HIAS-E-132

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Aug 2023

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This version: 27 August 2023

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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.

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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. Due to their scale these interventions have the potential for generating substantial portfolio-balance effects and due to their newsworthiness, in the sense that they occur after years of no intervention activity, have the potential for generating substantial signaling effects. 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.

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 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.

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 level of the exchange rate of pre-announced interventions in the BRL/USD 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.

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.

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.[1]

[1] 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.

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.[2] 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 and does not rely 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

[2] See Neely (2005) for a survey of the earlier intervention literature.

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.

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 for a number of reasons. First, 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. Second, while previous studies such as Fatum and Pedersen (2009) suggest that the direction of intervention must be consistent with the underlying monetary policy stance in order for intervention to be effective, our findings suggest that this need not be the case. The 2022 interventions are JPY purchases aimed at strengthening the JPY while the coinciding monetary policy stance is characterized by an increasing US-Japan interest rate differential which in and of itself is consistent with a weakening of the JPY. This is an interesting finding that may indicate that intervention can be a potentially more powerful policy instrument than previously thought. Importantly, this finding adds credence to the suggestion that intervention when carried out during certain circumstances and in a particular manner, such as large-scale and infrequently and against a persistent exchange rate trend, can be considered an independent policy instrument.

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 January 1, 2021 to December 31, 2022 period, encompassing the 2022 intervention period and a one year training sample period spanning January 1 to December 31, 2021.

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. Moreover, the 2022 interventions constitute the first JPY intervention purchases since 1998, and are the largest JPY intervention purchases in history.

There are no official statements available regarding whether the 2022 interventions under study are sterilized or unsterilized. 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. To address the issue we plot the 2022 interventions against daily changes in the Japanese monetary base. As Figure 2 shows, there is no indication that any of these interventions are associated with discernible changes in the monetary base, thereby implying that the interventions under study are sterilized and that any associated exchange rate effects occur via traditional transmission channels rather than via a monetary channel.[3]

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.[4] Figure 3 displays separately the evolution of each of the nine currency pairs over the sample period. As the first sub-figure shows, the JPY exhibits a depreciating trend relative to the USD.

Figure 4 shows separately for each non-US G10 country the short-term interest rate differential vis-à-vis the US.[5] The interest rate differentials are quite similar across all

[3] For a conceptual discussion of sterilized versus unsterilized intervention see Dominguez and Frankel (1993).
[4] See BIS (2022) for trading volume statistics.
[5] 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

countries considered, i.e. unchanged at the beginning and decreasing toward the end of the 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 5 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 $i = 1, \dots, N$ and $t = 1, \dots, T$, 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 volatility index VIX_t. We assume that UIP holds thus the coefficient estimate β

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.

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 ($S_{i,t}^c$), where super-script c indicates counterfactual. Accordingly, $S_{i,t}^c$ is the untreated exchange rate if no interventions are implemented:

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

where

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

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 $i = 1, \ldots, N-1$ are all control units. We also divide the entire time dimension into two by setting the training sample as $t = 1, \ldots, T_0$ and the testing sample as $t = T_0 + 1, \ldots, T$. 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 6, interventions are not random occurrences but typically conducted when the gap is large and expanding in an unwanted direction.[6] 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.[7]

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

[6] 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.

[7] 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.

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 $\hat{F}_t$ 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 $t = T_0 + 1, \ldots, T$ 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).[8] 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:

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

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

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 10% 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).

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

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:

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

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 $t = T_0 + 1, \dots, T$. 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 $j = 1, \dots, B$. The $100 \times (1-\alpha)\%$ confidence interval is then constructed using the percentile method, i.e. for every t, let the $100 \times \alpha$ percentile of $\{\tilde{\phi}^*_{N,t}(j)\}_{j=1}^{B}$ be $C_t^{\phi,\alpha}$. The confidence interval of the counterfactual rate is then described by $\left[\tilde{S}^c_{N,t} - C_t^{\phi,1-\frac{\alpha}{2}},\ \tilde{S}^c_{N,t} - C_t^{\phi,\alpha/2}\right]$ and the confidence interval of the gap sequence is described by $\left[\tilde{\phi}_{N,t} - C_t^{\phi,1-\frac{\alpha}{2}},\ \tilde{\phi}_{N,t} - C_t^{\phi,\alpha/2}\right]$. Finally, 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 $[\tilde{\theta} - C^{\theta,1-\frac{\alpha}{2}},\ \tilde{\theta} - C^{\theta,\alpha/2}]$.[9]

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,

[9] While the confidence intervals of the trend break dates in ϕ_{it} 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.

at the 5% level. The coefficient estimates associated with the global uncertainty measure are heterogeneous across the currencies considered. Of particular interest is that only for the JPY do we find that the global uncertainty coefficient estimate is negative and statistically significant at the 5% level. This is in line with Fatum and Yamamoto (2016) and other studies of safe haven currencies that typically identify the JPY as a currency that exhibits a particularly strong safe haven behavior.

Figure 7 displays the estimated currency factors $\tilde{F}_t^{TW}$. The number of factors is set to 3 following Aloosh and Bekaert (2022).[10] 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 of the JPY, the CHF, the SEK, and the NOK. The second factor captures co-movements of the EUR and the GBP. 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).

