RIETI Discussion Paper Series 25-E-079

Understanding How Exchange Rates are Perceived and How That Perception Affects Exchange Rate Forecasts (Revised)

YOSHIDA, Yushi
Shiga University

RIETI
Research Institute of Economy, Trade & Industry, IAA

The Research Institute of Economy, Trade and Industry
https://www.rieti.go.jp/en/

RIETI Discussion Paper Series 25-E-079
First Draft: August 2025
Revised: April 2026

Understanding How Exchange Rates are Perceived and How That Perception Affects Exchange Rate Forecasts*

Yushi Yoshida
Shiga University

Abstract

People perceive the same level of nominal exchange rate as overvalued at one point in time and undervalued at a different point in time. To capture the perception of the exchange rate at that time, we suggest constructing the perceived exchange rate by counting the newspaper articles with phrases 'appreciated currency' or 'depreciated currency.' A shift in the perceived exchange rate (PER) index alters the dynamic response of exchange rates in time series. The forecast model with the PER index as a threshold variable (PER TAR) outperforms the SETAR model with the lagged exchange rates as a threshold variable. We also show that the forecast precision of the PER TAR model is as good as the survey forecasts by market participants. In addition, we show that the PER index is relevant in the FX intervention response function.

Keywords: Dynamic Forecasting, Exchange Rate Expectations, Perceived Exchange Rates (PER) Index, Survey Forecasts, Threshold Autoregression.
JEL Classification codes: F31(Foreign Exchange), F37(International Finance Forecasting and Simulation: Models and Applications)

The RIETI Discussion Paper Series aims at widely disseminating research results in the form of professional papers, with the goal of stimulating lively discussion. The views expressed in the papers are solely those of the author(s), and neither represent those of the organization(s) to which the author(s) belong(s) nor the Research Institute of Economy, Trade and Industry.

* corresponding author: Yushi Yoshida, 1-1-1 Banba, Hikone, Shiga 522-8522, Japan. tel: 81-749-27-1089. email: yushi.yoshida@biwako.shiga-u.ac.jp. This study is conducted as a part of the Project "Exchange Rates and Japanese Economy," undertaken at the Research Institute of Economy, Trade and Industry (RIETI). The earlier draft of this paper was presented at seminars and workshops in the RIETI, Hokkaido University, and Shiga University. We would like to especially thank Shigenori Shiratsuka for his comments on the definition of information available within a month. Special thanks go to Yin-Wong Cheung for providing many thoughtful comments on the earlier version of this paper. We also thank Keiichiro Kobayashi, Junko Shimizu, Eiichi Tomiura, Takayuki Tsuruga, Weiyang Zhai, and the seminar participants for their helpful comments. Yoshida thanks Ayako Yamato and Qin Zhang for their outstanding research assistance. Yoshida gratefully acknowledges financial support from the JSPS KAKENHI 25K00649.

1 Introduction

Exchange rates fluctuate in a short period and experience large swings in the medium- and long-term. After an extended period, such as a decade or two, the exchange rate sometimes returns to the same previous level. For example, the monthly average of the Japanese yen per US dollar (JPY/USD) was 153.48 in February 1987. Thirty-seven years later, the monthly average of JPY/USD in April 2024 was 153.43. However, people perceive the same level of nominal exchange rate as overvalued at one point in time and undervalued at a different point in time. In 1987, the JPY/USD reached that level from 236.95 in September 1985 after France, West Germany, Japan, the UK, and the US agreed in the Plaza Hotel to jointly intervene in the foreign exchange markets to lower the value of the US dollar. In contrast, in 2024, the Japanese yen depreciated sharply in a short period to reach the same level when rising inflation in Japan had become an important policy issue. People perceived the same level of exchange rate as appreciation (overvalued) in 1987 and as depreciation (undervalued)in 2024.

The above example is a clear-cut case; however, how can we measure the people's perception of the exchange rate for each point in time, say annually, quarterly, or monthly? The perception is subjective, but the measurement of this subjectivity should be based on an objective methodology. Considering the lesson from the two episodes in 1987 and 2024, utilizing the changes in the exchange rate may be a good idea to distinguish between appreciation and depreciation perceptions. However, it is not that simple. For the perception of the exchange rate in the specific quarter, should we look at the past quarterly change in the exchange rate, a half-year change, or a one-year change? Is it sufficient to look at only the history of the exchange rate series, or expand the information set to include other macroeconomic variables as well as all other sources publicly available?

To address how we should measure the general perception of the exchange rates, we sidestep the issues raised above and propose a new approach of resorting to the opinions expressed in the newspaper. The attention to the movements of the exchange rate in the media is always substantial in Japan, where international trade occupies a large share of the national income. The business leaders, market participants, and academics, as well as newspaper journalists, contribute to the columns and articles in the newspaper. They express their subjective view on the exchange rates in the newspaper articles. The phrases 'yendaka', yen appreciation, or 'yenyasu', yen depreciation, are often used in the newspaper articles. For example, the monthly counts of newspaper articles containing the phrase 'yen appreciation' were over one thousand in consecutive three months from March 1995 to May 1995 when the Japanese yen hit the post-war historical high value against the US dollar. In contrast, the monthly average newspaper count of 'yen appreciation' was only 186.2 in 1998.

The use of texts in the newspaper and official documents has become popular in the economics literature. Baker et al. (2016) constructed the Economic Policy Uncertainty (EPU) Index, primarily based on counting the number of relevant keywords, such as 'uncertainty', in the local newspapers. The team of these authors continued to construct

the relevant macroeconomic indices after introducing the EPU index. In the literature on identifying a monetary policy shock, Hansen et al. (2018) and Shapiro and Wilson (2022) use the transcripts, minutes, and speeches of the FOMC. In the same vein, we construct the perceived exchange rate index by searching for and counting the relevant words in texts from the newspaper articles.

In this paper, we construct the perceived exchange rate (PER) index from January 1985 to March 2025.[1] The PER is based on the monthly counts of newspaper articles containing the phrase 'yen appreciation' or 'yen depreciation'. With a simple formula, we construct the PER index ranging from negative 100 to positive 100, as explained in detail in the next section. We found that the PER index is useful in the following sense. First, the division of appreciation and depreciation periods by the PER index looks consistent with the general public's impression of JPY/USD movements. Second, the PER successfully captures the long-lasting period of depreciation (or appreciation) as well as the short- to medium-term depreciation (or appreciation), including depreciation (or appreciation)in isolated months.

The PER does not simply represent the current change in the exchange rate. The empirical distribution of the current exchange rate conditional on the sign of the PER is skewed, but it still has substantial mass on both sides, see section 2.2. This means a month has a substantial chance to be perceived as depreciation (or appreciation) when the current change in the exchange rate is appreciating (or depreciating). Furthermore, to assess what the PER represents, we regress the PER on the current and the lagged exchange rate changes. Using the Bayesian information criterion to choose the optimal lag structure, the PER is shown to have a statistically significant relationship with the 29 lag terms. Therefore, the PER is a weighted reflection of more than two years of exchange rate movements if one argues that it reflects any changes in the exchange rate.

To examine the usefulness of the PER index, we apply it to the exchange rate forecast model. We start with a simple autoregressive model, AR(12), and show that it has a poor performance in dynamic forecasting, starting in January 2018 until March 2025, sequentially using the forecasted values to make a further forecast. We then extend it to a nonlinear threshold autoregressive model. The threshold regression model uses a threshold variable as an indicator variable to capture a shift between regimes, where each regime has heterogeneous parameters. We showed that a threshold autoregressive model with a lagged exchange rate as a threshold variable, i.e., a self-exciting TAR (SETAR), substantially improves the forecast precision over the simple AR model. Finally, we introduced the PER index as a threshold variable to capture the shift in the autoregressive process of the JPY/USD exchange rate time series. In a three-regime TAR model with the PER index as a threshold variable, forecast precision is improved through dynamic forecasting, in which the forecasted value is used as an input to further forecasts. Furthermore, we make the PER TAR model to race against the survey forecasts of market participants and show that the forecast error of the PER TAR model is as precise as the

[1]We intend to make the data series public and update it continuously once this study is published.

professional forecasts.

