HIAS-E-132

The Trend Effect of Foreign Exchange Intervention

Rasmus Fatum[a], Yohei Yamamoto[b], Binwei Chen[b]

(a) University of Alberta
(b) Hitotsubashi University

Aug 2023 (revised Sep, 2024)

The Trend Effect of Foreign Exchange Intervention

This version: 2 September 2024

Rasmus Fatum*
School of Business
University of Alberta
Edmonton, Alberta
Canada, T6G 2R6
Email: rasmus.fatum@ualberta.ca

Yohei Yamamoto
Department of Economics
Hitotsubashi University
2-1 Naka, Kunitachi
Tokyo 186-8601, Japan
Email: yohei.yamamoto@r.hit-u.ac.jp

Binwei Chen
Graduate School of Economics
Hitotsubashi University
2-1 Naka, Kunitachi
Tokyo 186-8601, Japan
Email: shasha_chan@yahoo.com

Abstract: The 2022 and the 2010-2011 Bank of Japan interventions provide an opportunity for investigating whether unusually large-scale and infrequent interventions are capable of generating trend effects. To this end, we estimate the counterfactual exchange rate and analyze structural changes in the level and the trend of the gap sequence between actual and counterfactual exchange rates. Our results show that the trend of the gap sequence reversed in the desired direction around the intervention dates, indicating that the intervention policy instrument is potentially powerful enough to generate long-term trend effects. This is an important insight not previously found in the intervention literature.

Key words: Foreign Exchange Intervention; Counterfactual Exchange Rate; Currency Factors; Synthetic Control Methods; Structural Changes.

JEL Classifications: F31, C38.

* Corresponding author. Fatum is also Research Associate at the Federal Reserve Bank of Dallas and member of the Economic Policy Research Unit (EPRU) at the University of Copenhagen. Yamamoto is also Professor at Tokyo Tech Academy of Energy and Informatics, Tokyo Institute of Technology. Fatum gratefully acknowledges financial support from Social Sciences and Humanities Research Council of Canada. We thank two anonymous referees, Kathryn Dominguez, Lukas Menkhoff, Toshitaka Sekine as well as participants at the 4th TWID International Conference and seminars at Keio University and National Taipei University for very helpful comments.

1. Introduction

The vast literature on central bank foreign exchange intervention is primarily focused on assessing contemporaneous or short-term exchange rate effects of intervention. This is appropriate when intervention operations are small-scale and carried out over several days in relatively short succession, and thus consistent with a policy-aim of influencing immediate currency price volatility or immediate relative currency values. Recently, in the fall of 2022, and prior to that in 2010 and 2011, the Bank of Japan (BoJ) on behalf of the Ministry of Finance carried out interventions that are anything but typical. Rather, these interventions are large-scale and occur against a backdrop of no BoJ intervention activity for more than a decade with respect to the 2022 interventions and for more than half a decade with respect to the 2010-2011 interventions. Clearly, the scale of these interventions have the potential for generating immediate and substantial portfolio-balance effects.[1] More importantly, it is the newsworthiness of these interventions, due to the fact that they occur after many years of no intervention activity, that gives these particular interventions the potential for also generating substantial signaling effects regarding the future monetary policy stance or for altering market expectations of future interventions. The 2022 BoJ interventions alongside the 2010-2011 BoJ interventions, therefore, provide an opportunity for investigating whether large and infrequent interventions are associated with longer-lasting exchange rate changes such as trend effects rather than just immediate or short-run exchange rate effects.

The 2022 BoJ interventions, carried out as unannounced purchases of domestic currency in the JPY/USD market on three days in September and October, are particularly

[1] See Fatum (2015) for an analysis of the portfolio-balance effects of BoJ intervention.

remarkable for several reasons. First, they mark the first time the BoJ intervenes in more than a decade. This is important, as years of no central bank intervention instills in the market a perception that the central bank in question may no longer consider intervention a viable or necessary policy instrument. By contrast, the sudden reemergence of central bank intervention may signal not only an immediate concern with relative currency values or market volatility but may also effectively switch the exchange rate regime from one characterized by no expectation of central bank trading activity, and thus no central bank signaling via intervention of future policy intentions, to one where markets price in not only realized interventions but also the possibility of future interventions and their effects on prices and expectations. Second, the 2022 interventions constitute the first time in almost 25 years that the BoJ intervenes with an aim towards strengthening the JPY, i.e. until the September 2022 intervention no BoJ intervention purchase of domestic currency had been carried out since 1998, thereby giving further credence to the suggestion that a dramatic policy change occurred that is likely to substantially influence market expectations of future central bank policy and willingness to actively attempt to manage exchange rates. Third, the intervention amounts - JPY2,838.2 (USD19.93) billion on September 22, JPY5,620.2 (USD38.06) billion on October 21, and JPY729.6 (USD4.90) billion on October 24 - are unusually large-scale to the point that the first two 2022 interventions are, respectively, the largest and second-largest intervention JPY purchases ever made and, in absolute terms, only surpassed by the massive 2011 intervention JPY sale.[2]

[2] While the total 2022 intervention amount of USD 62 billion is unusually large in the context of unannounced interventions carried out by an advanced economy over very few days, it is smaller than the cumulative amounts of a series of pre-announced interventions undertaken by some emerging market economies. We thank an anonymous referee for making this point.

The effectiveness of foreign exchange interventions has been studied from various angles. For example, a large body of the intervention literature assesses the contemporaneous effect of intervention on daily or higher frequency exchange rate returns in the context of linear event study regression models (e.g. Humpage, 1984, and Dominguez and Frankel, 1993). Other studies define short pre- and post-event windows, typically spanning a few days or at most a few weeks, around intervention episodes across which exchange rate movements are compared using various criteria for what constitutes intervention success or effectiveness (e.g. Fatum and Hutchison, 2003, Fratzscher et al., 2019). A recent exception to the short-term focus is the contribution by Menkhoff et al., (2021), in which structural vector autoregressions are used to assess the cumulative response of exchange rates to intervention over a time-horizon of one to four quarters. Importantly, their analysis does not consider trend shifts as these are intrinsically eliminated in the analysis of vector autoregressions.

An inherent concern in the context of intervention studies is that central bank intervention is undertaken in response to exchange rate market fluctuations and conditions. The self-selection aspect of intervention creates possible endogeneity issues that are more concerning the longer the time-horizon that is being considered. To address this concern, Chen et al. (2012) apply a data augmentation method in the system of simultaneous equations, including an intervention reaction function, while Fatum and Yamamoto (2014), Naef and Weber (2022) and Menkhoff et al. (2021) use various instrumental variable approaches, and Kearns and Rigobon (2005) develop heteroskedasticity-based identification methods.

Other strands of the intervention literature apply natural experiment methods to obtain stylized causal identifications of the effects of foreign exchange interventions. For example, Fatum and Hutchison (2010) use a propensity-score matching method, Kuersteiner et al. (2018) employ the regression discontinuity method to investigate the rule-based interventions. Chamon et al. (2017), Esaka and Fujii (2019) and Dominguez (2020) introduce the synthetic control method (SCM) to the intervention literature. More specifically, Chamon et al. (2017) study the influence on the exchange rate returns of pre-announced interventions in the BRL market, while Esaka and Fujii (2019) consider short-run effects of the 2011 BoJ interventions on JPY/USD exchange rate returns. Dominguez (2020) provides a comprehensive study of foreign exchange stabilizing intervention policies of emerging market countries in which she considers a quasi-experiment of stabilizing interventions in reaction to the second US quantitative easing (QE2) and the Taper Tantrum announcements.

From a policy perspective, intervening after no intervention activity for more than a decade, in massive amounts, and in the form of the first JPY purchases in 25 years, constitutes a policy shift that surely is implemented with the intention of generating short-term or transient JPY/USD rate effects; rather, this is consistent with a policy goal aimed at generating long-term or lasting effects. Consequently, the appropriate research question in this context, and from a policy stand-point the relevant issue, is not whether these interventions are associated with contemporaneous or short-lived exchange rate effects but whether they are associated with longer lasting effects and, specifically, if they are able to break the persistent downward trend of the relative value of the domestic currency that preceded the interventions.[3] As noted earlier, the majority of intervention studies focus on the short-term effects of intervention on exchange rate returns or on the persistence of the effect of intervention on exchange rate levels and, to the best of our knowledge, no previous study considers whether intervention is associated with long-term trend effects of the exchange rate.

Our analytical approach is based on the synthetic control method (SCM) originally proposed by Abadie et al. (2010, 2015), which in our context translates to using a control pool of no-intervention currencies for estimating a counterfactual currency that has not been treated by intervention even though the intervention was implemented to the actual currency.[4] The causal effect of intervention is then identified as the gap between the actual and the counterfactual rates. As we use the cross-sectional information of the control currencies, the level, the trend, and the time dependence of the treated currency are fully unrestricted.

The conventional SCM is based on a weighted average of the control units included in the analysis. In our context, where exchange rates form a system and there are several factors which determine the exchange rates, there is no theoretical justification for why a particular exchange rate, in our case the JPY/USD rate, would be determined as a weighted average of other rates. To address this concern, we use the so-called generalized version of the standard SCM in which a linear panel data model is applied to compute the synthetic treated unit. Our linear panel data model includes major determinants of exchange rates

[3] Coinciding with a widening interest rate gap between the US and Japan, due to the rapidly changing US monetary policy stance, from January to October 2022 the JPY/USD went from 115 to 150, constituting a JPY depreciation against the USD of more than 30%. Ito (2022) highlights the increase in global uncertainty stemming from the Russia-Ukraine war as a contributing factor to the depreciation of the JPY.
[4] See Neely (2005) for a survey of the earlier intervention literature.

and does not rely solely on one statistical criterion for weighting the control currencies, thereby resulting in a more theoretically justified estimated counterfactual rate. Specifically, we follow the framework of the generalized SCM proposed by Xu (2017), who considers a linear panel data model with unobserved common factors. In particular, our setting incorporates interest rate differentials, as suggested by the uncovered interest rate parity (UIP), global uncertainty, as suggested by the literature on safe haven currencies (Ranald and Söderlind, 2010, Habib and Stracca, 2012, and Fatum and Yamamoto, 2016), and unobserved common factors in global foreign exchange markets, as suggested by the currency factor literature (Lustig et al., 2011, Greenaway-McGrevy et al., 2018, and Aloosh and Bekaert, 2022). The unobserved common factors are intended to capture global fluctuations that are otherwise unaccounted for. Importantly, since interventions are not random assignments but typically conducted when the gap between the actual and the counterfactual rates is large and expanding in an unwanted direction, we augment the generalized SCM with a time-series analysis of structural changes in the level and trend of the gap sequence that allows us to investigate if any changes occur around the intervention dates.

It is important to point out that Chamon et al. (2017) and others use the log difference of the exchange rate as their outcome variable, while we instead use the exchange rate level. By using returns (i.e. first differences) to transform the data into stationary series any trend is eliminated from the data, thereby rendering an investigation of the trend effect impossible by construction. By contrast, we test for structural changes using the Kejriwal and Perron (2010) procedure which is robust to both stationary and nonstationary errors (i.e. both I(0) and I(1) errors), thereby ensuring that our results are valid regardless of whether the data series are stationary or not. This is an essential difference that, unlike Chamon et al. (2017) and the other studies cited, enables us to consider if the intervention episodes under study are associated with exchange rate trend effects.[5]

Our main findings are as follows. We provide significant evidence that the trend of the gap sequence reversed around the 2022 BoJ intervention dates. This is a new and important finding as it suggests that foreign exchange intervention when carried out in a certain manner – large-scale and after an extended lull of no intervention operations – is not only associated with contemporaneous or short-term exchange rate effects, as evidenced by numerous earlier studies, but also capable of generating a longer lasting trend effect in the intended direction. Moreover, the 2022 intervention purchases of JPY coincide with the highest Japanese inflation rates seen in decades, rising to 3.7% in October 2022 and peaking at 4.3% in January 2023. Since a weakening of the domestic currency typically increases inflationary pressure due to increases in both cost of imports in domestic currency terms and aggregate demand, the 2022 interventions aimed at strengthening the JPY are thus consistent with a policy aimed at decreasing the inflationary pressure and therefore also consistent with the possibility of a future tightening of monetary policy.[6] Overall, our findings indicate that intervention can be a potentially powerful policy instrument when

[5] Chamon et al. (2017) focus on pre-announced, rules-based interventions carried out by an emerging market central bank (the Central Bank of Brazil), we consider unannounced, discretionary advanced economy interventions. An important implication of this fundamental context difference is that pre-announced, rules-based interventions eliminate or dramatically reduce central bank discretion regarding whether or when to intervene, and in what amount whereas, by contrast, we assess the effects of the inherently endogenous unannounced, discretionary intervention variable.