Figure 8 shows the actual and the counterfactual JPY/USD rates. The upper panel presents the actual rate ($S_{N,t}$) in a solid thin line and the counterfactual rate ($\tilde{S}_{N,t}^{c}$) in a solid thick line along with the associated 95% confidence intervals. The lower panel plots the estimate of the gap sequence ($\tilde{\phi}_{N,t}$). The intervention dates are indicated by dotted vertical lines. The upper panel shows that starting in April, the actual rate moves upward while the counterfactual rate stays largely unchanged. As a result, the gap expands considerably, as

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

shown in the lower panel of Figure 8. Most importantly, the gap is large and expanding up until around the time when interventions are undertaken and subsequently, after the interventions are carried out, the gap sequence reverses, consistent with the suggestion 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. As the table shows, accounting for two breaks is optimal as the $F_T(1|0)$ and the $F_T(2|1)$ tests reject their null hypotheses at the 1% and the 10% significance level, respectively, and the $F_T(3|2)$ test does not reject the null hypothesis. The break dates are identified as April 22 and October 17. Figure 9 illustrates the estimated gap sequence (dotted line) and the conditional mean or fitted value (solid line). The amounts of interventions are also shown as (scaled) bars on the right vertical axis. The figure shows that the depreciating trend continued since the beginning of 2022 and reversed right around when the interventions are 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.[11]

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

[11] The first break is associated with a small level shift that is unrelated to intervention as no intervention occurred around the first break date. Since the gap sequence takes into account the possibility of currency-specific confounding factors, this finding is unsurprising.

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.

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.[12] 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,

[12] 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.

August 4; October 31 to November 4, 2011).[13] All of these interventions are sales of JPY against the USD, consistent with a policy aim towards preventing further JPY appreciation 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 October 1, 2009 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 2009-2011 sample. As before, the interest rate differential coefficient estimate is negative and highly significant, as expected, and the coefficient estimate associated with the VIX is once again also negative and highly significant for the JPY and the CHF, as well as for the EUR and the NZD.

Figure 10 presents the estimated currency factors. The first factor captures the appreciation trends of the JPY, the CHF, the SEK and the NOK while the second and the third factors show features similar to what we found for the 2022 period.

Figure 11 plots the actual and the counterfactual JPY/USD rates as well as the gap sequence for the 2010-2011 intervention period. The actual and the counterfactual rates do not show significant differences when the first two interventions are conducted, on September 15, 2010, and on March18, 2011, but move in opposite directions starting in May 2011, i.e. the actual rate appreciated (moved downward) while the counterfactual rate

[13] 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 March 16, 2011 Fukushima earthquake.

depreciated (moved upward). Then, following August 2011, the former stays stable whereas the counterfactual rate moves further downward. As a result, the gap sequence takes the form of a V-Shape, decreasing until August 2011 and recovering afterwards.

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 and the March 18, 2011 interventions occurred when both the actual and the counterfactual JPY rate appreciated and, consequently, the gap was insignificant and not expanding. By contrast, while the August 4, 2011 intervention was also conducted against an appreciating trend of the actual rate, the counterfactual rate at this time was moving in the opposite direction. Finally, the October 31- November 4, 2011 interventions took place when the actual rate was appreciating but the counterfactual rate was constant.

Turning to the structural change tests, Table 4 displays the results. As the table shows, we find that two breaks are present as the $F_T(1|0)$ and the $F_T(2|1)$ tests reject the null hypothesis at the 1% and at the 10% levels, respectively, while the $F_T(3|2)$ test does not. The optimal break dates are estimated at February 18, 2011 and September 2, 2011, thus very close to the March 18, 2011 and the August 4, 2011 intervention dates. Figure 12 shows the estimated gap sequence and the conditional mean function for the 2010-2011 period. There is a mild JPY appreciation trend occurring early in 2010 followed by a steepening of the trend subsequent to the first break date. Since all 2010-2011 interventions are JPY sales, including the September 15, 2010 and the March 18, 2011 interventions, these interventions are deemed ineffective in terms of having a trend effect. Subsequently, the trend of the gap sequence reversed in the intended direction, and the reversal occurred not far from the August 4 intervention with the second break date estimated at September 2, 2011, suggesting that these latter interventions are associated with trend effects.

To check the robustness of the previous findings we impose the same number of breaks as the number of intervention episodes, namely four. As shown in the lower panel of Figure 12, the four breaks are estimated at November 3, 2010, March 1, July 27, and October 11, 2011. The first break is quite far from the September 15, 2010, intervention, while the remaining three breaks are very close to subsequent intervention episodes. In particular, the July 27, 2011 break date is very close to the August 4, 2011 intervention date and associated with a steep shift in desired direction of the trend of the exchange rate, and the fourth and final break date, October 11, 2011 is close to the October 31-November 4, 2011 interventions and is thus also consistent with an intervention related correction of an unwanted local trend. It is not surprising to observe that the most effective intervention episodes in regards to trend effects are also the ones associated with the largest intervention amounts.

Overall, our results of the analysis of the 2010-2011 interventions further indicate that interventions have the potential to induce a trend effect. At the same time, the 2010-2011 results also show that not all interventions have trend effects. In particular, these findings suggest that in order 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.

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 inherently poor performance of empirical exchange rate models as well as 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 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 we observe that our findings are consistent with intervention being effective via the portfolio balance channel as well as through the signaling channel. Moreover, the sterilized nature of the 2022 interventions under study is consistent with the suggestion that an important policy implication of our analysis is that interventions when carried out during certain circumstances and in a particular manner, such as large-scale and infrequently and against a persistent exchange rate trend, can serve as an independent policy instrument.