Furthermore, beyond improving the exchange rate forecasting performance, we applied the PER index to the foreign exchange intervention reaction function and extended it to include 'uncertainty' measures. The PER index has been shown to be a relevant predictor of the policy decision to intervene in the foreign exchange market in a given month. The probability of the MOF intervening in the foreign exchange market by buying the JPY to help the Japanese yen appreciate increases by 7.1 percent when the PER index reaches 40.

The rest of the paper is constructed as follows. The next section describes how we constructed the perceived exchange rate index. Section 3 investigates how the perceived exchange rate index helps to improve the precision of JPY/USD exchange rate forecasts. We compare the JPY/USD forecasts incorporating the information of the PER index with alternative models and the survey forecasts of market participants. Section 4 discusses how we should interpret this new index, and the last section concludes.

2 The perceived exchange rate (PER) index

Given the same level of exchange rate, how does the different perception, i.e., subjective interpretation of what has been observed, affect how firms and consumers form forecasts of future exchange rates? In making a forecast, one first needs to observe the relevant markets and economic indicators, process and digest pieces of information, and then form an expectation. These steps consist of observations, perceptions, and the formation of expectations. To learn how market participants have formed expectations, we can resort to the survey forecasts. However, these forecasts are the outcome of how market participants see the current level of the exchange rate and perceive it in the current economic conditions.

Can we learn how they perceive the current exchange rates?[2] In addition to making professional forecasts, market participants in a much broader sense are often asked in interviews by the media, including newspapers. If we successfully extract their opinions from the newspaper articles, we can construct an index indicating the perception of the current exchange rates. This is exactly what we do in this study.

2.1 The construction of the PER index

Nikkei Inc., the publisher of The Nikkei newspaper, offers a search engine platform called the Nikkei Telecon, which allows users to find newspaper articles containing keywords typed in. By restricting the sample period to an entire month, e.g., January 1, 1985 through January 31, 1985, we counted the number of articles containing the Japanese

[2]In different contexts, Kuziemko et al. (2015) conducted randomized online survey experiments to learn the respondents' perception of inequality, and Binetti et al. (2024) investigates the perception of inflation causes, consequences, and trade-offs.

word "yen-daka (yen appreciation or yen overvaluation)" within a month. Similarly, we counted the number of articles containing the word "yen-yasu (yen depreciation or yen undervaluation)."[3] There is one caveat for non-natives about the exact interpretation of these keywords. The 'yen-daka' can be interpreted as the state of appreciation, or yen overvaluation, as a long-run term, as well as yen appreciating, or downward movement of the JPY/USD, as a short-run term. We will show in the next section that the phrase is more likely to capture the state of appreciation or yen overvaluation. Henceforth, we simply label 'yen-daka' as 'appreciation' for convenience. We constructed two series from January 1985 to March 2025. Figure 1 shows the number of newspaper articles that contain 'yen appreciation' in red solid line and that contain 'yen depreciation' in blue dashed line. These two lines frequently cross each other, showing that the two series alternately exceed the other in different periods. Two phenomenal episodes can be seen from the figure: the 1985 Plaza Accord and the historical high of the Japanese yen in 1995. The red solid line exceeds the blue dashed line by a substantial amount.

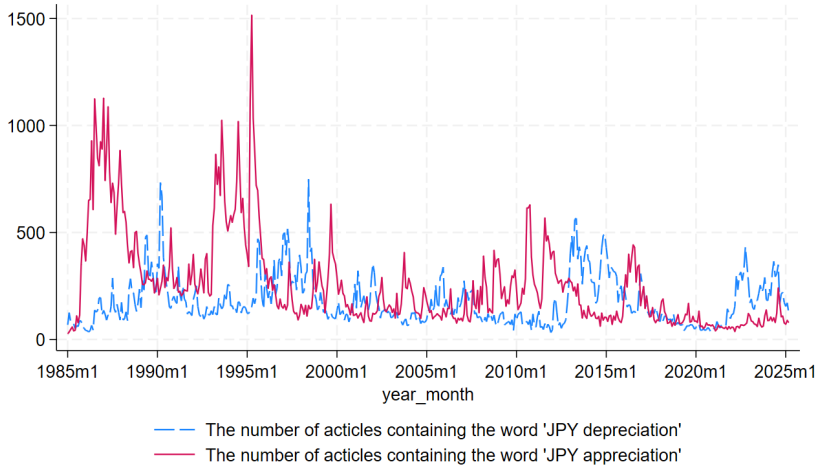

Figure 1: The number of newspaper articles containing the word appreciation versus depreciation, January 1985 - March 2025

Note: The perceived exchange rates of the Japanese yen and the JPY/USD exchange rates are plotted together.

The perceived exchange rate (PER) index is constructed as follows: The number of articles containing the word 'JPY depreciation' minus the number of articles containing 'JPY appreciation', standardized by dividing it by the sum of the two series and multiplying by 100. The PER index takes the value between -100 and +100, and a positive value indicates depreciation of the Japanese yen. By subtracting, the possibility of the

[3]The Nikkei Telecom allows search in eight different newspapers, three news bulletins, and press releases by firms. For this study, we selected The Nikkei newspaper's morning and evening issues because we can trace back to the articles from 1985.

simultaneous appearance of both 'yen appreciation' and 'yen depreciation', which may cause a biased impression when looking at each series individually, can be removed.

$$PER = \frac{No.dep - No.app}{No.dep + No.app} \times 100 \tag{1}$$

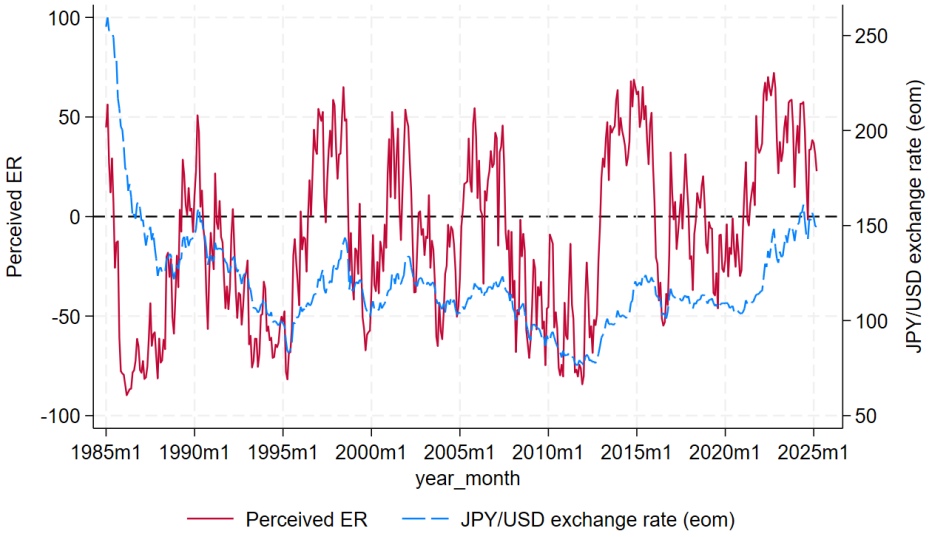

Figure 2: The perceived exchange rates versus the JPY/USD exchange rates

Note: The perceived exchange rates of the Japanese yen and the JPY/USD exchange rates are plotted together.

Among possible exchange rates for this study, we chose nominal JPY/USD exchange rates because the US dollar is the dominant currency, and the JPY/USD is the exchange rate in the minds of people when the value of the Japanese yen is discussed in the media. The exchange rate series is taken from International Financial Statistics, IMF: Exchange Rates, national currency per U.S. dollar, end of period. Figure 2 shows both the JPY/USD exchange rates and the PER index. Two series are plotted on different scales, the JPY/USD rate on the left vertical and the PER index on the right vertical. As we expected a priori, these two series do not exactly represent the same movements: They tend to move weakly together, with the concurrent correlation being 0.2277.