[6] See, for example, Fatum and Pedersen (2009) for a study suggesting that the direction of intervention must be consistent with the direction of monetary policy in order for intervention to be effective.

carried out during certain circumstances and in a particular manner, such as large-scale and infrequently and against a persistent exchange rate trend.

The rest of this paper is organized as follows. Section 2 describes the data. Section 3 discusses the econometric methodology. Section 4 presents the results and Section 5 extends the analysis to consider the 2010-2011 BoJ interventions. Section 6 concludes.

2. Data

Our data set consists of official Bank of Japan intervention data, daily frequency spot exchange rates, short-term interest rates, and a global uncertainty measure. Our main data spans the April 1 to December 31, 2022 period, encompassing the 2022 intervention period and a four-month training sample period spanning April 1 to July 31, 2022.

Figure 1 shows the BoJ intervention amounts juxtaposed against the JPY/USD exchange rate. To provide historical context we show daily intervention and exchange rate data spanning from 1998 to the end of our sample period. As can be seen in the figure, the 2022 interventions are the first since 2011 and, as noted earlier, the 2022 intervention amounts in absolute terms are similar to those of the 2010-2011 interventions.[7] Moreover, the 2022 interventions constitute the first JPY intervention purchases since 1998, and are the largest JPY intervention purchases in history.

[7] It is important to note that the 2022 and the 2010-2011 intervention episodes are fundamentally different. The 2022 interventions are consistent with a policy aim of strengthening the domestic currency and consist of sales of foreign currency reserves. In principle, interventions of this nature are limited by the amount of foreign currency reserves. By contrast, the 2010-2011 are consistent with a policy aim of weakening the domestic currency and consist of sales of domestic currency that are in principle unlimited as the central bank can print domestic currency (but not foreign currency). This difference may have implications for the interpretation of our findings, as discussed in Section 5.

There are no official statements available regarding whether the 2022 interventions under study are sterilized or unsterilized.[8] However, whether or not the interventions under study are sterilized or unsterilized is an important issue in terms of possible policy implications of our analysis, since only sterilized intervention can be considered an independent policy instrument, as well as for the possible transmission mechanisms through which intervention might work. In essence, unsterilized intervention changes the monetary base in which case any effects of intervention on exchange rates may occur not only via transmission channels such as the signaling or the portfolio balance channel, but also via a likely stronger monetary channel stemming from the intervention induced change in relative money supplies. Since relying solely on the monetary base for a sterilization analysis may not be entirely appropriate during a period of limited monetary base changes, we plot the 2022 interventions against not only the Japanese monetary base but also against Japanese short-term and long-term interest rates. As the upper panel of Figure 2 shows, there is no indication that any of the 2022 interventions are associated with discernible monetary base changes. Similarly, when we plot the 2010-2011 interventions against the monetary base (depicted in the lower panel of Figure 2), we find no indication of coinciding monetary base changes with the possible exception of the March 18, 2011 intervention.[9] In Figure 3, we plot intervention amounts against daily short-term and long-term interest rates, where the former is captured by the Tokyo Overnight Average Rate (TONAR) and the latter by the 10-year Japanese government bond yields. The upper (lower) panel shows no

[8] The interventions under study are unannounced on the day that they occur and subsequently reported by the Japanese Ministry of Finance as follows. Monthly intervention amounts are published at the end of the month in which interventions occur, while daily amounts are published quarterly such that, for example, daily intervention amounts for the April 1 to June 30 period are published at the beginning of August.

[9] Note that daily Japanese monetary base data is not publicly available prior to 2018, thus the 2010-2011 sterilization analysis relies on monthly data.

indication of concurrent 2022 (2010-2011) interventions and changes in either short-term or long-term interest rates. Since the interventions under study are sterilized, i.e. they are not associated with changes in monetary base or interest rates, we can safely assume that any associated exchange rate effects occur via traditional transmission channels rather than via a monetary channel.[10]

We follow Aloosh and Bekaert (2022) and Engel and Wu (2023) in selecting series of relative currency values vis-à-vis the USD for all the non-US G10 countries, thereby incorporating the most liquid currencies that account for almost 90% of total currency market trading volume.[11] Figure 4 displays separately the evolution of each of the nine currency pairs over the sample period. As it shows, most G10 currencies exhibit a depreciating trend relative to the USD, with the JPY showing a particularly stronger depreciation than any other currency.

Figure 5 shows separately for each non-US G10 country the short-term interest rate differential vis-à-vis the US.[12] The interest rate differentials are quite similar across all countries considered, i.e. unchanged at the beginning and decreasing toward the end of the

[10] For a conceptual discussion of sterilized versus unsterilized intervention see Dominguez and Frankel (1993).
[11] See BIS (2022) for trading volume statistics.
[12] In their recent UIP study, Ismailov and Rossi (2018) use three-month Euro LIBOR rates to capture country-specific interest rate differentials relative to the US rate. However, due to the 2021 benchmark rate reform these rates are now unavailable for several countries. We therefore use instead the following interest rate measures (Bloomberg mnemonics listed in parentheses). The swap OIS rate for the US (USSOC), the TIBOR fixing for Japan (TI0003M), the ESTR rate for the Euro area (EESWEC), the SARON rate for Switzerland (SFSNTC), the USSONIA swap rate for the UK (BPSWSC), the OIS rate for Australia (ADSOC), Canada (CDSOC), Sweden (SKSOC), and New Zealand (NDSOC), and the NIBOR for Norway (NIBOR3M). As a robustness check, we use instead three-month interbank deposit rates for all countries (USDRC for US, JYDRC for Japan, EUDRC for Euro area, SFDRC for Switzerland, BPDRC for the UK, CDDRC for Canada, SKDRC for Sweden, NKDRC for Norway, ADDRC for Australia, and NDDRC for New Zealand) as well as, subsequently, ten-year government bond yields computed using Bloomberg Generic (BGN) methodology. Our findings are qualitatively unchanged regardless of which interest rate series we use.

sample period when the pace of the US interest rate hike increases. As the figure shows, the magnitude of the change in the interest rate differential is largest for Japan.

Figure 6 displays the global uncertainty measure, the VIX. The VIX, provided by the Chicago Board Options Exchange, is a forward-looking, model-free measure of the near-term (30-day) implied volatility of S&P 500 index options.

3. Econometric Methodology

We first estimate the following panel data exchange rate model:

$$S_{i,t} = \mu + \phi_{i,t} + \beta R_{i,t} + \gamma_i VIX_t + \lambda'_i F_t + u_{i,t} \tag{1}$$

where $S_{i,t}$ is the log of the value of the currency of country i relative to the USD at time t for $i = 1, \ldots, N$ and $t = 1, \ldots, T$, with N and T denoting the number of cross-sectional units and time observations, respectively. Equation (1) considers the bilateral exchange rate as determined by two observed covariates, namely the interest rate differential $R_{i,t}$ (the difference between short-term interest rates of country i and that of the US, in basis points) and the log of volatility index VIX_t. We assume that UIP holds thus the coefficient estimate β associated with $R_{i,t}$ is the same across all currencies whereas the influence of global uncertainty is assumed to be country-specific. Moreover, we include the term $\lambda'_i F_t$ to capture time-varying unobserved heterogeneity, where F_t is an $r \times 1$ vector of common factors and λ_i is an $r \times 1$ vector of factor loadings. This term is included to capture global co-movements not accounted for by the interest rate differentials and the global uncertainty index. The model also includes a common intercept μ and an error term $u_{i,t}$.

Most importantly, and the focal point of our analysis, the model contains the unknown nonrandom parameter $\phi_{i,t}$. This is the key parameter of interest as it captures the effects of intervention. By contrast, a model without $\phi_{i,t}$ forms the counterfactual exchange rate ($S^c_{i,t}$), where super-script c indicates counterfactual. Accordingly, $S^c_{i,t}$ is the untreated exchange rate if no interventions are implemented:

$$S_{i,t} = S^c_{i,t} + \phi_{i,t}, \tag{2}$$

where

$$S^c_{i,t} = \mu + \beta R_{i,t} + \gamma_i VIX_t + \lambda'_i F_t + u_{i,t}. \tag{3}$$

To identify the causal effects, we divide the cross-sectional units into two by, in our context, setting the JPY/USD rate as the treated unit and the exchange rates of the other eight countries as the control group. For convenience, we reorder the data such that the treated unit is located at the end of the reordered series, i.e. $i = N$, and the units $i = 1, \dots, N-1$ are all control units. We also divide the entire time dimension into two by setting the training sample as $t = 1, \dots, T_0$ and the testing sample as $t = T_0 + 1, \dots, T$. The gap sequence $\phi_{i,t}$ is by construction assumed to be zero for the control units over the entire sample period. It is also assumed to be zero for the treated unit in the training sample but not in the testing sample.

The standard SCM procedure would set T_0 at the intervention date, and label the two samples the pre- and the post-intervention samples. However, doing so would be concerning for two reasons. First, since it is well-known that empirical exchange rate models are inherently associated with a poor fit of actual data, the gap between the actual and the counterfactual rates is likely substantial and may include various confounding factors for inference. Second, and more importantly, as illustrated in Figure 7, interventions are not random occurrences but typically conducted when the gap is large and expanding in an unwanted direction.[13] To address these concerns, we introduce a model of the gap $\phi_{i,t}$ as a linear trend with multiple endogenously determined structural breaks:

$$\phi_{i,t} = D_{i,t}\pi_i, \tag{4}$$

where $D_{i,t} = [1, c_{i,t}^1, \dots, c_{i,t}^m, t, d_{i,t}^1, \dots, d_{i,t}^m]$ with $c_{i,t}^l = I(t > T_{i,l})$ and $d_{i,t}^l = I(t > T_{i,l})(t - T_{i,l})$ for $l = 1, \dots, m$ with coefficient vector π_i.[14]

3.1. Estimation

The expression described in Equation (1) is a linear panel data model with a common factor structure in the error term and it is estimated using the following standard econometric techniques. First, we standardize $S_{i,t}$ by subtracting the sample mean and dividing by the sample standard deviation for each i. We then use ordinary least squares (OLS) to estimate the regression model with the standardized $S_{i,t}$ as the dependent variable and $R_{i,t}$ and VIX_t as the independent variables to obtain the residuals $z_{i,t}$. Next, let Z denote a $T \times N$ matrix of the residuals with the (t, i)th element being $z_{i,t}$. Then, the r principal components, i.e. the eigenvectors corresponding to the r largest eigenvalues of $ZZ'/(NT)$ denoted by $\hat{F}_t$

[13] Chamon et al. (2017) account for the first concern by adjusting the counterfactual values to match the actual value at the date of intervention. Doing so, however, does not take into account the second concern, i.e. that the distance between the actual and the counterfactual exchange rates is determined endogenously.

[14] Note that $c_{i,t}^l$ accounts for the change in the intercept such that $\phi_{i,t}$ can be associated with jumps or level shifts while $d_{i,t}^l$ captures shifts in the linear trends.

with normalization $T^{-1}\sum_{t=1}^{T}\hat{F}_t\,\hat{F}'_t = I_r$, are our estimates of the unobserved common factors. The factor loadings λ_i are subsequently estimated by the least squares of $z_{i,t}$ on $\hat{F}_t$ such that $\hat{\lambda}_i = T^{-1}\sum_{t=1}^{T}\hat{F}_t z_{i,t}$.