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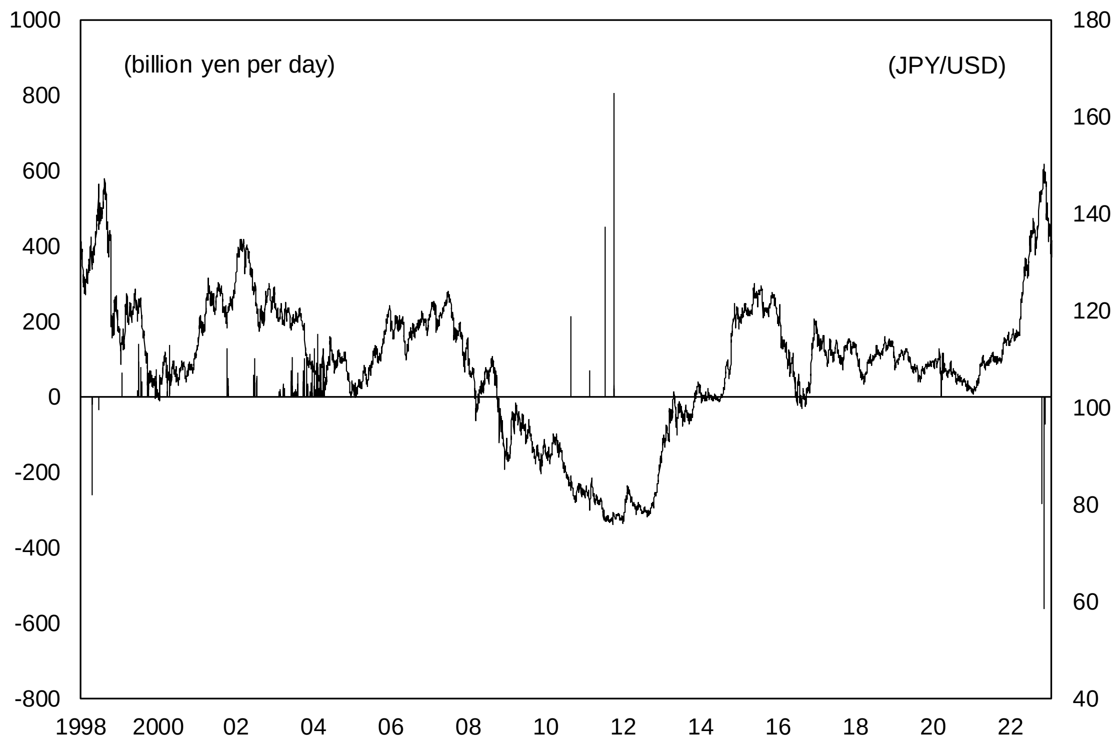
Figure 1. Foreign Exchange Interventions in JPY/USD Market



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. Daily Amount of Monetary Base and Intervention Amount in 2022