In Figure 3, we shaded those periods with gray by defining the depreciation period as the PER index being positive,i.e., the 'yen depreciation' articles appear more than the 'yen appreciation' articles. From this figure, the PER index responds more to the depreciation/appreciation trend than to the absolute level of the JPY/USD exchange rates. The unshaded periods, therefore, represent appreciation periods. Instead, we can consider three regimes: appreciation, depreciation, and a neutral regime, which includes periods with the values of the PER index within a certain range. In Figure A.1, the

depreciation periods are defined as when the PER index is equal to or less than negative 40, and are shaded with a gray color. Similarly, the appreciation periods are defined as when the PER index is equal to or greater than 40, and are shaded with light blue. In this figure, the white area represents the neutral regime, in which people do not consider the current exchange rate to be either appreciated or depreciated.

The advantages of using the PER index are highlighted below. First, it correctly captures the upward trend, i.e., continuous depreciation in consecutive months, without saying the same for the downward trend. Second, it sometimes picks up an isolated month or a two-month depreciation period with no shades in the periods before and after. Importantly, many short depreciation periods are not reflected in the PER index as 'perceived depreciation'. Again, the same for 'perceived appreciation'. Third, the same level of JPY/USD can be classified as 'depreciation' or 'appreciation', conditional on unobserved economic situations and backgrounds.

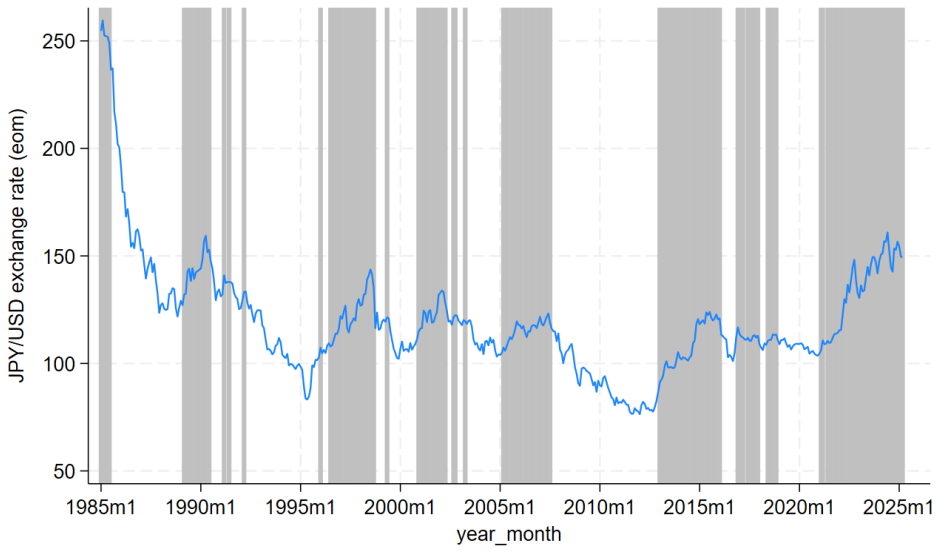

Figure 3: The depreciation versus appreciation period by perceived exchange rates

Note: A month is defined as the 'perceived depreciation' period if the perceived exchange rate index takes a positive value and is shaded in gray. Naturally, the white area represents 'perceived appreciation' period.

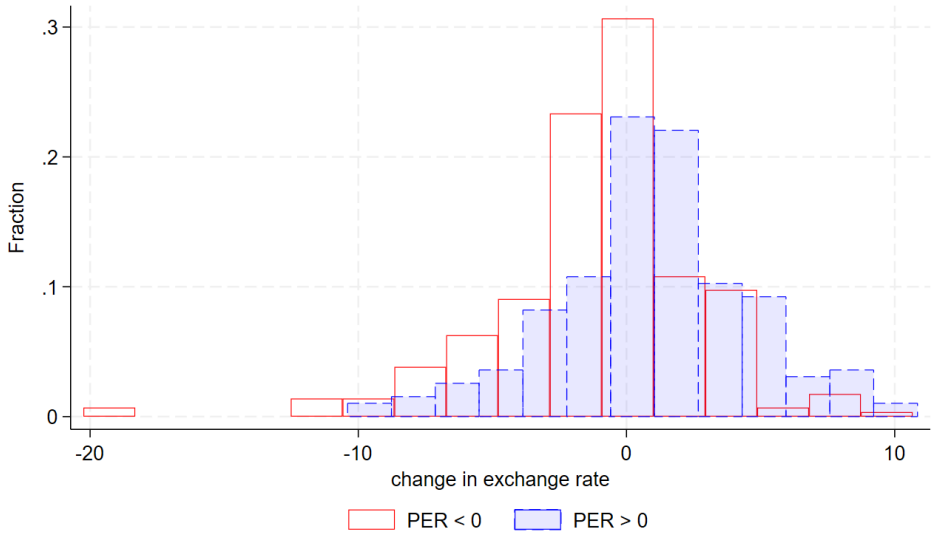

Figure 4: The distribution of exchange rate changes by PER index

Note: The distributions of exchange rate changes, i.e., $\Delta e_t = e_t - e_{t-1}$, are shown in two histograms. The transparent bar with red solid lines is the fraction of Δe when PER ¡ 0. The shaded bar with blue dashed lines is the fraction of Δe when PER¿0.

2.2 The distribution of exchange rate changes by PER

We associated the phrase 'yen-daka' with 'appreciation' as an English translation for convenience; however, the phrase 'yen-daka' in Japanese carries a meaning of the state of appreciation, not necessarily a current movement. Therefore, 'yen-daka' could indicate 'appreciation' or 'over-valuation'. We can argue similarly for 'yen-yasu'. The following figure demystifies a false interpretation of the PER index that it simply captures the movement of the current exchange rate. Figure 4 shows the distribution of exchange rate changes when PER is greater than zero and when it is less than zero. As expected, the distribution is left-skewed, i.e., more frequent observations for appreciation, when the PER index indicates there are more articles on 'yen-daka', $PER < 0$, as shown in transparent bars with a solid line.[4] Analogically for $PER > 0$, indicated by a shaded bar with a dashed line, the distribution is right-skewed.[5] We obtain similar results even when we restrict $PER > 20$ or $PER < -20$, see the appendix Figure A.2.

Having described the skewness of the distribution of exchange rate changes, however, there remain a substantial number of months with exchange rate changes moving in the

[4]The 287 months are associated with $PER < 0$. Positive changes in the exchange rate, indicating depreciation, occur 116 times, and negative changes occur in 171 months.

[5]The 205 months are associated with $PER > 0$. Positive changes in the exchange rate, indicating depreciation, occur 136 times, and negative changes occur in 68 months.

opposite direction. At least, this fact refutes the false claim that the PER index simply reflects the underlying movements of exchange rates. In fact, the current exchange rate movement accounts for only a small part of the PER index.

2.3 What does the PER index capture

We have shown above that the PER index is not a simple reflection of the current change in the underlying exchange rate. At the same time, we observed a weak relationship between the PER and the current change in exchange rate,Δe_t. A natural next question is how much the PER index is affected by the past exchange rate changes. Will figures similar to Figure 4 be more extreme, such that a distribution shifts to one side, if the past exchange rate changes are used instead of the current change? We test this hypothesis by regressing the PER index on the current and the past exchange rate changes.

$$PER_t = \alpha^0 + \sum_{j=0}^{J} \alpha^j \Delta e_{t-j} + \epsilon_t \tag{2}$$

where Δe_t denotes the change in exchange rate from the previous period, $e_t - e_{t-1}$. The exchange rate is the value of the Japanese yen per US dollar at the end of the month. The adequate number,J, of the lagged terms cannot be determined a priori, so we use the Bayesian information criterion to choose the optimal lag length. To retain the comparison meaningful, the starting sample period is fixed at January 1989 so that the number of observations is maintained at 434 throughout all specifications up to the 48-month lag specification.

The optimal number of lagged terms of exchange rate changes is determined by the Bayesian information criterion. The plot of BIC is shown in Appendix figure A.3. The BIC chose the specification of 29 lagged coefficients. The estimated coefficients in the optimal lag specification are shown in Table 1. Note that all current and 29 lag coefficients are statistically significant at the five percent level, except for the 27th lag term.

It is anticipated a priori that the collection of the past exchange rate changes has a substantial explanatory power for the PER index; however, it is surprising to find out that each of the current month and the 28 lagged months of exchange rate changes contributes to the movement of the PER index, which is purely based on the counts of newspaper articles in the current month. To interpret the PER literally from this exercise, a similar index to PER can be constructed as the weighted average of current and dozens of past exchange rate changes, with weights corresponding to the estimated coefficients in Table 1.