The efficiency of the OLS coefficient estimators for $\theta \equiv \{\mu, \beta, \gamma_i\}$ can be improved by accounting for the unobserved factor structure in the errors. To this end, we apply the interactive fixed effects estimation procedure proposed by Bai (2009). This procedure is implemented by rather than using the dependent variable $S_{i,t}$ and the regressors $R_{i,t}$ and VIX_t, we use the complementary projections of these variables on the space spanned by the estimated factors. Doing so yields new coefficient estimates $\tilde{\theta} \equiv \{\hat{\mu}, \tilde{\beta}, \tilde{\gamma}_i\}$ and associated residuals $\tilde{z}_{i,t}$. Subsequently, the common factors and the factor loadings are then re-estimated using the principal components of the updated residuals $\tilde{z}_{i,t}$, denoted by $\tilde{F}_t$ and $\tilde{\lambda}_i$.

Importantly, if the residuals $z_{i,t}$ do not include the gap $\phi_{i,t}$, the unobserved common factors can be consistently estimated. However, since the residuals do include $\phi_{i,t}$ for the treated units in the testing sample, estimating the unobserved common factors would lead to inconsistent estimates of the factors and the factor loadings. To circumvent this problem we exclude the sample for $i = N$ and $t = T_0 + 1, \dots, T$ by employing the tall-wide (TW) algorithm proposed by Bai and Ng (2021) in the context of matrix completion algorithm. Their method uses $z_{i,t}$ (or $\tilde{z}_{i,t}$) for $i = 1, \dots, N-1$ and all t to estimate F_t for $t = 1, \dots, T$. We thus follow the Bai and Ng (2021) procedure to obtain $\hat{F}_t^{TW}$ (or $\tilde{F}_t^{TW}$) and, in turn, the factor loading estimates $\hat{\lambda}_i^{TW}$ (or $\tilde{\lambda}_i^{TW}$) for $i = 1, \dots, N$ are obtained from the OLS coefficients of regressing $z_{i,t}$ (or $\tilde{z}_{i,t}$) on $\hat{F}_t^{TW}$ (or $\tilde{F}_t^{TW}$) using $t = 1, \dots, T_0$ and $i = 1, \dots, N$.

Once we obtain the estimates for the coefficients, common factors, and factor loadings, the counterfactual rate is constructed as the fitted value of the model described by Equation (5):

$$\tilde{S}_{i,t}^{c} = \tilde{\mu} + \tilde{\beta}R_{i,t} + \tilde{\gamma}_i VIX_t + \tilde{\lambda}_i^{TW'}\tilde{F}_t^{TW} \tag{5}$$

Subsequently, the gap between the actual and the counterfactual rates is obtained by subtracting the latter from the former:

$$\tilde{\phi}_{i,t} = S_{i,t} - \tilde{S}_{i,t}^{c} \tag{6}$$

for $i = N$ and $t = T_0 + 1, \dots, T$. At this stage, we retrieve the original scales of the exchange rates by multiplying the sample standard deviation and by adding the sample mean of the original data for each country i.

Once we have estimated the gap $\phi_{i,t}$, our strategy for estimating the trend break is the following. We first fit an intercept and a linear trend with possible structural breaks to $\tilde{\phi}_{i,t}$ using generalized least squares, and then we apply the multiple structural change test proposed by Kejriwal and Perron (2010).[15] This test considers multiple breaks at $t = T_1, \dots, T_m$ in the trend and/or the intercept where the estimation errors are accounted for by the noise component. The noise component can either be stationary or integrated such that:

[15] Kejriwal and Perron (2010) extends the single break model developed by Perron and Yabu (2009) to consider multiple breaks.

$$\tilde{\phi}_{i,t} = D_{i,t}\pi_i + v_{i,t} \tag{7}$$

$$v_{i,t} = \rho v_{i,t} + \varepsilon_{i,t} \tag{8}$$

for $t = T_0 + 1, \dots, T$, where $v_{i,t}$ captures estimation errors, ρ $(|\rho| \leq 1)$ is a persistence parameter in the noise component, and $\varepsilon_{i,t}$ is assumed to be an i.i.d. sequence.

The procedure first determines the number of structural breaks in the trend and/or intercept by using the sequential tests for no break in the null hypothesis H_0 against one break in the alternative hypothesis H_1. If the test rejects H_0, it proceeds to a test for one break in H_0 against two breaks in H_1, and so on. We denote the test statistic for l breaks against $l+1$ breaks by $F_T(l+1|l)$. The number of breaks in H_0 when the test stops rejecting is considered as the number of breaks present. We follow Bai and Perron (1998) and set the required data points between the two adjacent breaks to 5% of the entire sample size. The critical values of the $F_T(l+1|l)$ test are provided by Kejriwal and Perron (2010).

3.2. Confidence Intervals

We construct the confidence intervals of $\phi_{i,t}$ and other coefficient estimates included in Equation (1) by employing the residual-based bootstrap method proposed by Xu (2017). The key objective here is to generate the bootstrap samples "as if no $\phi_{i,t}$ is present". This is detailed in Step 2 of the bootstrap algorithm described below.

Bootstrap Algorithm

Step 1. We first estimate the model described in Equation (1) in order to obtain $\tilde{S}_{i,t}^{c}$ and $\tilde{\phi}_{i,t}$ and, in turn, the coefficient estimate $\tilde{\theta} = \{\tilde{\mu}, \tilde{\beta}, \tilde{\gamma}_i\}$ and the residuals $\tilde{u} = [\tilde{u}_1, \tilde{u}_2, \dots, \tilde{u}_N]$, where $\tilde{u}_i = [\tilde{u}_{i,1}, \tilde{u}_{i,2}, \dots, \tilde{u}_{i,T}]'$.

Step 2. Next, we generate the bootstrap residuals for the treated unit (JPY/USD; $i = N$). To ensure that the treated unit is free of $\phi_{i,t}$ we do as follows. We first randomly select one control unit from $i = 1, \dots, N-1$, and consider this a "fake treated unit". We then randomly select the rest of the control units with replacement $N-1$ times to form a set of "fake control units". Subsequently, we combine the fake control units and the fake treated unit to produce new residuals with $N-1$ control units and one treated unit. Finally, we re-estimate Equation (1) using the new and modified data and obtain the associated residuals for $i = N$, denoted by $u_N^* = [u_{N,1}^*, u_{N,2}^*, \dots, u_{N,T}^*]'$. We repeat this B times and store $[u_N^*(1), u_N^*(2), \dots, u_N^*(B)]$.

Step 3. We generate the bootstrap residuals for the control units $u_{i,t}^*$ for $i = 1, \dots, N-1$ by resampling the residual vectors of size $T \times 1$ from the pool of $(N-1)$ units with replacement. This way the bootstrap retains time dependence in the residuals. We also use the bootstrap residuals for the treated unit $i = N$ from Step 2.

Step 4. We generate the bootstrap sample free of $\phi_{i,t}$ by estimating the following expression:

$$S_{i,t}^* = \tilde{\mu} + \tilde{\beta} R_{i,t} + \tilde{\gamma}_i VIX_t + \tilde{\lambda}_i^{TW\prime} \tilde{F}_t^{TW} + u_{i,t}^* \quad (9)$$

for $i = 1, \dots, N$ and $t = 1, \dots, T$. We then implement the same estimation method described in Step 1 using the bootstrapped sample $S_{i,t}^*$. We obtain the bootstrap counterfactual rate for the treated unit $\tilde{S}_{N,t}^*$ for $t = T_0 + 1, \dots, T$, and the bootstrap estimate for the gap sequence $\tilde{\phi}^*_{N,t}$ for $t = T_0 + 1, \ldots, T$. We also obtain the bootstrap coefficient estimate $\tilde{\theta}^* \equiv \{\tilde{\mu}^*, \tilde{\beta}^*, \tilde{\gamma}^*_i\}$.

Step 5. We repeat Steps 3-4 B times and store the counterfactual rates $\{\tilde{S}^*_{N,t}(j)\}_{t=T_0+1}^{T}$ and the gap sequence $\{\tilde{\phi}^*_{N,t}(j)\}_{t=T_0+1}^{T}$ for $j = 1, \ldots, B$. The confidence interval of the counterfactual rate is then constructed by $\left[\tilde{S}^c_{N,t} - z_{0.025} SE_t^{\tilde{S}^*},\ \tilde{S}^c_{N,t} + z_{0.025} SE_t^{\tilde{S}^*}\right]$, where z_α is the $100(1-\alpha)$ percentile of the standard normal distribution and $SE_t^{\tilde{S}^*} = \sqrt{\frac{1}{B-1}\sum_{j=1}^{B}\left[\tilde{S}^*_{N,t}(j) - \frac{1}{B}\sum_{l=1}^{B}\tilde{S}^*_{N,t}(l)\right]^2}$ is the sample standard deviation of the bootstrapped counterfactual rate at period t. The confidence interval of the gap sequence is similarly constructed by $\left[\tilde{\phi}_{N,t} - z_{0.025} SE_t^{\tilde{S}^*},\ \tilde{\phi}_{N,t} + z_{0.025} SE_t^{\tilde{S}^*}\right]$. To construct the confidence interval of the coefficient estimates we set the $100 \times \alpha/2$ and the $100 \times (1 - \frac{\alpha}{2})$ percentiles for each element of $(\tilde{\theta}^* - \tilde{\theta})$ to $C^{\theta,\alpha/2}$ and $C^{\theta,1-\alpha/2}$. The confidence interval of each coefficient in θ is then described by $[\tilde{\theta} - C^{\theta,1-\frac{\alpha}{2}},\ \tilde{\theta} - C^{\theta,\alpha/2}]$.[16]

It is important to note that attempting to identify causal effects through timing without direct measurement is challenging. This is an issue inherent to not only the SCM literature but also in a broader context of difference-in-differences methodologies where changes in expected values before and after treatment are interpreted as causal effects. Unlike studies concerned with the effects of a randomly assigned variable where other possible determinants of an outcome variable can be isolated and controlled for, in our context we assess the effects of the inherently endogenous unannounced intervention

[16] While the confidence intervals of the trend break dates in $\phi_{i,t}$ would also be of interest, to the best of our knowledge a method for calculating such confidence intervals has not been developed, and it is beyond the scope of this study for us to attempt to do so.

variable. Consequently, we do not impose timing as in the standard SCM but instead we estimate the break dates in the exchange rate misalignment and, in turn, investigate if the identified trend break dates are consistent with the intervention dates. Doing so does not entirely exclude the possibility that, for example, the exchange rate misalignment automatically self-corrected and coinciding interventions had no effect and just happened to occur around the time that the misalignment disappeared or diminished. While not impossible, this would seem a less likely occurrence.

4. Results

Table 1 reports the results of estimating Equation (1). As the table shows, the interest rate differentials coefficient estimate is negative, as expected, as well as statistically significant even at the 1% level. The coefficient estimates associated with the global uncertainty measure are relatively consistent across the currencies considered. This finding contrasts with existing studies on safe haven currencies, which typically identify the JPY and the CHF as exhibiting particularly strong safe haven behavior during the Global Financial Crisis. This discrepancy is partly due to our sample period not being under such financial distress. Additionally, the inconsistency arises from our use of the levels of the exchange rate and the VIX index, whereas existing studies typically use the first differences. Although this difference is worth exploring, it is beyond the scope of the present paper.

Figure 8 displays the estimated currency factors $\tilde{F}_t^{TW}$. The number of factors is set to 3 following Aloosh and Bekaert (2022).[17] To compare the estimated currency factors

[17] While several statistical methods are proposed for determining the number of factors present in the data, e.g. Bai and Ng (2002), Onatski (2010) and Ahn and Horenstein (2013), none is suitable in our context of only 9 currency pairs. We therefore set the number of currency factors to 3 and subsequently change that

with the intrinsic values of the USD, the nominal broad USD index is also presented in the upper right panel. It is known that the estimated factors are orthogonal by assumption and their signs are indeterminant, hence rigorous interpretations of individual factor estimates are not applicable. Nonetheless, the figures show that the first factor captures the depreciation trends experienced by most G10 currencies against the USD during this period. Interestingly, the first factor closely resembles the nominal trade-weighted broad USD index. This indicates that our counterfactual estimate of the JPY/USD reasonably controls for variations in the intrinsic value of the USD, ensuring that our treatment effect is not influenced by these fluctuations. To provide context, it is worth noting that the USD depreciated by approximately 4.7% in trade-weighted terms during 2022Q4, but in our analysis such variations are captured by the first factor so that our causal effect is free from the broad change of the USD itself.