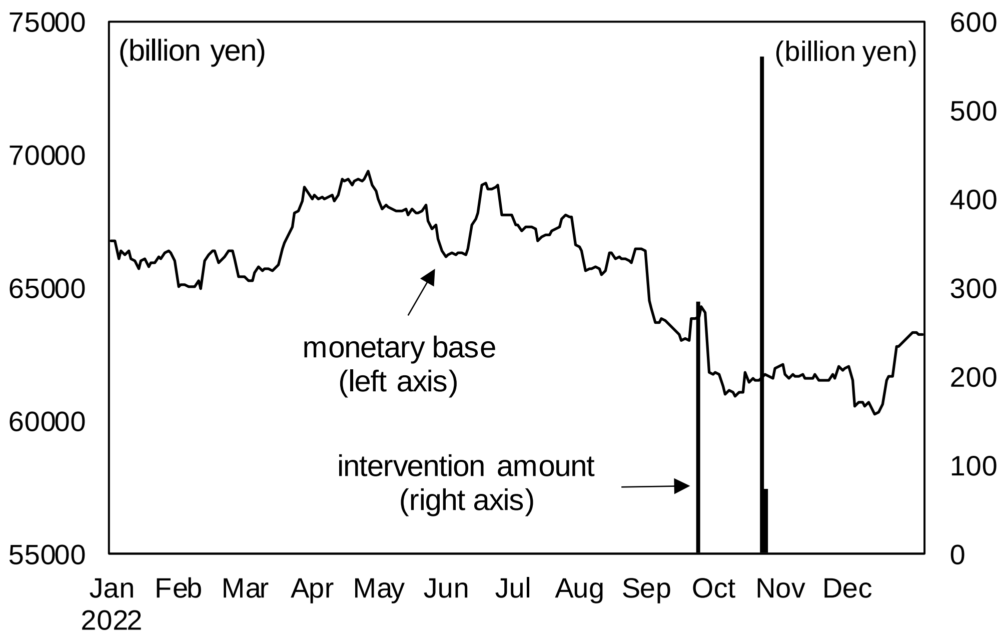
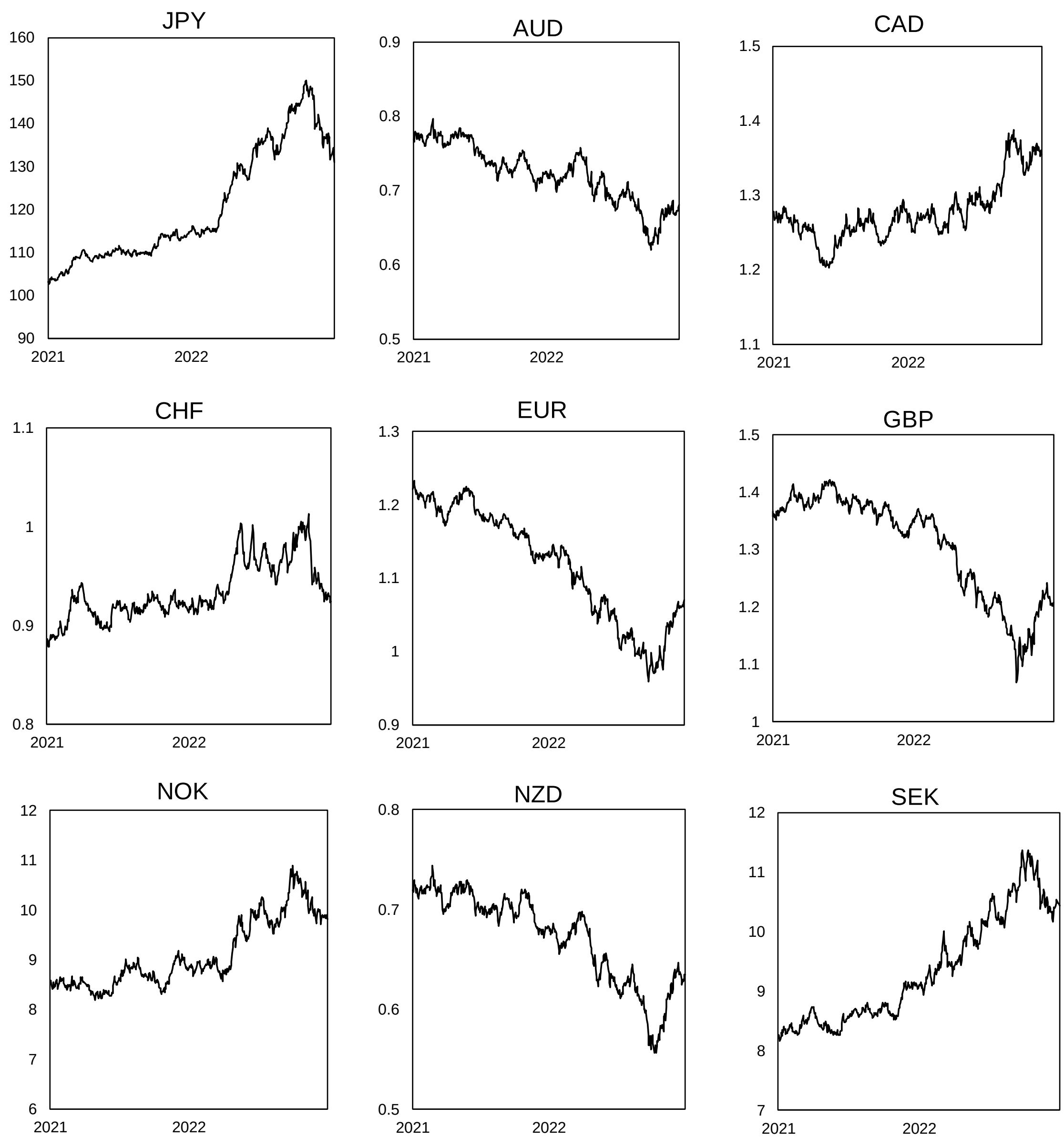
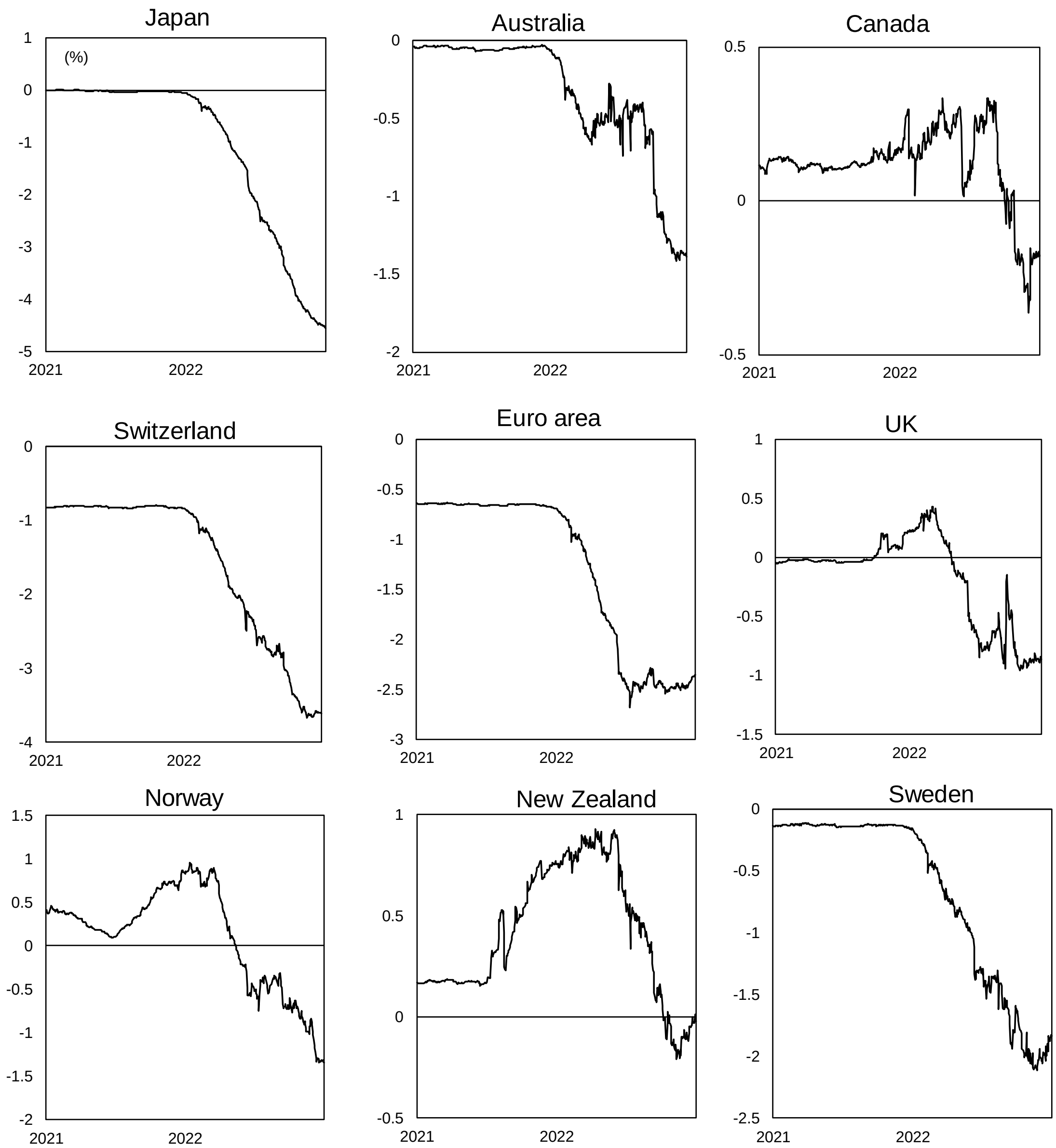