Table 1: Estimation results of PER regression model

	coef. (std)
Δe_t	3.762** (0.245)
Δe_{t-1}	4.014** (0.245)
Δe_{t-2}	3.040** (0.245)
Δe_{t-3}	2.543** (0.244)
Δe_{t-4}	2.413** (0.242)
Δe_{t-5}	2.280** (0.243)
Δe_{t-6}	2.123** (0.247)
Δe_{t-7}	1.959** (0.247)
Δe_{t-8}	2.093** (0.250)
Δe_{t-9}	1.983** (0.249)
Δe_{t-10}	1.687** (0.250)
Δe_{t-11}	1.743** (0.250)
Δe_{t-12}	1.811** (0.251)
Δe_{t-13}	1.481** (0.250)
Δe_{t-14}	1.611** (0.249)
Δe_{t-15}	1.406** (0.249)
Δe_{t-16}	1.028** (0.248)
Δe_{t-17}	0.933** (0.247)
Δe_{t-18}	1.078** (0.246)
Δe_{t-19}	0.846** (0.245)
Δe_{t-20}	0.774** (0.246)
Δe_{t-21}	0.783** (0.248)
Δe_{t-22}	1.169** (0.247)
Δe_{t-23}	0.862** (0.246)
Δe_{t-24}	0.741** (0.245)
Δe_{t-25}	0.625* (0.243)
Δe_{t-26}	0.489* (0.244)
Δe_{t-27}	0.417 (0.245)
Δe_{t-28}	0.699** (0.245)
Δe_{t-29}	0.716** (0.247)
Intercept	-7.375** (0.807)
Number of observations	434
Adjusted R-squared	0.82

** p<.01, * p<.05

3 The literature review on the exchange rate forecasting

The main objective of this study is to develop a new index that captures perceptions of the exchange rate among market participants and the general public. The forecasting of the exchange rate per se is not the focus of this study, but it is just one example among many applications to show that the PER index is useful. Nevertheless, we should discuss how this paper relates to the literature on exchange rate forecasting models and professional forecasters.

Before delving into discussing the literature, we emphasize that we carefully manage the data structure of variables to be comparable among forecasting models. First, the PER index is based on the current information of newspaper articles until the end of the month. Second, therefore, we chose the second survey in the month for the JCIF forecasts, which is collected at the end of the month. Third, we chose the end-of-month exchange rate series.

Observing exchange rate fluctuations as outcomes of the data-generating process, one strand of research applied various time-series models to fit exchange rates and examined out-of-sample forecasts. The forecast performance of non-linear models relative to simple linear models has been well investigated, (Kräger and Kugler (1993); Clements and Smith (1999); Boero and Marrocu (2002); Huber (2016)). The threshold autoregressive (TAR) model is a nonlinear model in which the parameters vary across regimes. The regime changes are determined by the threshold variable crossing the threshold values. The self-exciting threshold autoregressive (SETAR) model of exchange rate is a variant of the TAR models that uses the past exchange rate as the threshold variable. In the forecasting literature, the nonlinearity in higher moments, as captured in ARCH and GARCH models, is less discussed because these models do not improve forecast point estimates.

Kräger and Kugler (1993) estimates the weekly exchange rates of five currencies, including the Japanese yen, against the US dollar in the 1980s using three-region SETAR models. Clements and Smith (1999) formally tested the forecasting performance of exchange rates in the past studies between a linear model and SETAR models. Boero and Marrocu (2002) examined the longer sample between January 1973 and July 1997 for the French franc, the German mark, and the Japanese yen against the US dollar. Their results did not show significant forecast gains for the non-linear models over the linear model. The more recent study of Huber (2016) examines the EUR/USD exchange rate using a SETAR model and other various models in a VAR framework. These studies use the return of exchange rates, i.e., the log difference of the nominal exchange rates.

There is another strand of studies based on the purchasing power parity (PPP) of international macroeconomic models, similar in analyzing the non-linearity of exchange rates, but differs in that it examines real exchange rates, (Obstfeld and Taylor (1997); Rapach and Wohar (2006); Yoon (2010)). The seminal work of band-TAR, in fact, band-SETAR, was developed by Obstfeld and Taylor (1997). The finding in Rapach and Wohar (2006) is of particular interest to this study because they found that the band-SETAR

model produced significantly better forecast performance than a linear AR model for the Japanese yen against the US dollar at long horizons.[6]

In the literature on exchange rate forecasting based on the international macroeconomics models beyond the PPP, the seminal work of Meese and Rogoff (1983) showed that empirical models based on theoretical models do not perform well in out-of-sample forecasts. As the survey of Rossi (2013) concludes, the toughest competing model is the random walk without drift. Some researchers suggest that there is no single consistent model that can explain all currency exchange rates at all times. Bacchetta and Wincoop (2004) introduced the scapegoat model in which the weights attributed to fundamentals can vary over time. The essential assumption is that agents have heterogeneous information. Cheung et al. (2025) examines empirically how the weights attributed to the 14 variables change over time across different currency exchange rates. They conclude that there is no single model that can explain every currency exchange rate, nor can it explain the fluctuations of a single exchange rate over the years.

Regarding the literature of heterogeneous professional forecasters, Frankel and Froot (1990) showed that the weights of investment strategies between the chartist technique and fundamental models varied over the years between 1978 and 1988. This finding is empirically supported by the work of Menkhoff et al. (2009), which showed that heterogeneous expectations by about 300 forecasters can be explained by the chartist-fundamentalist approach. Combining the two literatures, Jongen et al. (2012) showed that time-varying weights among chartists, fundamentalists, and carry traders can outperform the random walk model. Dick et al. (2015) found that an individual forecaster with a better exchange rate forecasting performance also has smaller forecasting errors in predicting a future interest rate.

This study is similar to the studies in the heterogeneous professional forecasters literature that model parameters change over time, conditional on the level of the PER index. However, the forecasting model in this study does not rely on the international macroeconomic models as in Cheung et al. (2025). In addition, the forecasting model in this study is shown to outperform the professional forecasters.

4 Forecasting JPY/USD exchange rates with the perceived exchange rates

In this section, we investigate how the PER index can help contribute to modelling exchange rate time series. Here, we start with a simple AR model and extend it to a non-linear model with heterogeneous parameters across regimes. We apply a threshold autoregressive (TAR) model as a nonlinear AR model, with the lagged exchange rate as the threshold variable. Comparisons of forecast performance between a linear model and a non-linear model are standard in the literature, see the meta-analysis of Jackson and

[6]See Table 2 of Rapach and Wohar (2006) on page 350

Magkonis (2024). Then, as a new contribution to the literature, we incorporate the PER index as the threshold variable to indicate parameter switches across regimes. There is one caveat for the empirical form of the exchange rate. In the literature, the return of the exchange rate, i.e., the log-difference form, is the standard, partly because it ensures stationarity by taking the first difference. In this study, we use the raw level of the exchange rate because in the next section, we compare the time-series forecast model with the professional surveys, in which the first difference cannot be applied.

A linear AR model

We start with a linear AR(K) model for the JPY/USD exchange rate at the end of the month, e_t, as the base model in equation (3).

$$e_t = \alpha + \sum_{k=1}^{K} \beta^k e_{t-k} + \epsilon_t \tag{3}$$

After estimating parameters,$(\tilde{\alpha}, \tilde{\beta}^k)$, we define the dynamic forecasts,$\tilde{e}$, in equation (4).

$$\tilde{e}_{t*+h} = \hat{\alpha} + \sum_{k=1}^{K} \hat{\beta}^k e_{(t*+h)-k} \tag{4}$$

where $h = 1, 2, ...$ and $e_{(t*+h)-k} = \tilde{e}_{(t*+h)-k}$ if $k \leq h$. $t*$ is the initial date from which the dynamic forecast starts. When h=0, it is equivalent to a one-period ahead forecast with only the past realized values as explanatory variables. To show more explicitly for a few horizons,

$$\text{For } h = 0,\ \tilde{e}_{t*} = \hat{\alpha} + \hat{\beta}^1 e_{t*-1} + ...$$
$$\text{For } h = 1,\ \tilde{e}_{t*+1} = \hat{\alpha} + \hat{\beta}^1 \tilde{e}_{t*} + \hat{\beta}^2 e_{t*-1} + ...$$
$$\text{For } h = 2,\ \tilde{e}_{t*+2} = \hat{\alpha} + \hat{\beta}^1 \tilde{e}_{t*+1} + \hat{\beta}^2 \tilde{e}_{t*} + \hat{\beta}^3 e_{t*-1} + ...$$

It is worth noting that forecasted exchange rates are used in subsequent forecasts, which can lead to potentially larger forecast errors.