The second factor captures co-movements of the CHF and EUR which depreciated against the USD earlier in 2022. The third factor represents features of the AUD, the NZD and the CAD, consistent with the presence of a "commodity factor", as suggested by Greenaway-McGrevy et al. (2018) and Aloosh and Bekaert (2022).[18]

Figure 9 shows the actual and the counterfactual JPY/USD rates. The upper panel presents the actual rate ($S_{N,t}$) in a solid line and the counterfactual rate ($\tilde{S}^c_{N,t}$) in a dotted line along with the associated 95% confidence intervals by shadow. The lower panel plots the estimate of the gap sequence ($\tilde{\phi}_{N,t}$). The intervention dates are indicated by vertical lines. The upper panel shows that the actual and counterfactual rates closely followed an

number to 1, 2 and 4. Doing so yields qualitatively identical results as well as points to the first factor being particularly important.

[18] The second factor can be interpreted as the EUR factor while the third factor can be seen as representing global risk, as suggested by Fink et al. (2022).

upward trend in the beginning of the testing period, consistent with the overall movement of G10 currencies captured by the currency factors. However, the actual JPY depreciated even faster before the September 22 intervention. After the intervention, the actual rate returned to the path of the counterfactual rate. Then, the actual rate depreciated again before the October 21-24 interventions, at a pace faster than the counterfactual rate. However, both rates changed direction following the interventions. An interesting question is whether the JPY's appreciation after these interventions was steeper than that of the counterfactual rate. To explore this, we examine the gap sequence presented in the lower panel of Figure 9. We observe that the gap widened in September but disappeared after the September 22 intervention. Most importantly, following the October 21-24 interventions, the gap sequence reversed, supporting the idea that the 2022 interventions are associated with a trend effect.

Turning to the formal analysis of the trend break in the gap sequence, we report the results of the structural change tests in Table 2. The test of no break versus one break $F_T(1|0)$ rejects the null hypothesis at the 1% level. The test for one break versus two breaks, however, is not significant even at the 10% level. Therefore, we conclude that accounting for a single break in the trend is optimal. The break date is identified as November 7, 2022. Figure 10 illustrates the estimated gap sequence (dotted line) and the conditional mean or fitted value (solid line). The amounts of interventions are also shown as bars on the right vertical axis. The figure shows that the depreciating trend stopped and reversed right around when the interventions were carried out. As the interventions under study are all JPY purchases, and thus consistent with a policy objective aimed at preventing further JPY depreciation, our results are consistent with the notion that the 2022 BoJ interventions were instrumental in breaking the trend of the JPY depreciation.

Dominguez (2020) finds that intervention operations in the form of accumulation of reserves in response to the US QE2 were successful as the actual exchange rate depreciated more than its counterfactual rate. Moreover, she finds that the selling of reserves in some countries following the Taper Tantrum were also successful as these operations were associated with the actual exchange rate appreciating more than its counterfactual rate. Her results also show persistence in the effects of intervention on the gap between the actual and counterfactual rates. Although our context is very different, as the large-scale BoJ interventions are conducted in response to domestic currency market conditions rather than in response to exogenous US monetary policy shocks, our results also document long-term effects of interventions and are thus in that sense consistent with the findings of Dominguez (2020).

To ensure robustness of our findings, we first consider if the observed covariates (interest rate differentials and VIX) drive our main results. Replacing our short-term interest rates with long-term interest rate measures as discussed in Section 2 and using a model without the VIX does not affect our results. Next, we consider if our findings are sensitive to the number of common factors included. In the baseline analysis we follow the recent literature on currency factors (e.g. Aloosh and Bekaert, 2022) and use three factors ($r = 3$). As it turns out, estimating the gap between the actual and counterfactual JPY/USD rates with instead $r = 1, 2,$ or 4 does not qualitatively change our results. Additional details and associated figures of the gap sequences are available upon request.

To allow for the possibility that the interest rate differential has different impacts on different currencies, e.g. due to carry trade effects, we re-estimate the model after allowing for the coefficients associated with the interest rate differentials in Equation (1) to be heterogenous across the different currencies. The results of the re-estimation indicate variations in some currency pairs, as expected, while the main results are qualitatively unchanged. The results are available from the authors upon request.

Finally, we complement the synthetic control analysis with standard event study regressions of log-returns of the JPY/USD. While the results of the complementary analysis indicate that the interventions under study are associated with same-day exchange rate affects, they do not necessarily provide additional support to our main findings since the data series used for the event study regressions are first-differenced and thus any information regarding trend effects is by construction eliminated prior to the analysis. The event study analysis results are available from the authors upon request

5. The 2010-2011 Intervention Period

We extend our analysis to consider if the 2010-2011 BoJ interventions are also associated with a trend effect.[19] As shown in Figure 1, during the 2010-2011 intervention period the BoJ carried out intervention operations on eight days (September 15, 2010; March 18, August 4; October 31 to November 4, 2011).[20] All of these interventions are sales of JPY against the USD, consistent with a policy aim towards preventing further JPY appreciation

[19] Similar to the 2022 interventions, no official statements are available regarding whether the 2010-2011 interventions are sterilized or not. When we plot the 2010-2011 interventions against changes in the Japanese monetary base we again find no indication that the interventions are associated with discernible changes in the monetary base.

[20] The March 18, 2011 intervention differs from the other interventions considered in this study due to it being carried as part of a concerted G7 intervention effort to stem the the sudden JPY appreciation following the Great East Japan Earthquake on March 11, 2011.

following the Global Financial Crisis. The 2010-2011 interventions are large-scale, including JPY4,512.9 (USD57.2) billion on August 4 and JPY9,091.7 (USD116.30) billion over the October 31-November 4 5-day period. To carry out the trend effect analysis we use daily observations spanning the April 1, 2010 to December 31, 2011 period, and we set the training sample from the beginning of the sample period to July 31, 2010 and the testing sample from August 1, 2010 to the end of the sample period.

Table 3 reports the results of re-estimating the counterfactual model over the 2010-2011 sample. As before, the interest rate differential coefficient estimate is negative and highly significant, as expected. The coefficient estimate associated with the VIX is again positive and highly significant, although the magnitudes are somewhat smaller than those estimated during the 2022 intervention period.

Figure 11 presents the estimated currency factors together with the broad nominal USD index. The first factor captures the appreciation trends of many currencies against the USD while the second and the third factors show features similar to what we found for the 2022 intervention period. Again, our first factor is very similar to the nominal trade-weighted broad USD index shown in the upper right panel, indicating that our causal effect estimate is not driven by changes in the USD.

Figure 12 plots the actual and the counterfactual JPY/USD rates as well as the gap sequence for the 2010-2011 intervention period. The actual and counterfactual rates do not show significant differences after the first intervention on September 15, 2010. However, by December 2010, they move in opposite directions: the actual rate appreciated (moved downward) while the counterfactual rate depreciated (moved upward). After the March 15, 2011, intervention, the actual rate rises, whereas the counterfactual rate remains stable.

Consequently, the gap sequence forms a V-shape, decreasing until March 2011 and then recovering. After March 15, both the actual and counterfactual rates appreciate rapidly, reducing the gap. The August 4, 2011, intervention occurs when the counterfactual rate is appreciating, but the actual JPY/USD rate remains steady. Finally, the October 31 - November 4 interventions take place when the actual JPY is not stronger than the counterfactual. The actual rate increases immediately, but the overall trend remains unchanged.

It is interesting to notice that the four intervention episodes were carried out during different exchange rate conditions and associated with different outcomes. The September 15, 2010, intervention occurred when both the actual and counterfactual JPY rates were appreciating, resulting in an insignificant and non-expanding gap. In contrast, the March 15, 2011, intervention took place when the gap was significantly negative and expanding. Finally, both the August 4, 2011, and October 31-November 4, 2011, interventions occurred when the actual rate was not significantly stronger than the counterfactual rate.

Turning to the structural change tests, Table 4 displays the results. As the table shows, we find that three breaks are present as the $F_T(1|0)$, the $F_T(2|1)$ and the $F_T(3|2)$tests reject the null hypothesis at the 1% level, while the $F_T(4|3)$ test does not. The optimal break dates are estimated at February 24, 2011, May 19, 2011 and August 3, 2011, thus the first and the third breaks are very close to the March 18, 2011 and the August 4, 2011 intervention dates. Figure 13 shows the estimated gap sequence and the conditional mean function for the 2010-2011 period. The most significant observation is that the gap was expanding in the negative direction (indicating the JPY was overly appreciated) until February 2011, but it reversed direction around the time of the March 15 intervention. After the May 2011 break, the trend shifted back to the negative direction. The August 4, 2011, intervention adjusted the gap level in the desired direction, but the negative trend persisted. The October 31-November 4, 2011, interventions, conducted when the gap was positive and not expanding, did not appear to effectively change the trend.

Overall, our results of the analysis of the 2010-2011 interventions further indicate that interventions have the potential to induce a trend effect. The March 15, 2011, intervention clearly suggests a trend effect, as it was conducted while the gap was expanding in an unwanted direction. The August 4, 2011, intervention, carried out when both the actual and counterfactual rates were appreciating, seems consistent with some level effect but only slightly altered the trend. By contrast, the September 15, 2010, and October 31-November 4, 2011, interventions seem to have been not effective in changing the trend. These observations point to the importance of the timing of intervention in order to induce a trend effect: interventions need to be implemented when the gap is large, when the gap is expanding in an unwanted direction (i.e., interventions against the trend), and when furthermore interventions need to be carried out in very large amounts.

As noted earlier, the 2022 and the 2010-2011 intervention episodes are fundamentally different, yet the two episodes seem associated with similar trend effects. While we recognize that any inference from comparing two observations, i.e. the 2020 and the 2010-2011 intervention episodes, is a stretch, it is nevertheless interesting to note that the key difference between the two episodes is that the earlier is characterized by sales of domestic currency where the amount of reserves held play no role, while the recent is characterized by sales of foreign currency where finite reserves in principle restricts how much additional intervention can be undertaken. At a first glance, the similar trend effect associated with both episodes could suggest that the direction of intervention, and thus whether reserves constrain the path of future interventions or not, is not a factor in regards to the associated trend effects. However, the fact that BoJ holds a very large amount of reserves makes it plausible that the reserve constraint is in this particular context of little importance, whereas this would not be the case for most emerging markets where reserve holdings are smaller. It is also interesting to note that the key common characteristics are large intervention amounts and infrequent interventions, suggesting that these are necessary components for intervention to generate not just short-term but also long-term effects in the form of trend reversal.

6. Conclusion

We investigate the trend effect of the 2022 BoJ intervention episode by employing a counterfactual estimate of the JPY which incorporates major exchange rate determinants such as interest rate differentials, global uncertainty, and unobserved currency factors. We address the issue of the endogeneity concern stemming from leaning-against-the-wind characteristics of the interventions and consider structural changes in the level and the trend of the gap sequence between actual and counterfactual exchange rates.

Our results show that the trend of the gap sequence reversed in the desired direction around or shortly after the 2022 intervention dates, indicating that the intervention policy instrument is potentially powerful enough to generate not only immediate and short-term exchange rate effects, as shown by earlier intervention studies, but also long-term effects in the form of trend reversals. This is an in important insight not previously found in the intervention literature.

We also analyze the 2010-2011 intervention period and in this context provide further evidence to suggest that interventions have the potential to induce a trend effect. At the same time, the 2010-2011 results show that not all interventions have trend effects. The latter is not surprising but nevertheless important as it adds more than just nuance to the interpretation of our findings. In particular, while our main result is that intervention is capable of influencing the long-term path of the exchange rate, our findings also show that this is not always the case. Since our 2022 and 2010-2011 samples encompass three and eight intervention days, respectively, we are unable to provide insights based on rigorous analysis in regards to why some intervention episodes are associated with trend effects and why others are not. However, anecdotal evidence based on the data at hand suggests that for a trend effect to materialize interventions have to be implemented when the gap is large, when the gap is expanding in an unwanted direction, i.e. interventions occur as leaning against the wind, and when interventions are carried out in very large amounts.