Figure 3. Bilateral Exchange Rates Against the USD



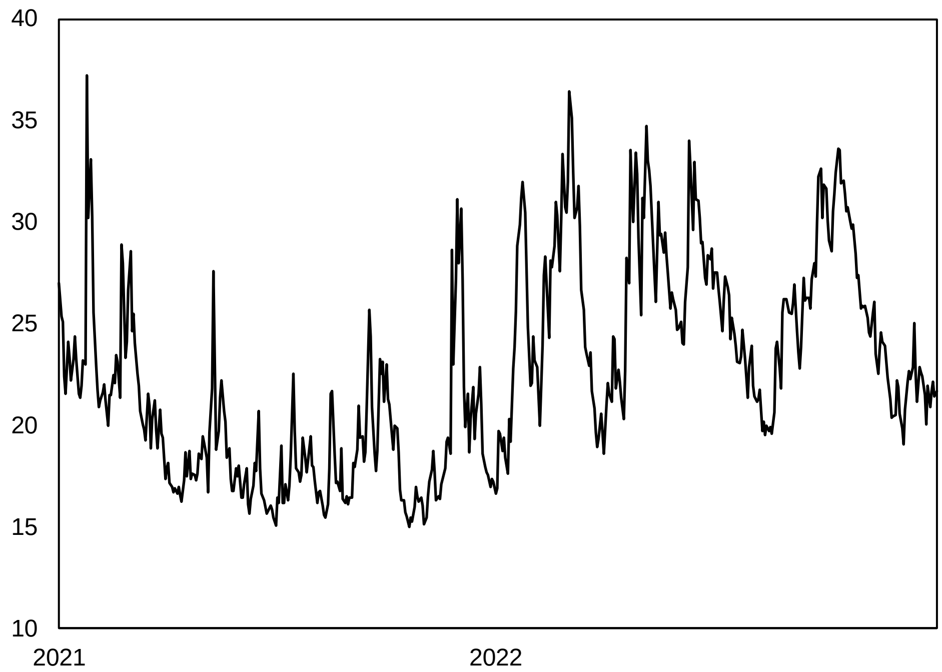
Source: Bloomberg

Figure 4. Interest Rate Differentials relative to the US



Source: Bloomberg

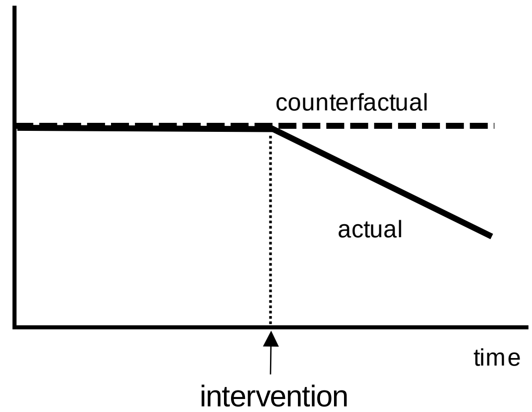
Figure 5. VIX Index



Source: Chicago Board Options Exchange

Figure 6. Randomly Assigned and Lean Against the Wind Interventions

(a) Randomly Assigned Intervention



(b) Lean Against the Wind Intervention

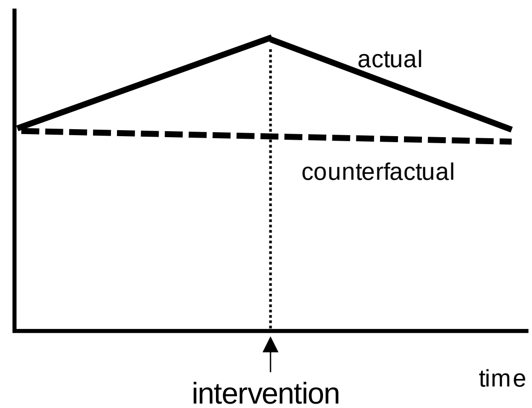
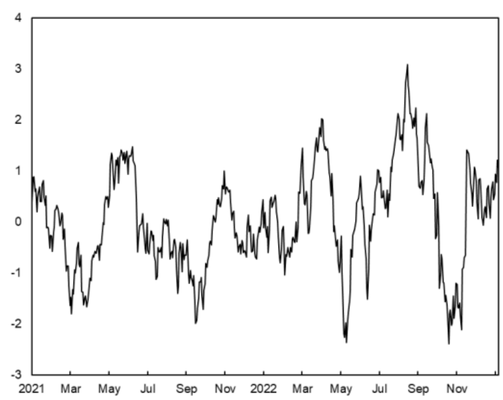