A nonlinear threshold AR model

To capture possible nonlinearities in the dynamics of exchange rate time series, we introduce a threshold autoregressive model (TAR), which allows heterogeneous model parameters with a threshold variable, TV, which acts as an indicator of regimes. A nonlinear TAR(K) model with two regimes is defined as follows.

$$
\begin{aligned}
e_t &= \alpha_1 + \sum_{k=1}^{K} \beta_1^k e_{t-k} + \epsilon_t \;\; if \;\; TV_t \leqq \lambda \\
e_t &= \alpha_2 + \sum_{k=1}^{K} \beta_2^k e_{t-k} + \epsilon_t \;\; if \; \lambda < TV_t
\end{aligned}
\tag{5}
$$

where λ, the threshold value, is determined endogenously by minimizing the sum of squares with alternate values of λ. Analogously, a TAR(K) with multiple thresholds can be defined as in equation (6), and the Bayesian information criterion can determine the number of thresholds.

$$
e_t = \alpha_n + \sum_{k=1}^{K} \beta_n^k e_{t-k} + \epsilon_t \;\; if \; \lambda_{n-1} < TV_t \leqq \lambda_n, \; for \; n \in (1, ..., N+1) \tag{6}
$$

where the number of thresholds is N, and λ_0 is equal to the lowest value of TV [7] and λ_{N+1} is equal to the greatest value of TV.

The dynamic forecasts of two-threshold (three-regime) TAR models can be defined as follows.

$$
\tilde{e}_{t*+h} = \hat{\alpha}_n + \sum_{k=1}^{K} \hat{\beta}_n^k e_{(t*+h)-k} \;\; if \; \hat{\lambda}_{n-1} < TV_{t*+h} \leqq \hat{\lambda}_n, \; for \; n \in (1, 2, 3) \tag{7}
$$

$$
\text{where} \;\; e_{(t*+h)-k} = \tilde{e}_{(t*+h)-k} \, \text{if} \, k \leq h
$$

4.1 The out-of-sample forecast of AR model

The left panel of Figure 5 represents the dynamic forecasts of a simple AR(12) model.[8] After January 2018,i.e., $t*$=January 2018, the dynamic forecasts are sequentially estimated as in equation (4). As seen clearly from the figure, a simple linear AR model with constant parameters is not capable of generating forecasts that align with the fluctuations of the market rates. This failure of forecasts of a constant parameter model leads us to non-linear models.

[7] We abuse the notation here. To be exact, λ_0 is equal to the lowest value of TV minus any infinitesimal value.

[8] We checked for the optimal lag length for the exchange rate by comparing information criteria with maximum lags up to 24. Akaike IC and Likelihood Ratio indicate 12 lags, whereas Hannan-Quinn IC and Bayesian IC indicate only one lag. We also pre-tested for the non-stationarity of the exchange rate. By the ADF tests with 12 lags, the null of non-stationarity is rejected at the five percent level for without-drift, is rejected at one percent for with-drift, and cannot be rejected at ten percent for with-trend. For one lag, the null of non-stationarity is rejected in all specifications for the ADF test. The PER is shown as stationary by the ADF tests.

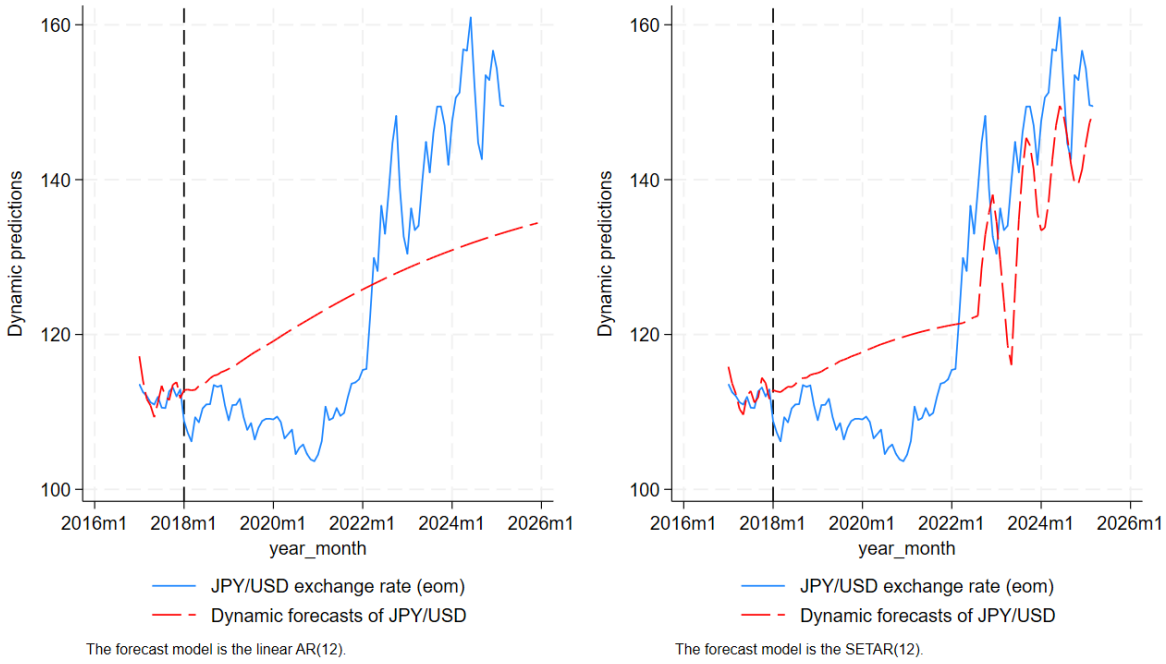

Figure 5: The JPY/USD exchange rates dynamic forecasts

Note: The forecast begins in January 2018. On the left panel, the dynamic predicted values are forecasted by the linear autoregressive model with 12 lags. On the right panel, the dynamic predicted values are forecasted by the three-regime SETAR with 12 lags.

4.2 lagged ER SETAR model

For a threshold variable, we simply choose the first lag of the exchange rate, i.e., $TV_t = e_{t-1}$. This model is assumed to capture the shifts in parameters at different levels of the most recent exchange rates. This model is called a self-exciting TAR model in the literature. The number of threshold values, N, is chosen to be two, to be comparable with an alternative model that will be introduced shortly. The first threshold is estimated as 122.45, and the second threshold is 137.80. For the appreciation periods, from the perspective of the Japanese yen, the lagged exchange rate takes the value less than 122.45. For the neutral period, the lagged exchange rate ranges between 122.45 and 137.80. The depreciation regime consists of exchange rates greater than 137.80. The heterogeneity in parameters among regions in the lagged exchange rate variables is relatively modest. However, the constant term, α_n, differs widely between regimes: 2.04 in regime 1, 25.66 in regime 2, and 40.24 in regime 3. A shift in regimes, which occurs when the lagged exchange rate crosses the threshold values of 122.45 and 137.80, moves the exchange rate forecast by 23 to 15 yen per US dollar. The dynamic predictions of the SETAR model

are shown in the right panel of Figure 5.

The improvement in exchange rate forecasts is expected, naturally, due to the expansion of the number of parameters to triple. However, the improvement is neither clear nor substantial. To compare the forecast precision numerically, we calculate the root mean squared error (RMSE).

$$RMSE = \sqrt{\frac{\sum_{h=0}^{H-1}(\tilde{e}_{t*+h} - e_{t*+h})^2}{H}}$$

The RMSE of the SETAR(12) for the period between January 2018 and March 2025 is 10.02, whereas the RMSE of the AR(12) is 13.38. The statistical test of equal accuracy for two forecasts is provided in Diebold and Mariano (1995) and Diebold (2015). The null hypothesis of equal accuracy is rejected at the five percent level by the Diebold-Mariano test with the Bartlett kernel, indicating the TAR(12) outperforms AR(12) for this out-of-sample forecast period.