While it is beyond the scope of this study to investigate the transmission channels driving the trend effect of intervention, it is important to note that although intervention can permanently affect the relative supply of JPY securities and hence the exchange rate through the portfolio channel, this would not in itself affect future exchange rates. In order for intervention to influence future exchange rates, intervention must change expectations about future policy actions and in turn market conditions. The observed exchange rate trend effect, therefore, is consistent with intervention working through some form of signaling, whether through the signaling channel in the traditional sense, i.e. by changing expectations about future monetary policy, or in a broader sense by changing expectations about future interventions.

References

Abadie, A., Diamond, A., Hainmueller, J., 2010. Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. Journal of the American Statistical Association 105, 493-505.

Abadie, A., Diamond, A., Hainmueller, J., 2015. Comparative politics and the synthetic control method. American Journal of Political Science 59, 495-510.

Ahn, S.C., Horenstein, A.R., 2013. Eigenvalue ratio test for the number of factors. Econometrica 81, 1203-1227.

Aloosh, A., Bekaert, G., 2022. Currency factors. Management Science 68, 4042-4064.

Bai, J., 2009. Panel data models with interactive fixed effects. Econometrica 77, 1229-1279.

Bai, J., Ng, S., 2002. Determining the number of factors in approximate factor models. Econometrica 70, 191-221.

Bai, J., Ng, S., 2021. Matrix completion, counterfactuals, and factor analysis of missing data. Journal of American Statistical Association 116, 1746-1763.

Bai, J., Perron, P., 1998. Estimating and testing linear models with multiple structural changes. Econometrica 66, 47-78.

Bank for International Settlements (BIS), 2022. Triennial central bank survey: OTC foreign exchange turnover in April 2022.

Chamon, M., Garcia, M., Souza, L., 2017. FX interventions in Brazil: A synthetic control approach. Journal of International Economics 108, 157-168.

Chen, C.-N., Watanabe, T., Yabu, T., 2012. A new method for identifying the effects of foreign exchange interventions. Journal of Money, Credit and Banking 44, 1507-1533.

Dominguez, K., 2020, Revisiting exchange rate rules. IMF Economic Review 68, 693-719.

Dominguez, K., Frankel, J., 1993. Does foreign exchange intervention work?. Washington DC: Institute for International Economics.

Engel, C., Wu, S.P.Y., 2023. Forecasting the U.S. Dollar in the 21st century. Journal of International Economics 141.

Esaka, T., Fujii, T., 2019. Evaluating the effectiveness of foreign exchange intervention using counterfactual analysis: Evidence from Japanese intervention episodes, 2010-2011. Working Paper.

Fatum, R., 2015. Foreign exchange intervention when interest rates are zero: Does the portfolio-balance channel matter after all? Journal of International Money and Finance 57, 185-199.

Fatum, R., Hutchison, M.M., 2003. Is sterilised foreign exchange intervention effective after all? An event study approach. Economic Journal 113, 390-411.

Fatum, R., Hutchison, M.M., 2010. Evaluating foreign exchange market intervention: Self-selection, counterfactuals and average treatment effects. Journal of International Money and Finance 29, 570-584.

Fatum, R., Pedersen, J., 2009. Real-time effects of central bank intervention in the Euro market. Journal of International Economics 78, 11-20.

Fatum, R., Yamamoto, Y., 2014. Large versus small foreign exchange interventions. Journal of Banking and Finance 43, 114-123.

Fatum, R., Yamamoto, Y., 2016. Intra-safe haven currency behavior during the global financial crisis. Journal of International Money and Finance 66, 49-64.

Fink, F., Frei, L., Gloede, O., 2022. Global risk sentiment and the Swiss franc: A time-varying daily factor decomposition model. Journal of International Money and Finance 122.

Fratzscher, M., Gloede, O., Menkhoff, L., Sarno, L., Stohr, T., 2019. When is foreign exchange intervention effective? Evidence from 33 countries. American Economic Review: Macroeconomics 11, 132-156.

Greenaway-McGrevy, N., Mark, Sul, D., Wu, J.-L., 2018. Identifying exchange rate common factors. International Economic Review 59, 2193-2218.

Habib, M.M., Stracca, L., 2012. Getting beyond carry trade: What makes a safe haven currency?. Journal of International Economics 87, 50-64.

Humpage, O.F., 1984. Dollar intervention and the Deutschemark-Dollar exchange rate: A daily time-series model. Federal Reserve Bank of Cleveland working paper 8404.

Ismailov, A., Rossi, B., 2018. Uncertainty and deviations from uncovered interest rate parity. Journal of International Money and Finance, 88, 242-259.

Ito, T., 2022. Down Goes the Yen. Project Syndicate, October 20, 2022.

Kearns, J., Rigobon, R., 2005. Identifying the efficacy of central bank interventions: The Australian case. Journal of International Economics 66, 31-48.

Kejriwal, M., Perron, P., 2010. A sequential procedure to determine the number of breaks in trend with an integrated or stationary noise component. Journal of Time Series Analysis 31, 305-328.

Kuersteiner, G.M., Phillips, D.C., Villamizar-Villegas, M., 2018. Effective sterilized foreign exchange intervention? Evidence from a rule-based policy. Journal of International Economics 113, 118-138.

Lustig, H., Roussanov, N., Verdelhan, A. 2011. Common risk factors in currency markets. Review of Financial Studies 24, 3731-3777.

Naef, A., Weber, J.P., 2022. How powerful is unannounced, sterilized foreign exchange intervention?. Journal of Money, Credit and Banking (forthcoming).

Menkhoff, L., Rieth, M., Stohr, T., 2021. The dynamic impact of FX interventions of financial markets. Review of Economics and Statistics 103, 939-953.

Neely, C.J., 2005. An analysis of recent studies of the effect of foreign exchange intervention. Federal Reserve Bank of St. Louis Review 87, 685-717.

Onatski, A., 2010. Determining the number of factors from empirical distribution of eigenvalues. Review of Economics and Statistics 92, 1004-1016.

Perron, P., Yabu, T., 2009. Estimating deterministic trends with an integrated or stationary noise component. Journal of Business and Economic Statistics 27, 369-396.

Ranaldo, A., Söderlind, P., 2010. Safe haven currencies. Review of Finance 14, 385-407.

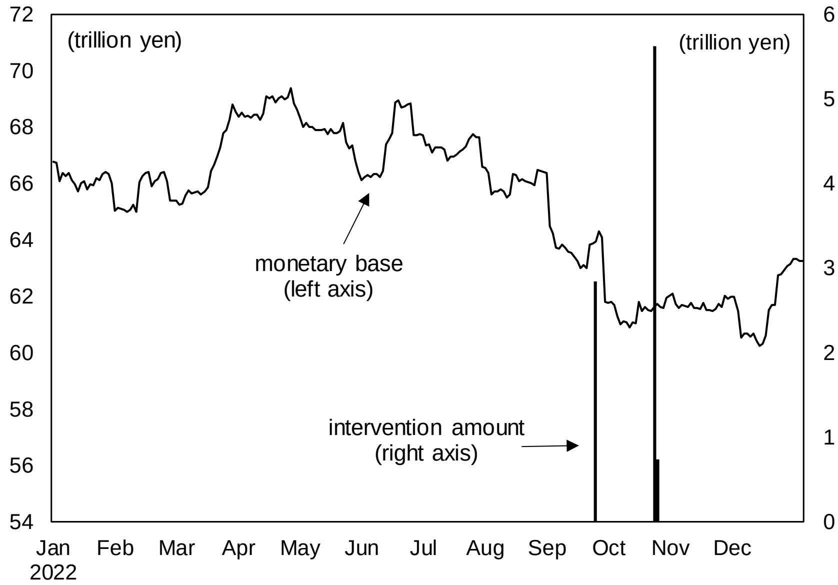
Xu, Y., 2017. Generalized synthetic control method: Causal inference with interactive fixed effects models. Political Analysis 25, 57-76.

Figure 1. Foreign Exchange Interventions in JPY/USD Market

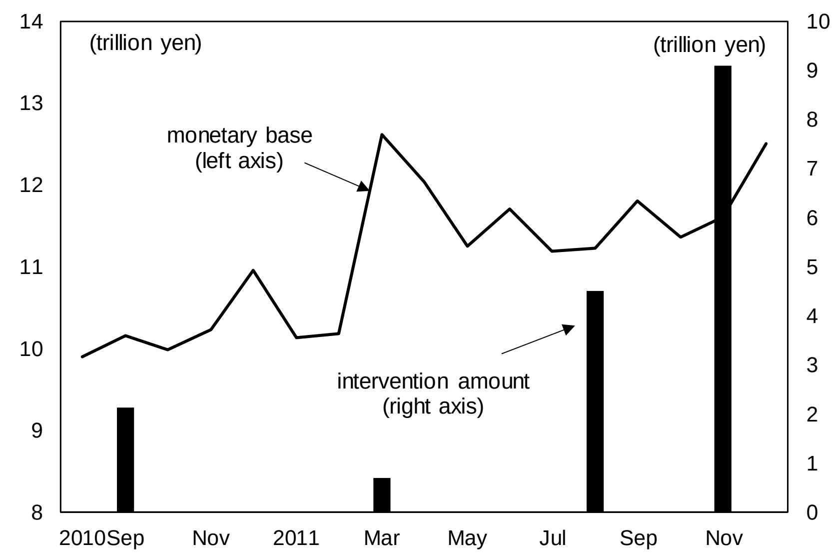
Note: The bar chart indicates the intervention amounts in the left axis, whereas a positive amount corresponds to yen selling intervention and a negative amount is yen purchasing intervention.
Source: Ministry of Finance Japan and Bloomberg

Figure 2. Monetary Base and Intervention Amount

The 2022 Intervention Period



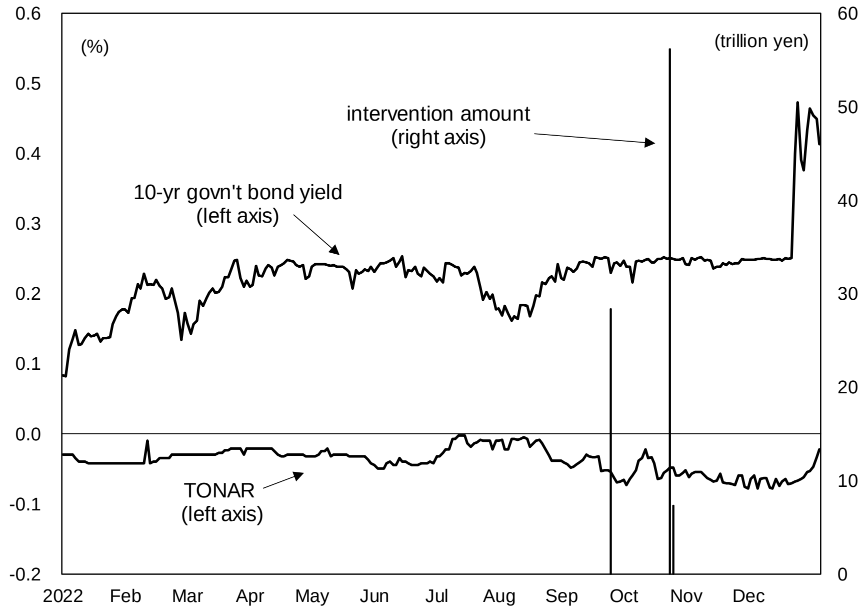
The 2010-2011 Intervention Period



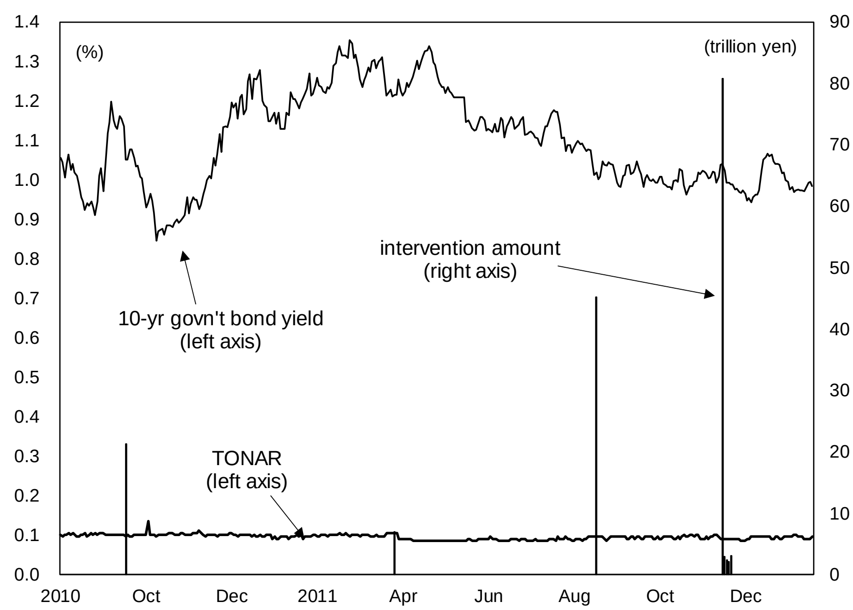
Note: The intervention amounts are those of JPY purchasing for the 2022 intervention period and those of JPY selling intervention for the 2010-2011 intervention period. Therefore, unsterilized intervention is considered to decrease the monetary base in the former and to increase the monetary base in the latter.
Source: Ministry of Finance Japan and Bank of Japan