Figure 7. Estimated Currency Factors

First Factor

Second Factor

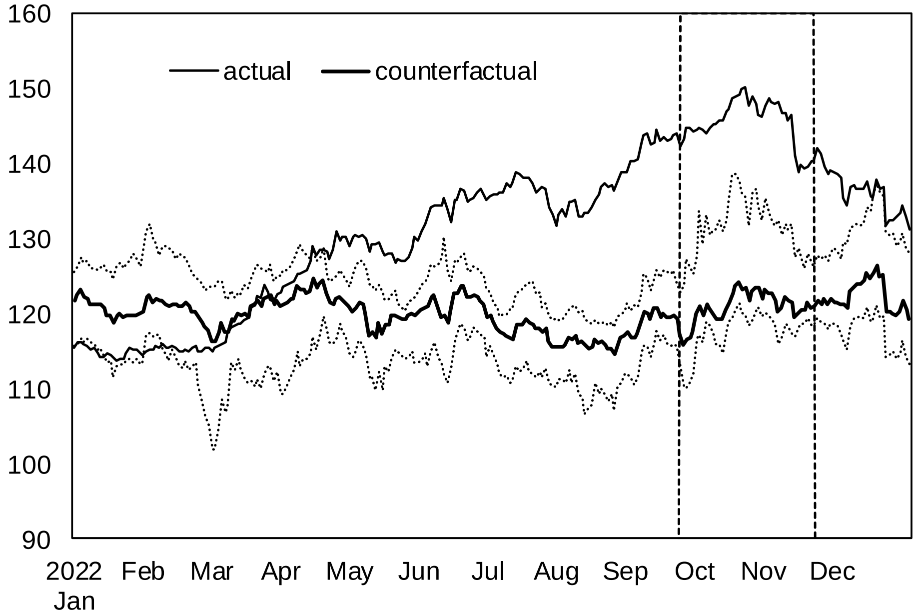
Third Factor



Note: The series are normalized such that $\tilde{F}^{TW'}\tilde{F}^{TW}/T = I_r$.

Figure 8. The Counterfactual Rate and the Gap Sequence

Actual and Counterfactual Rates



Gap Sequence

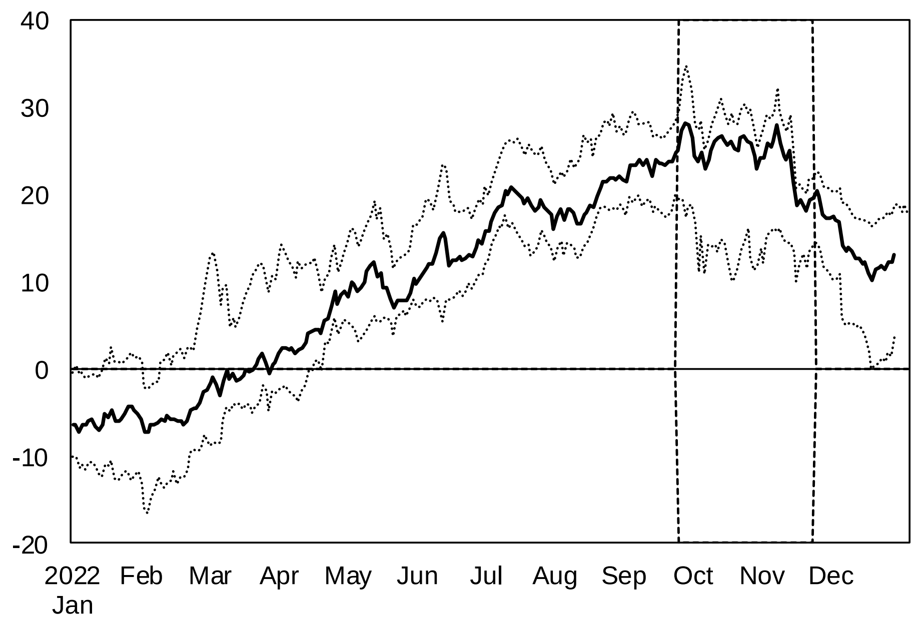


Figure 9. Trend Breaks in the Gap Sequence

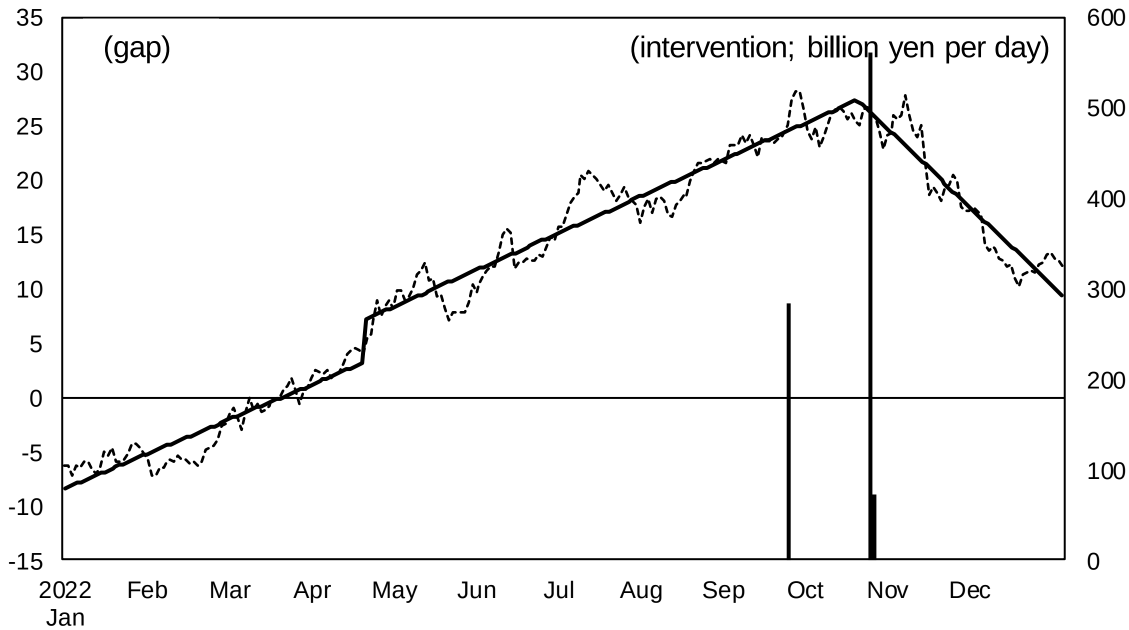
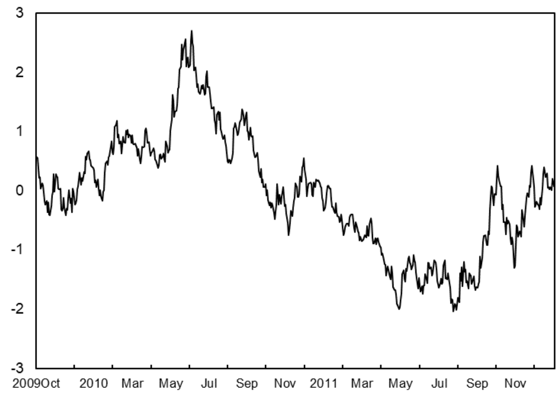