However, this seemingly superior SETAR(12) forecast over AR(12) should be interpreted with caution. As a robustness check, we conducted the forecast comparison for 60-month forecast periods with the out-of-sample starting month rolling from January 2008 to January 2020.[9] The DM statistics are plotted for the corresponding starting months in Figure 6. The solid blue line indicates the DM test statistics for the corresponding month. The dashed horizontal line indicates the significance level at the 95 percent. The solid blue line exceeding 1.96 indicates that the SETAR(12) outperforms the AR(12). The SETAR(12) model has better forecasts in 44 subsamples with statistical significance at the five percent level, but worse forecasts in 32 subsamples with statistical significance. From these results, we conclude that the SETAR(12) model is just as good as the linear AR model, but definitely not better. This is consistent with the findings in the meta-analysis of Jackson and Magkonis (2024) that a non-linear model in empirical studies tends to be associated with a deteriorating forecast performance relative to the benchmark model.[10]

[9]The 60 observations for the out-of-sample forecast comparison are moderate. Pippenger and Goering (1998) uses 40 one-step ahead forecasts for monthly data. Boero and Marrocu (2002) use 50 observations for out-of-sample forecasts for monthly series. Rapach and Wohar (2006) uses approximately 100 observations for forecast comparisons for monthly data.

[10]This weak evidence of better forecast performance of a non-linear model also appears in the forecasts of other macroeconomic variables, see Ferrara et al. (2015).

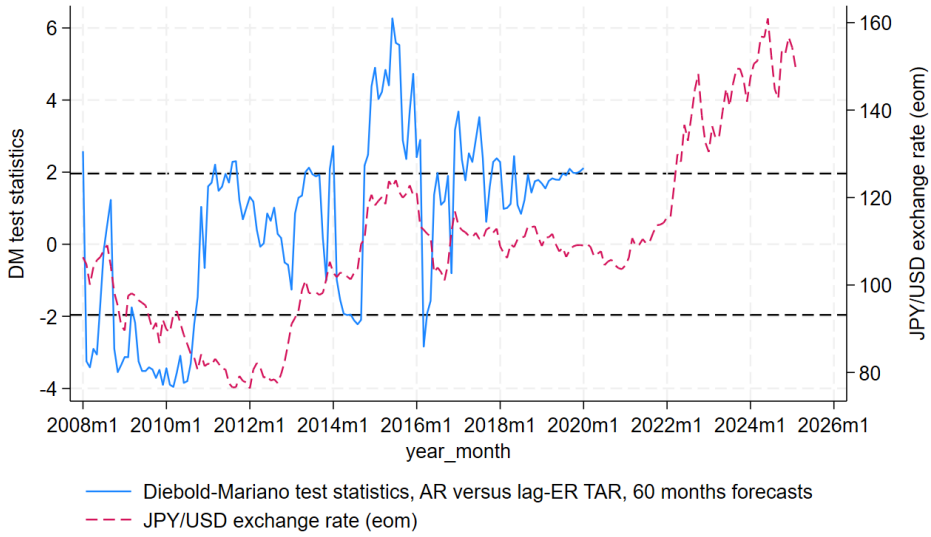

Figure 6: The comparison of forecast models: the AR(12) versus the lagged-ER TAR(12)

Note: The forecast intervals are 60 months. The starting month for forecasts is from January 2008 to January 2020. Positive DM test statistics indicate that the TAR(12) model has better forecast accuracy. The horizontal dashed lines indicate statistical significance at the five percent level. The lagged ER-TAR(12) model has outperformed the AR(12) model in 44 times with statistical significance at the five percent level, out of 145 different forecast starting months. 32 for vice versa.

4.3 PER TAR model

Now, we will investigate whether the information on the perception of the exchange rates helps improve the accuracy of forecasts. We use the PER index as a threshold variable. By the Bayesian information criterion, the number of thresholds is chosen to be two. Table A.1 shows the estimated results for the three-regime TAR(12) model. The first threshold is -25.73, and the second threshold is 17.53. For the perceived appreciation period, PER index taking the value less than -25.73, the estimated coefficients are shown in the first column under Regime 1. For the perceived neutral period, the PER index being between -25.73 and 17.53, the coefficients of the lagged exchange rates are shown in the middle column under Regime 2. The autoregressive coefficients for the perceived depreciation period are shown in the right column under Regime 3.

To visualize how much this extra information contributed to a JPY/USD exchange rate autoregressive model, we show the dynamic predictions after January 2018 for a three-regime PER TAR(12) model, i.e., a three-regime TAR with PER as a threshold variable. To be clearer about dynamic predictions, the forecasts of JPY/USD exchange rates use as inputs the realized values until December 2017 and forecasted values after January 2018, see equation (8). Therefore, forecast errors tend to grow as the forecasted period moves away from January 2018.

$$\tilde{e}_{t*+h} = \hat{\alpha}_n + \sum_{k=1}^{K} \hat{\beta}_n^k e_{(t*+h)-k} \;\; if \; \hat{\lambda}_{n-1} < PER_{t*+h} \leqq \hat{\lambda}_n, \; for \; n \in (1,2,3) \tag{8}$$

$$\text{where } e_{(t*+h)-k} = \tilde{e}_{(t*+h)-k} \text{ if } k \leq h$$

Figure 7 shows the dynamic prediction values of the PER TAR model, along with the realized values of the JPY/USD exchange rates and the dynamic forecasts by the lagged-ER SETAR model. The improvements in the PER TAR model's dynamic predictions are clear.

At the five-year forecast horizon up to December 2022, the RMSE of PER TAR(12) is 4.65, whereas the RMSE of lagged-ER SETAR(12) is 9.49. The information of PER reduced RMSE by more than half. The precision of both models significantly reduces as the forecast horizon extends further.[11] This superior forecasting performance of PER TAR(12) does not depend on this particular sample. As a robustness check, we conducted the forecast comparison for 60-month forecast periods with the out-of-sample starting month rolling from January 2008 to January 2020, see Figure 8. The PER TAR(12) model has better forecasts with statistical significance at the five percent level for 112 subsamples out of 145, whereas there is only one case for vice versa, see Table 2. Similar results are obtained when compared against the AR(12) model, see Figure A.4.

[11]The RMSE of the lagged ER TAR(12) model from January 2018 to March 2025 is 10.02, whereas the RMSE of PER TAR(12) is 7.70. Still, the information of PER reduced RMSE by 23 percent.

Table 2: Summary of forecasting performance

	2018M1-2025M3		60 month rolling windows		
	RMSE	DM statistics	PER TAR better	equal	PER TAR worse
AR(12)	13.38	3.27**	104	40	1
SETAR(12)	10.02	1.21	112	32	1
PER TAR(12)	7.70				

Note: The first column shows the root mean squared error of each model between January 2018 and March 2025. The second column shows the DM test against PER TAR(12). ** and * indicate one and five percent statistical significance, respectively. The third through fifth columns show the number of DM test results at the five percent significance level. The third column indicates that PER TAR has a better forecasting performance. The fifth column indicates the opposite. The fourth column indicates that these forecasting accuracies are equal.

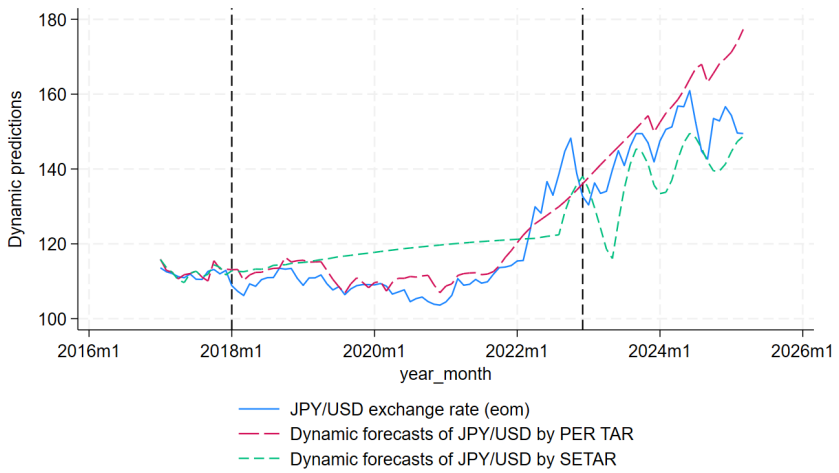

Figure 7: The JPY/USD exchange rates dynamic forecasts by two-threshold TAR(12)

Note: The forecast begins in January 2018. The dynamic predicted values are forecasted by the two-threshold 12-lag autoregressive model with the PER index or the lagged exchange rate as a threshold variable.