Figure 3. Interest Rates and Intervention Amount

The 2022 Intervention Period

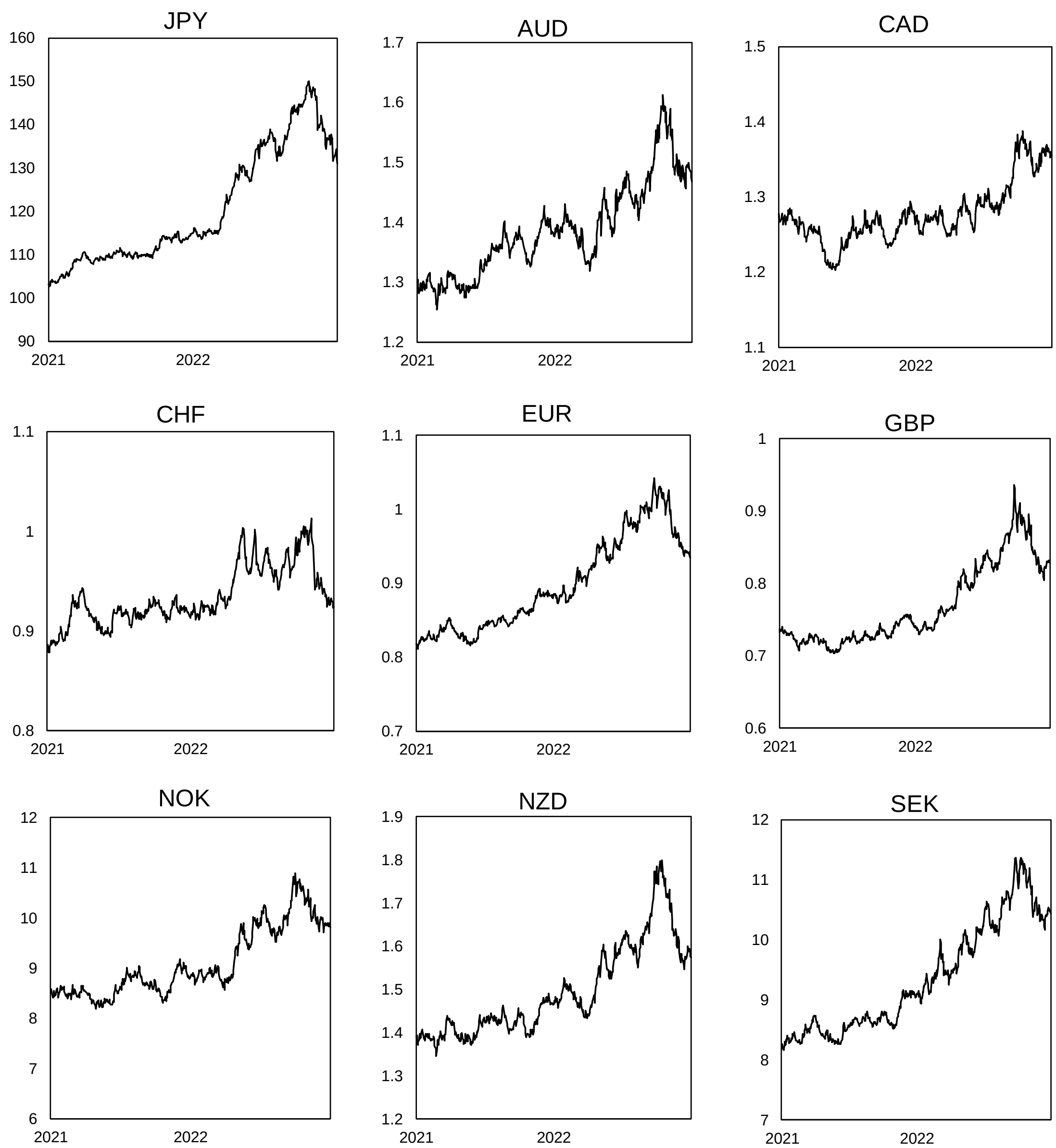


The 2010-2011 Intervention Period



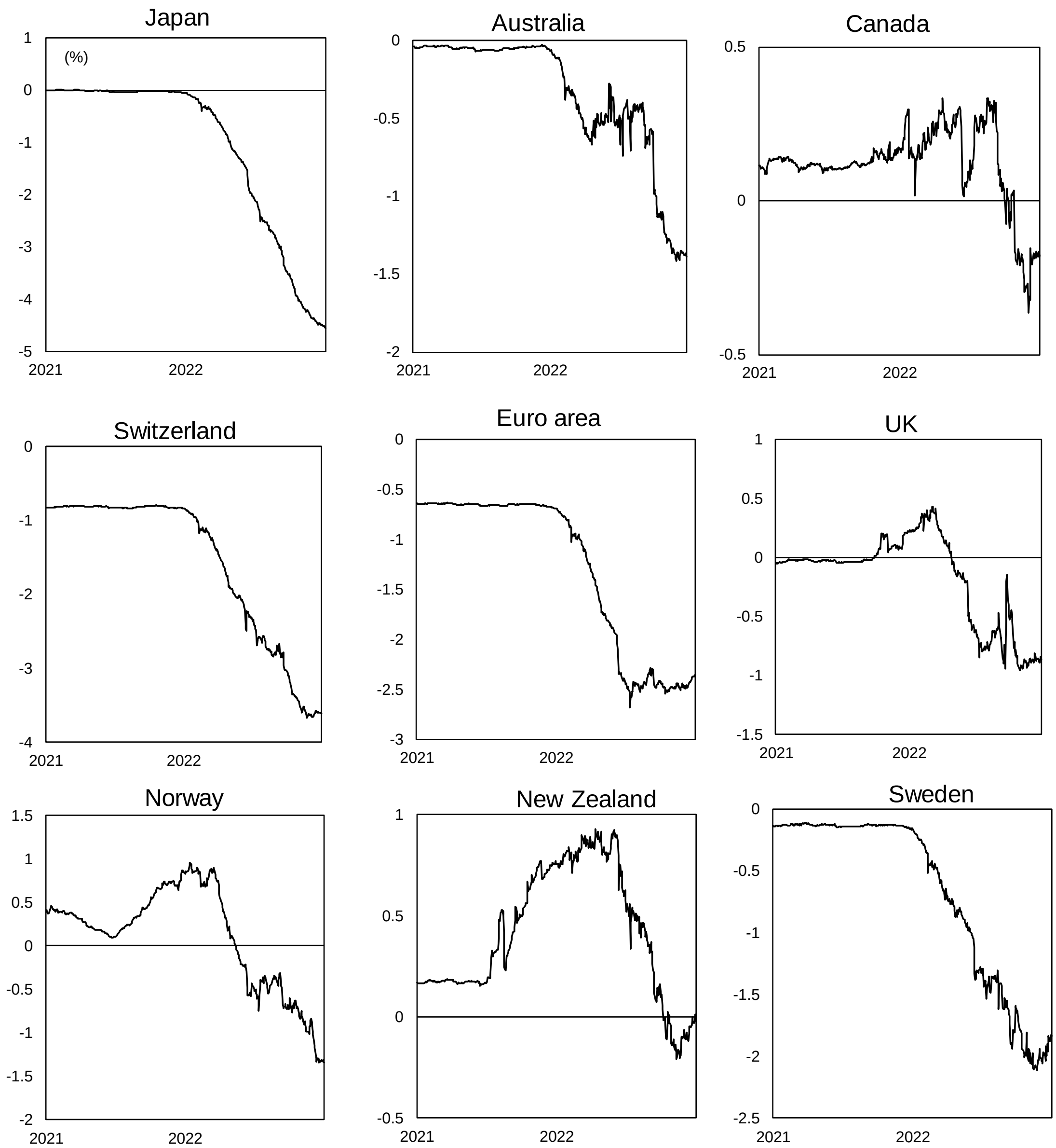
Note: The intervention amounts are those of JPY purchasing for the 2022 intervention period and those of JPY selling intervention for the 2010-2011 intervention period. Therefore, unsterilized intervention is considered to increase the interest rate in the former and to decrease the interest rate in the latter.
Source: Ministry of Finance Japan and Bloomberg

