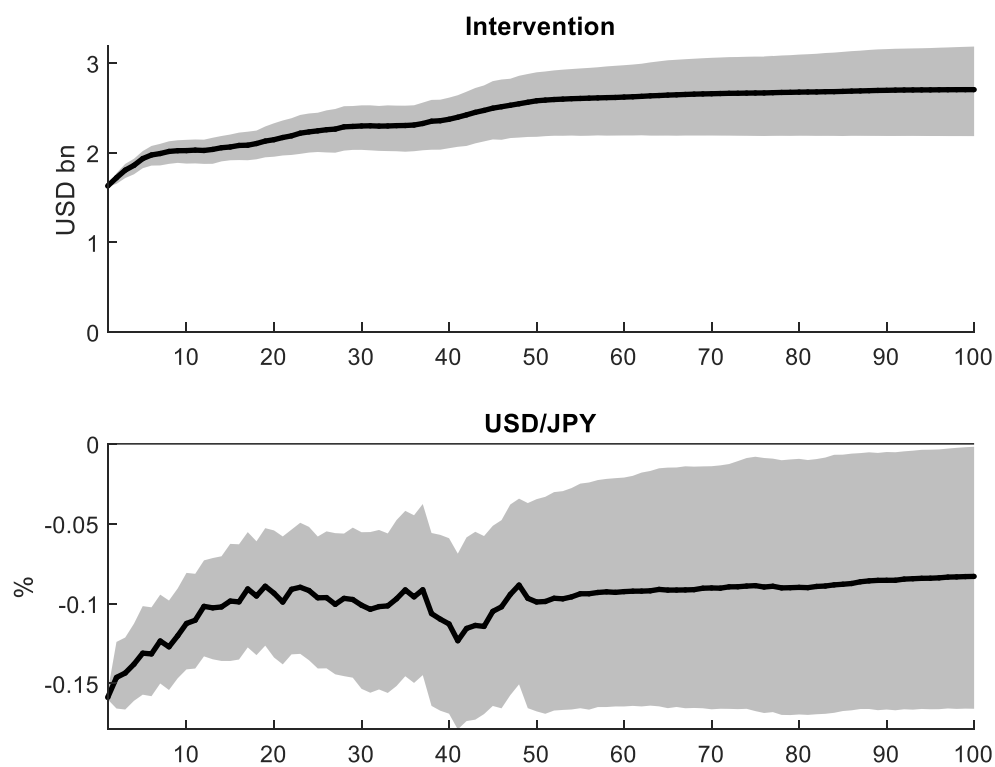


Figure A4: Robustness in subsamples

The figure shows the responses of the endogenous variables to an intervention shock of one standard deviation over a horizon of 100 trading days from an SVAR(50) identified with an external instrument in 25 subsampled constructed by cutting 1, 2, 3, 4, and 5 years at the start or the end of the sample, along with 90-percent confidence bands of the baseline specification using the full sample and 200 bootstrap replications.