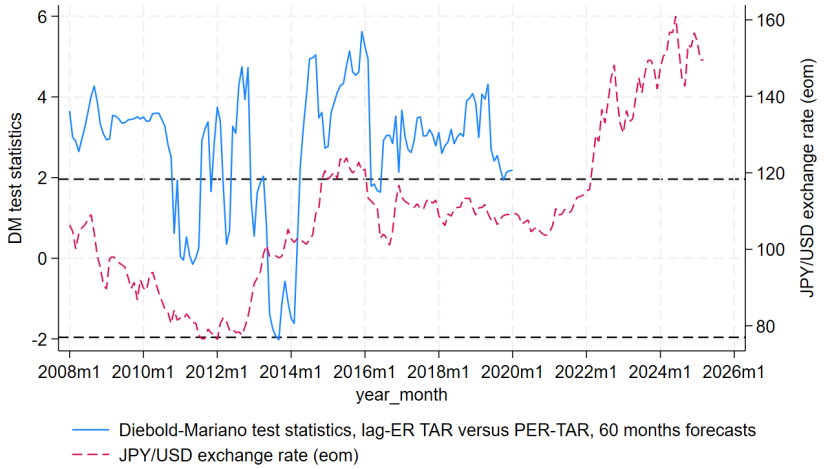

Figure 8: The comparison of forecast models: the lagged-ER TAR(12) versus the PER-TAR(12)

Note: The forecast intervals are 60 months. The starting month for forecasts is from January 2008 to January 2020. Positive DM test statistics indicate that the PER-TAR(12) model has better forecast accuracy. The horizontal dashed lines indicate statistical significance at the five percent level. The PER-TAR(12) model has outperformed the lagged ER-TAR(12) model in 112 times with statistical significance at the five percent level, out of 145 different forecast starting months. Only one for vice versa.

5 dynamic forecasts versus the survey forecasts

In the preceding section, we presented the evidence that the information on the frequency of keywords appearing in the newspaper articles helps improve the accuracy of exchange rate forecasts. The improvement was shown by comparing our model with an alternative threshold model using the past exchange rate information. To put this PER threshold model to further testing, it is in the interest of academicians and policy makers, as well as business practitioners, to compare the accuracy of the PER threshold AR model with the survey forecasts of market participants.

The Japan Center for International Finance (JCIF) collects forecasts from market participants for one, three, and six months ahead for exchange rates. The survey started in May 1985 with 44 respondents, including banks, short-term money market intermediaries, securities companies, Shosha (trading companies), exporting companies, insurance companies, and importing companies. The survey is conducted twice a month, at the mid-month and at the end of the month; except in August and December, only one survey is conducted at the end of the month.

Investigating the JCIF data for two years, Ito (1990) found out the tendency of wishful expectations, i.e., a favorable outcome for the forecasters. For example, exporting companies tend to have a depreciation bias for future JPY/USD exchange rates, whereas importing companies tend to have overvalued forecasts. Takagi (1991) also used the JCIF survey data in his literature review on the empirical works using five sets of survey forecasts of exchange rates. More recently, Asako et al. (2007) investigated the statistical properties of the JCIF survey dataset for the period between June 1985 and February 2004. In the following analysis, we use the mean of all survey participants, with the premise that this will smooth out their heterogeneous forecasts across groups, for the period between January 1985 and March 2025. To be consistent with the end-of-month exchange rate, we selected the forecasts surveyed at the end of the month.

In Figure 9, the dynamic forecasts of the PER TAR model and the mean six-month JCIF forecasts are plotted along the JPY/USD exchange rates. The dynamic forecasts of the PER TAR model, represented by the long-dashed line in red, are the same as in Figure 7.

The short-dashed line in green represents the six-month JCIF survey forecast. The six-month JCIF forecast in t-period is the mean of surveys taken in t-6-period. The forecast aligns closely with the market rate, denoted as the solid blue line, between 2018 and 2020; However, it overvalues the Japanese yen and undervalues the US dollar, especially after 2021.[12] With a visual inspection, it is clear that the PER TAR forecasts outperform those of the JCIF survey forecasts up to the five-year horizon, namely from July 2018 and June 2023.

The RMSE of the JCIF 6-month ahead survey forecasts between July 2018 and June

[12]This coincides with the number of survey participants of exporting companies decreasing in this period. This is consistent with the finding of Ito (1990) that exporters tend to undervalue the Japanese yen.

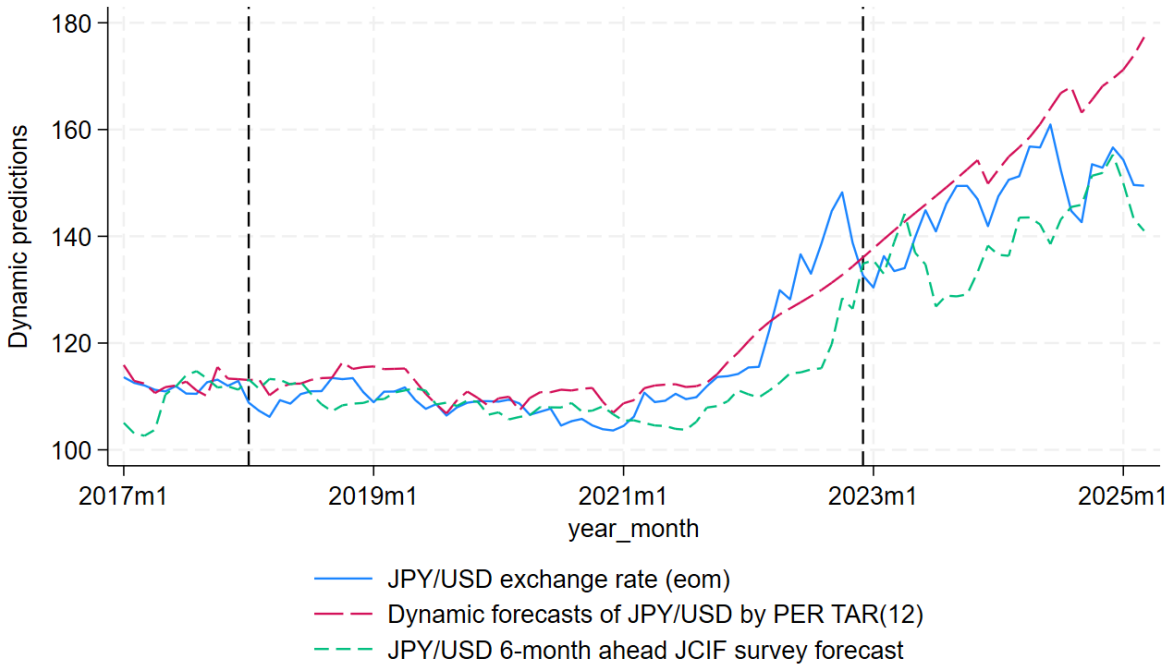

Figure 9: The dynamic forecast by the PER index versus the JCIF six-month ahead survey forecasts

Note: The forecast begins in January 2018. The dynamic predicted values are forecasted by the two-threshold 12-lag autoregressive model with the PER index as a threshold variable. The 6-month ahead JCIF survey forecast is the mean of survey correspondents' responses taken six months earlier.

2023 is 8.11. The RMSE of the three-region PER TAR(12) for the same period is 4.87. To bear in mind that this is not a fair competition between the PER TAR(12) model and the JCIF forecasts. On one hand, the forecasts of PER TAR(12) are greater than a 6-month horizon, except at the first forecast, and the forecasts beyond 12 months ahead will be estimated with the forecasted exchange rates. On the other hand, the PER TAR(12) utilizes the concurrent PER for forecast horizons.