Figure 4. Bilateral Exchange Rates Against the USD



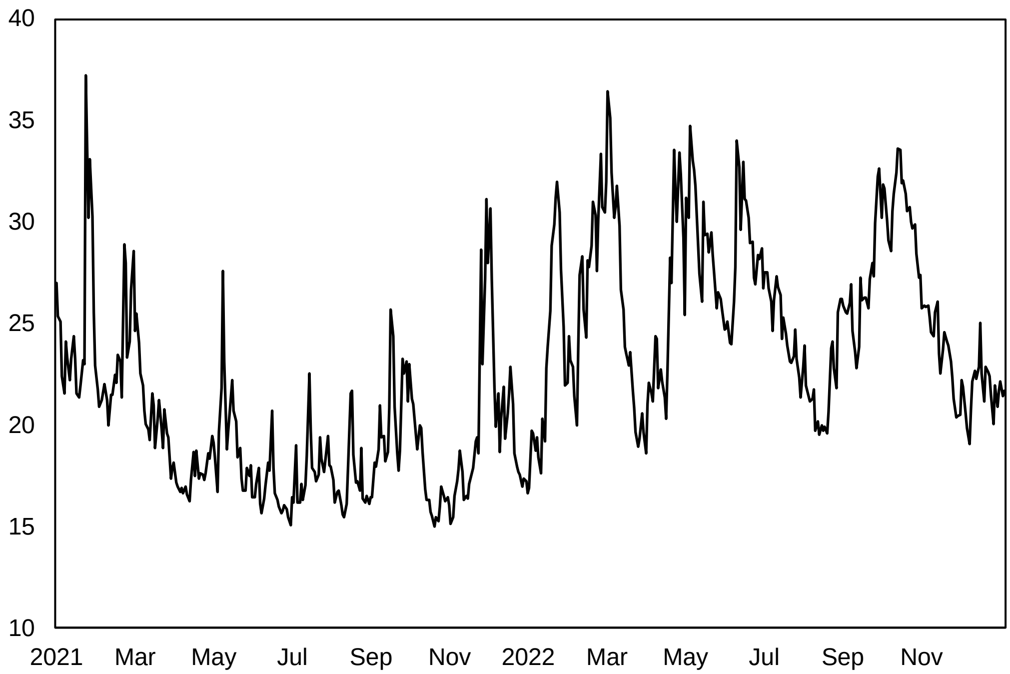
Source: Bloomberg

Figure 5. Interest Rate Differentials Relative to the US



Source: Bloomberg

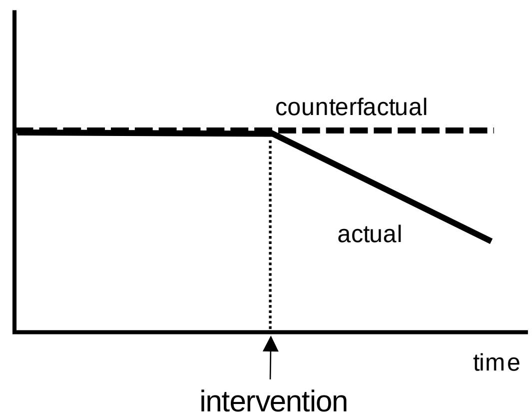
Figure 6. VIX Index



Source: Chicago Board Options Exchange

Figure 7. Randomly Assigned and Lean Against the Wind Interventions

Randomly Assigned Intervention



Lean Against the Wind Intervention

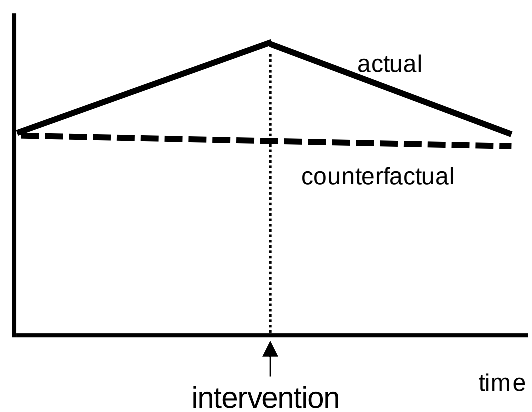
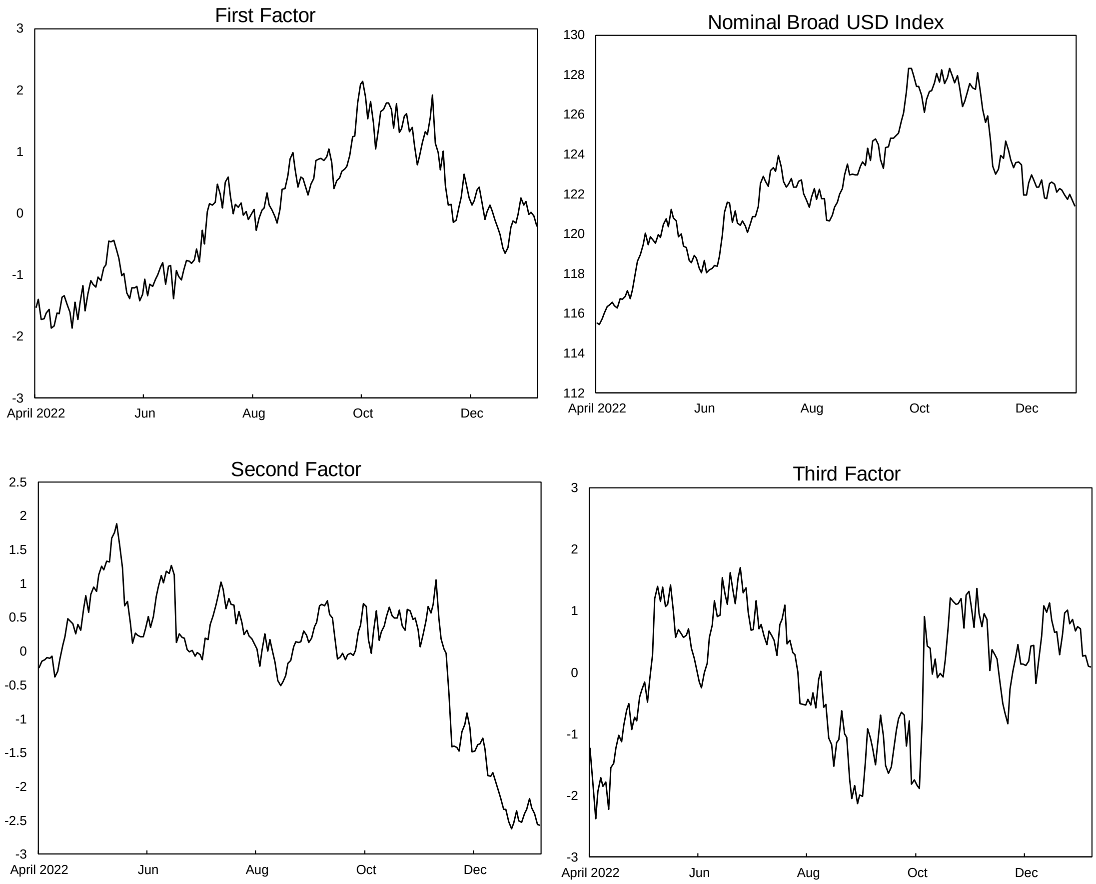


Figure 8. Estimated Currency Factors and the Nominal Broad USD Index



Note: The series are normalized such that $\tilde{F}^{TW\prime}\tilde{F}^{TW}/T = I_r$.
Source: Authors' calculation and the Federal Reserve Board