Figure 10. Estimated Currency Factors
The 2010-2011 Intervention Period

First Factor



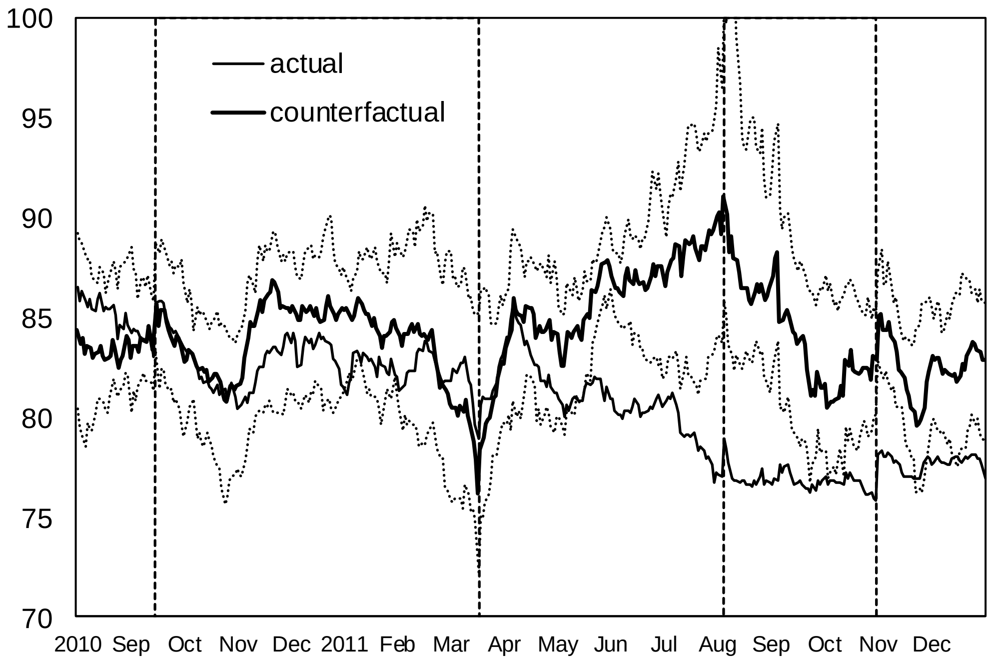
Second Factor

Third Factor

Note: The series are normalized such that $\tilde{F}^{TW'}\tilde{F}^{TW}/T = I_r$.

Figure 11. The Counterfactual Rate and the Gap Sequence
The 2010-2011 Intervention Period