Figure 9. The Counterfactual Rate and the Gap Sequence

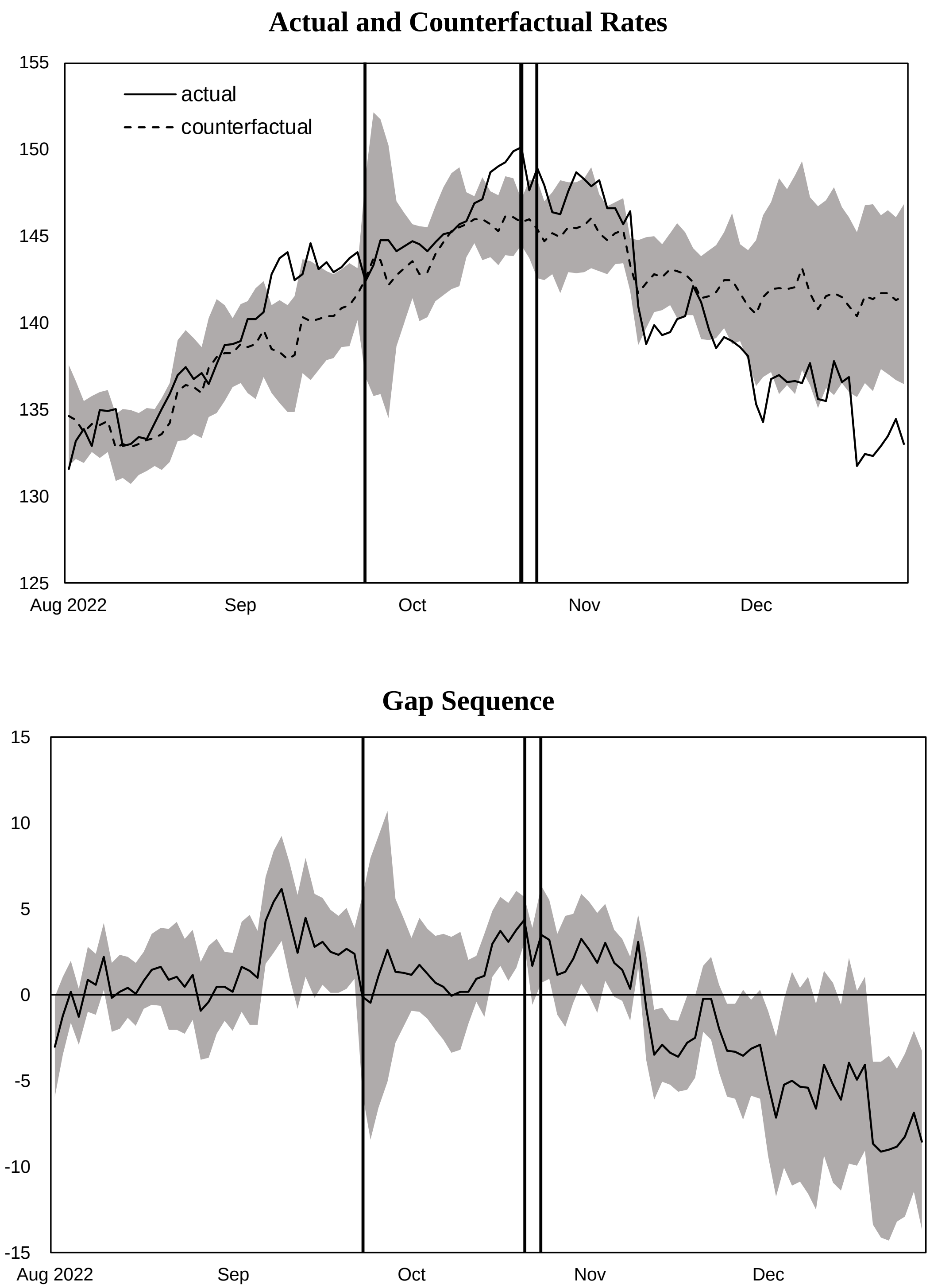


Figure 10. Trend Breaks in the Gap Sequence

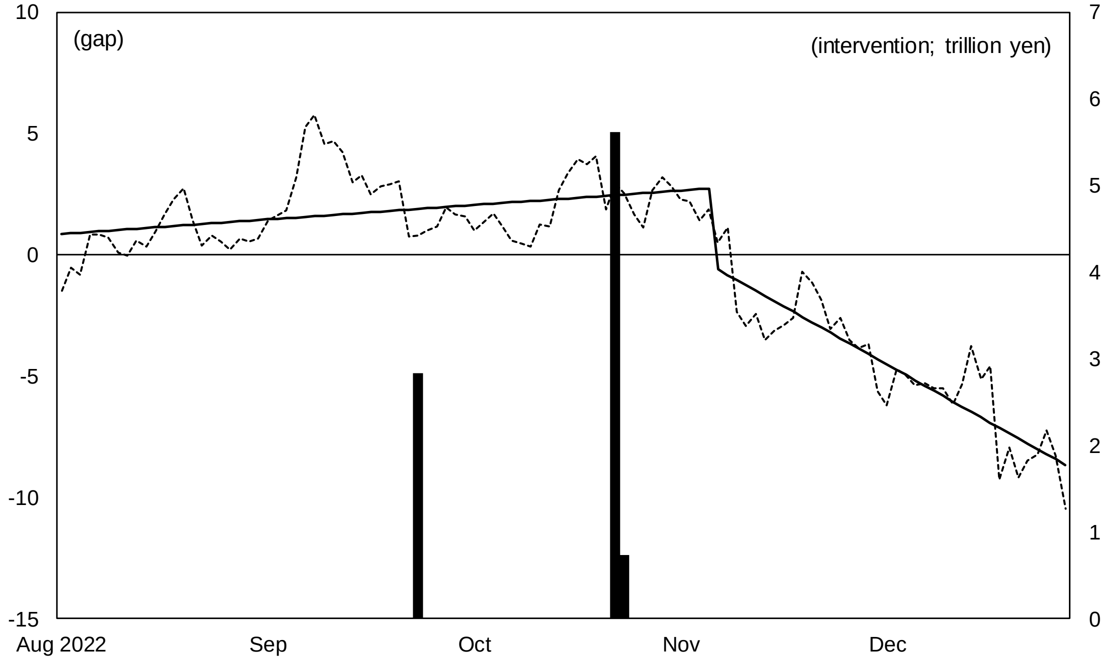
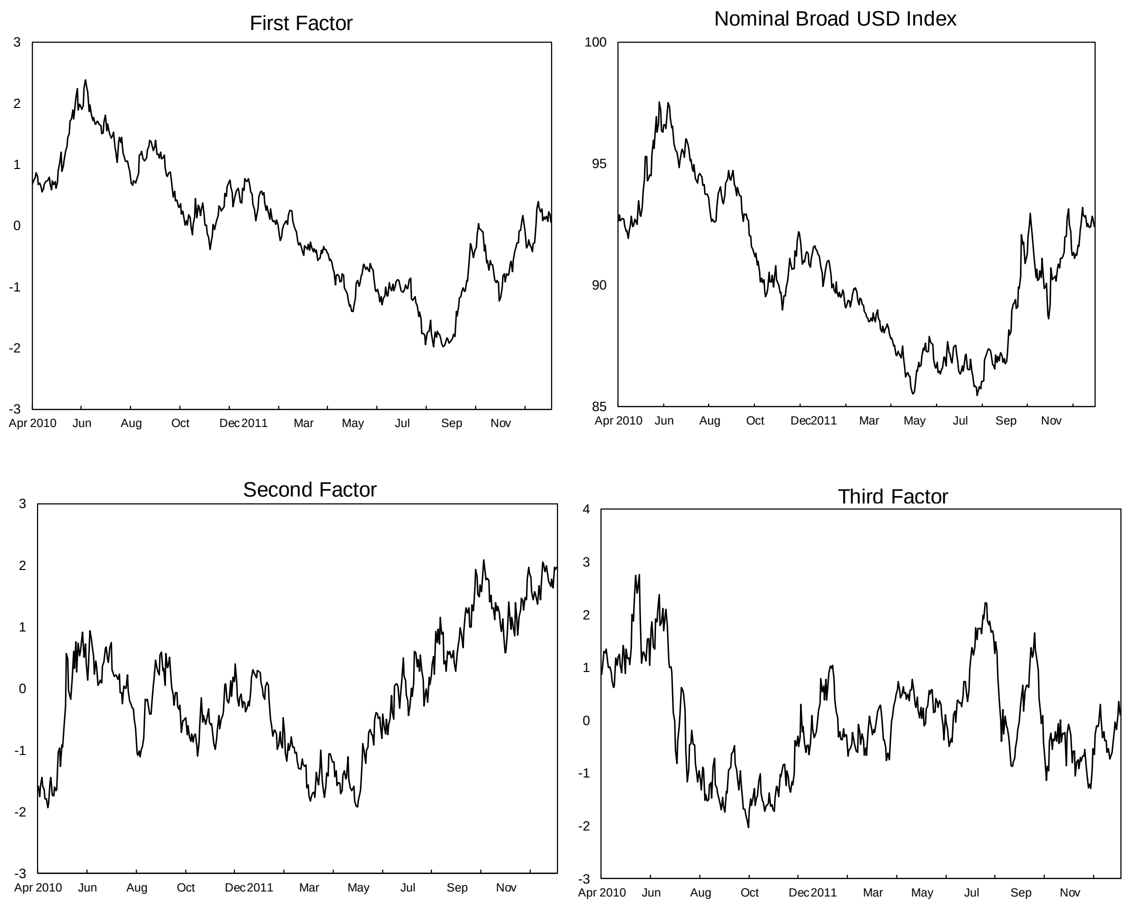
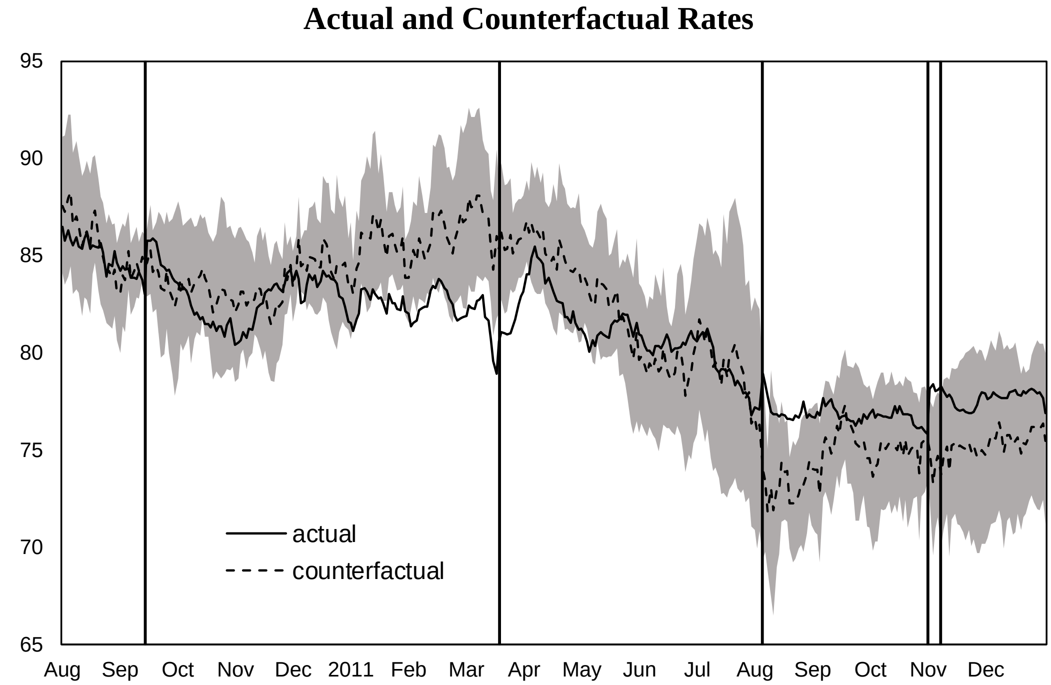


Figure 11. Estimated Currency Factors and the Nominal Broad USD Index
The 2010-2011 Intervention Period



Note: The series are normalized such that $\tilde{F}^{TW'}\tilde{F}^{TW}/T = I_r$.
Source: Authors' calculation and the Federal Reserve Board

Figure 12. The Counterfactual Rate and the Gap Sequence
The 2010-2011 Intervention Period



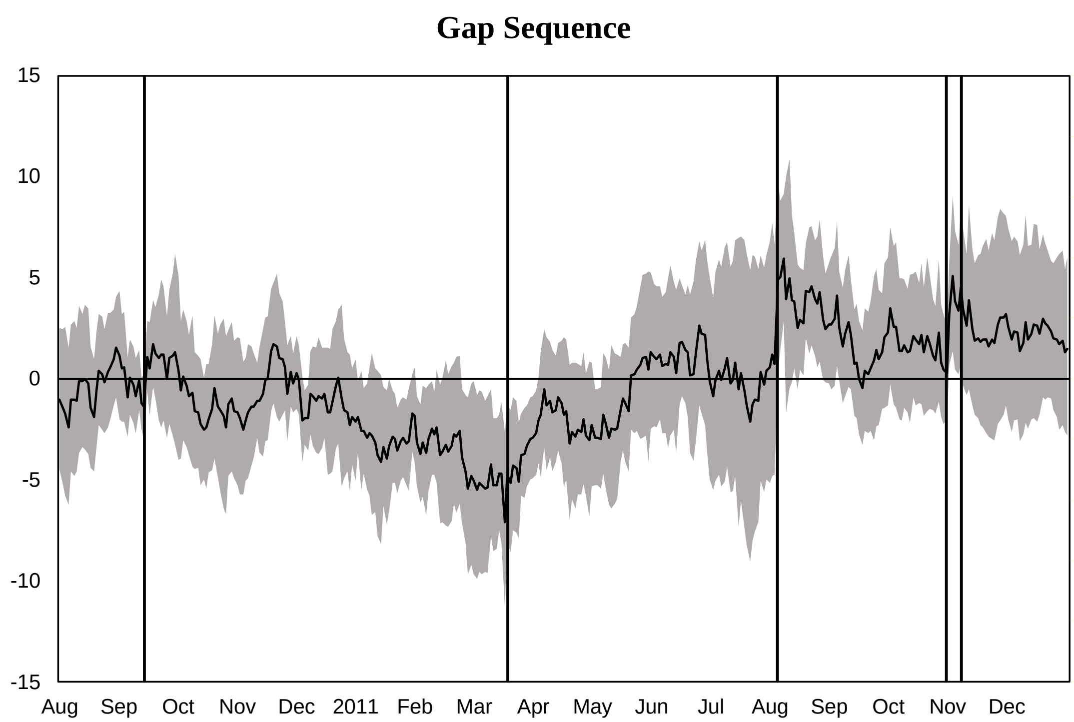


Figure 13. Trend Breaks in the Gap Sequence
The 2010-2011 Intervention Period

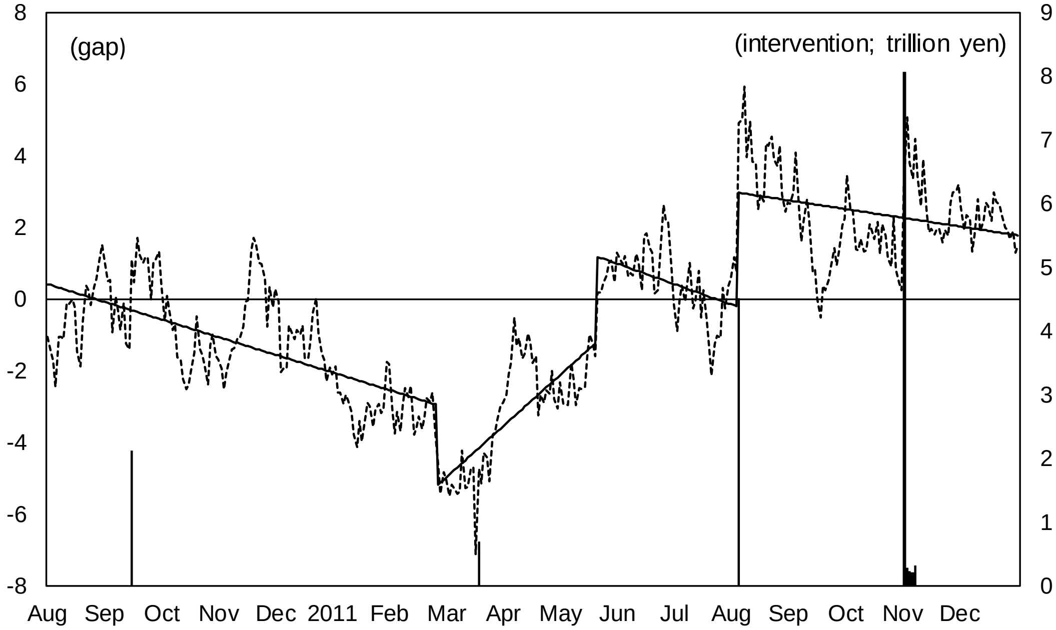


Table 1. Coefficient Estimates of the Counterfactual Model

		Coefficient	95% Confidence Interval
$R_{i,t}$		-0.94***	[-1.05, -0.72]
VIX_t	JPY	1.42***	[1.05, 1.87]
	EUR	1.57***	[1.20, 2.00]
	CHF	1.44***	[1.07, 1.89]
	GBP	2.06***	[1.70, 2.47]
	CAD	2.24***	[1.88, 2.64]
	SEK	1.79***	[1.43, 2.21]
	NOK	2.07***	[1.71, 2.48]
	AUD	2.00***	[1.64, 2.41]
	NZD	2.33***	[1.97, 2.71]
Const.		-7.18***	[-8.46, -6.01]

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 2. Structural Change Tests for the Trend of the Gap Sequence

Tests	$F_T(1\|0)$	$F_T(2\|1)$
	8.10***	2.85
Break Dates	November 7, 2022	

Note: Same as Table 1.

Table 3. Coefficient Estimates of the Counterfactual Model
The 2010-2011 Intervention Period

		Coefficient	95% Confidence Interval
$R_{i,t}$		-0.97***	[-0.99, -0.56]
VIX_t	JPY	0.21***	[0.17, 0.42]
	EUR	0.32***	[0.26, 0.51]
	CHF	0.07**	[0.01, 0.31]
	GBP	0.27***	[0.23, 0.47]
	CAD	0.40***	[0.32, 0.58]
	SEK	0.58***	[0.45, 0.74]
	NOK	0.96***	[0.70, 1.11]
	AUD	1.51***	[1.03, 1.67]
	NZD	0.94***	[0.69, 1.09]
Const.		-0.47***	[-1.17, -0.42]

Note: Same as Table 1.

Table 4. Structural Change Tests for the Trend of the Gap Sequence
The 2010-2011 Intervention Period

Tests	$F_T(1\|0)$	$F_T(2\|1)$	$F_T(3\|2)$	$F_T(4\|3)$
	10.43***	9.86***	10.07***	4.10
Break Dates	February 24; May 19; August 3 2011			

Note: Same as Table 1.