Actual and Counterfactual Rates



Gap Sequence

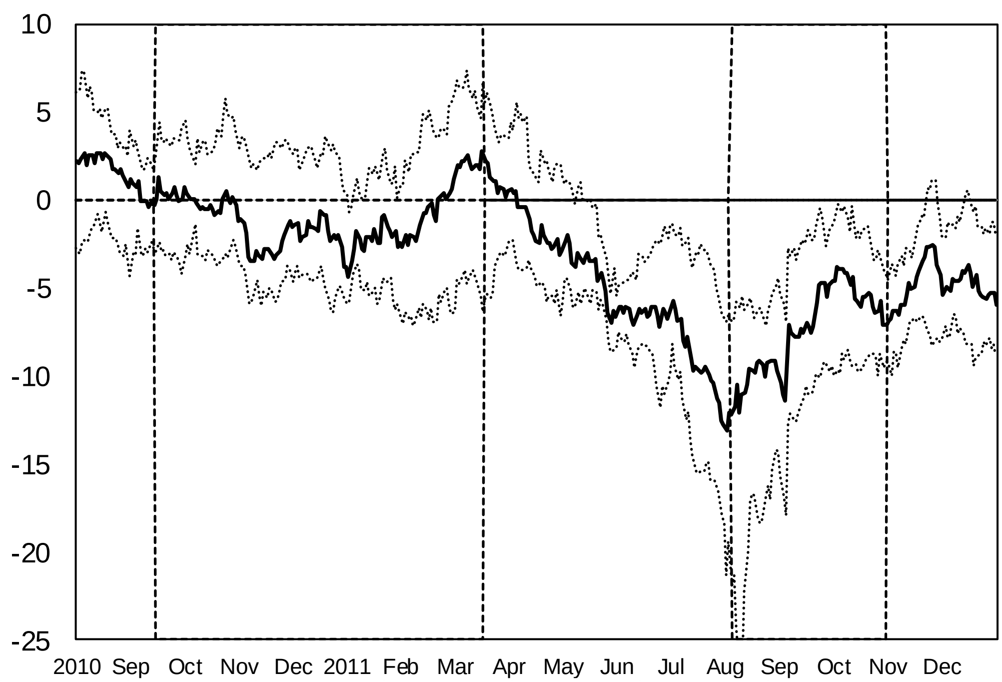
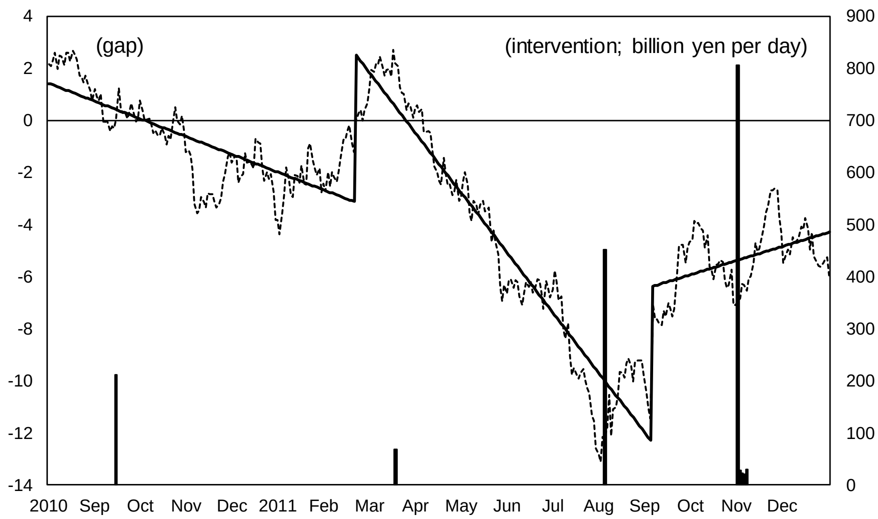


Figure 12. Trend Breaks in the Gap Sequence
The 2010-2011 Intervention Period

Two Breaks



Four Breaks

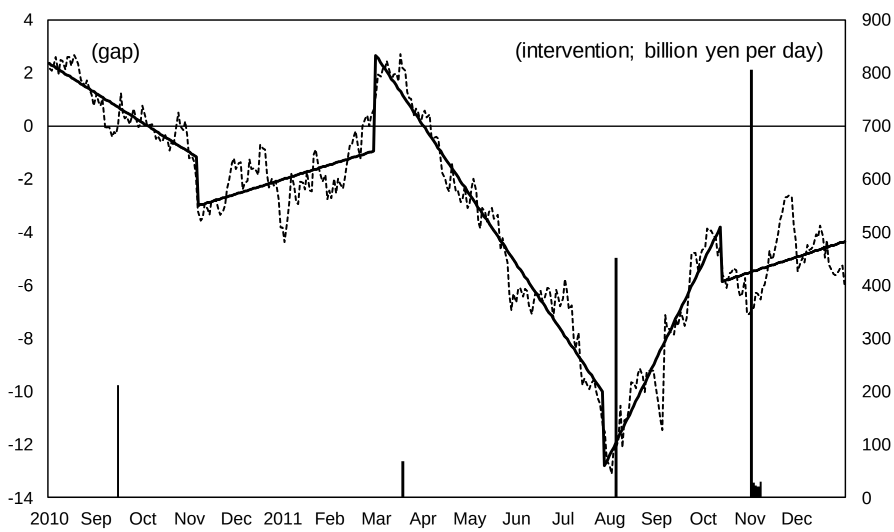


Table 1. Coefficient Estimates of the Counterfactual Model

		Coefficient	95% Confidence Interval
$R_{i,t}$		-20.05**	[-27.54, -3.22]
VIX_t	JPY	-1.35**	[-1.73, -0.26]
	AUD	0.16	[-0.35, 0.59]
	CAD	0.24*	[-0.01, 0.92]
	CHF	-0.34*	[-0.64, 0.06]
	EUR	-0.56	[-1.04, 0.72]
	GBP	0.93***	[0.56, 1.30]
	NOK	-0.45*	[-0.70, 0.02]
	NZD	-0.26	[-0.60, 0.73]
	SEK	0.92***	[0.56, 1.29]
Const.		-7.95*	[-16.89, 0.18]

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	$F_T(1\|0)$	$F_T(2\|1)$	$F_T(3\|2)$
	6.36***	3.69*	3.09
Break Dates	April 22 ; October 17		

Note: Same as Table 1.

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

		Coefficient	95% Confidence Interval
$R_{i,t}$		-18.28***	[-32.37, -5.63]
VIX_t	JPY	-1.46***	[-2.07, -0.61]
	AUD	0.37	[-0.69, 1.49]
	CAD	-0.39	[-0.98, 0.35]
	CHF	-1.50***	[-2.14, -0.65]
	EUR	-1.78***	[-2.66, -0.71]
	GBP	-1.40*	[-1.23, 0.12]
	NOK	1.40	[-0.40, 3.40]
	NZD	-1.62***	[-2.28, -0.74]
	SEK	0.55	[-0.49, 1.66]
Const.		37.45***	[13.03, 56.19]

Note: Same as Table 1.

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

Tests	$F_T(1\|0)$	$F_T(2\|1)$	$F_T(3\|2)$
	31.06***	27.92*	1.65
Break Dates	February 18; September 2		

Note: Same as Table 1.