A fair competition of forecasts among alternative models requires all models to have the same length of forecast horizon, forecasted at the same date, and restricted to information only available at the time of forecasting. Therefore, the six-month ahead forecasts by the PER TAR model are estimated by sequentially adjusting t* in equation (9).

$$\tilde{e}_{t*+6} = \hat{\alpha}_n + \sum_{k=1}^{5} \hat{\beta}_n^k \tilde{e}_{(t*+6)-k} + \sum_{k=6}^{12} \hat{\beta}_n^k e_{(t*+6)-k} \;\; if \; \hat{\lambda}_{n-1} \leqq \widetilde{PER}_{t*+h} \leqq \hat{\lambda}_n, \tag{9}$$

for $n \in (1,2,3)$ and $t* \in (January\ 2018, April\ 2024)$. $\widetilde{PER}$ represents the forecasted

PER. For these forecasts, we applied a simple AR(12) model to PER. The corresponding root mean square error is calculated as follows.

$$RMSE = \sqrt{\frac{\sum_{t*=2018JAN}^{2018Jan+H-1}(\tilde{e}_{t*+6} - e_{t*+6})^2}{H}}$$

In Figure 10, both six-month ahead JCIF survey forecasts and six-month ahead dynamic forecasts by PER TAR(12) are plotted along with the market JPY/USD exchange rates from 2018 July to 2024 October, amounting to 76 months of observations. The RMSE of the JCIF survey forecasts in this period is 9.50, whereas the RMSE of six-month ahead dynamic forecasts by PER TAR is 8.93. Their precision is almost equal. The DM test statistic with the Bartlett kernel, 1.342, cannot reject the null of equal accuracy.[13] For a robustness check, we conducted the same exercise for 3-month and 1-month forecasts. For the 3-month forecasts, the RMSE of the JCIF survey forecasts in this period is 6.49, whereas the RMSE of dynamic forecasts by PER TAR is 7.13. The DM tests statistics, -0.86, indicate their forecasts accuracies are similar. For the 1-month forecasts, the RMSE of the JCIF survey forecasts in this period is 3.86, whereas the RMSE of dynamic forecasts by PER TAR is 5.21. By the DM test statistic of -1.959, the professional forecasts beat PER TAR(12) forecasts with the p-value of 0.0501. Based on these findings, we conclude that the PER TAR model can forecast as well as the professional forecasters in the market for the horizons longer than three months.

6 Applications and extensions of PER

How may this perception of exchange rates matter for the economy? A change in the perception of the current exchange rate may affect the optimal behavior of firms and consumers. One example is the responses of prices to exchange rates. The effects of a change in exchange rate on prices are thought to be different when it is appreciating or depreciating, and whether the swing is large or small. The exchange rate changes may induce the nonlinear pricing behavior of exporters and importers. Baldwin and Lyons (1994) showed in their theoretical model that a large misalignment of the exchange rate induces a hysteresis change in market structure that alters the relationship between the exchange rate and trade balance. Alternatively, the same magnitude of a change in exchange rate affects exporters and importers differently, whether the direction of exchange rate change is appreciation or depreciation, Knetter (1994). Nguyen and Sato (2019) apply the nonlinear autoregressive distributed lag model to the exchange rate pass-through of Japanese exports, using firms' exchange rate forecasts surveyed by the Bank of Japan as a threshold variable. They showed that the exchange rate pass-through differs between appreciation and depreciation periods. This is one of many applied topics where we can introduce the PER index.

[13]However, with the uniform kernel, the DM test indicates that PER TAR(12) performs better with statistical significance at the ten percent level.

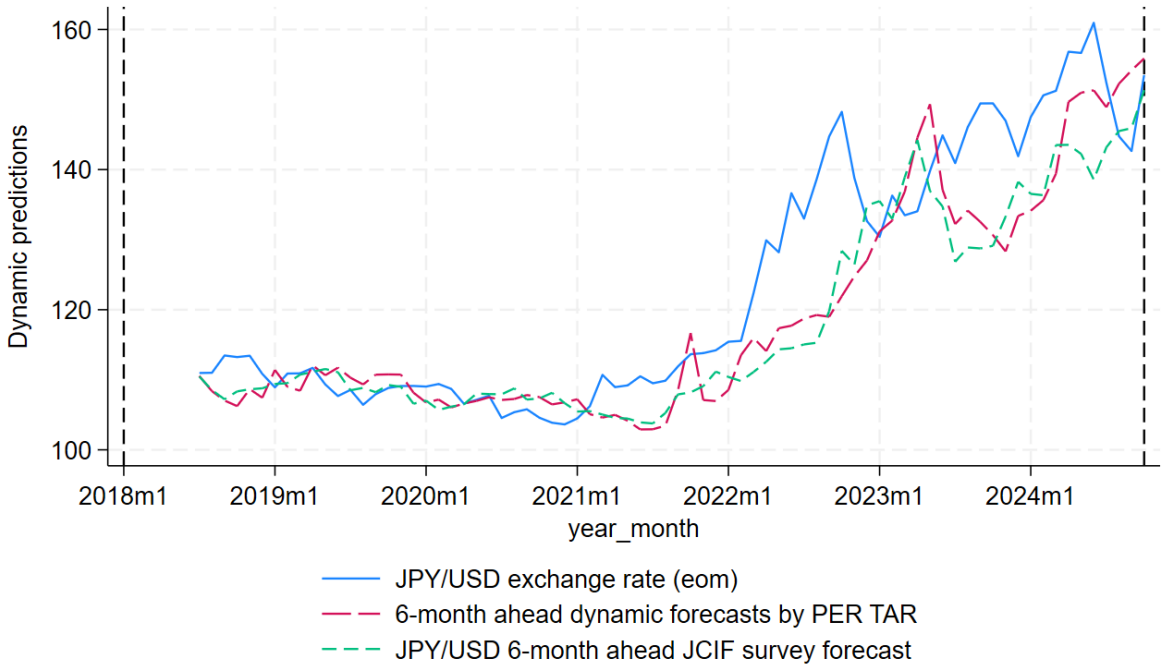

Figure 10: The direct comparison of six-month ahead forecasts: dynamic forecast by the PER index versus the JCIF survey forecasts

Note: The six-month ahead JPY/USD is forecasted at every month since January 2018. The dynamic predicted values are forecasted by the two-threshold 12-lag autoregressive model with the PER index as a threshold variable.

Another interesting application is estimating the response function of the foreign exchange market interventions, as in Ito and Yabu (2007). We will see this application in the following subsection. An interesting extension of the PER index is to use an alternative definition to construct it. We focus on adding the 'uncertainty' keyword to extract the number of articles as a monthly series, serving as a basis for constructing the PER index. This extension is discussed in subsection 6.2.

6.1 Detecting FX interventions

The Ministry of Finance (MOF) began disseminating the detailed information on foreign exchange interventions in April 1991. The MOF intervened in the foreign exchange market by buying the Japanese yen in 21 months and selling it in 57 months over the 408-month sample period between April 1991 and March 2025.

The dependent variable is a ternary indicator of intervention that takes +1 when interventions are buying the JPY, -1 when interventions are selling the JPY, and 0 when

there are no interventions.[14] This is a natural extension of a binary intervention indicator that takes the value of one when any intervention was conducted in the month.

Table 3: ternary intervention indicator

	ternary intervention indicator (-1, 0, +1)				
	(1)	(2)	(3)	(4)	(5)
PER_t	0.004**				0.004**
	(0.000)				(0.001)
e_t		0.009**		0.009**	0.003*
		(0.001)		(0.001)	(0.002)
Δe_t			0.014*	0.009	-0.003
			(0.006)	(0.006)	(0.006)
Intercept	-0.061**	-1.088**	-0.089**	-1.065**	-0.450**
	(0.020)	(0.137)	(0.021)	(0.138)	(0.173)
Number of observations	408	408	408	408	408
Adjusted R-squared	0.17	0.12	0.01	0.12	0.18

Note: Standard errors in parentheses. ** p<.01, * p<.05 The dependent variable is the ternary intervention indicator variable, which takes the value of -1 in the JPY selling interventions and +1 in the JPY buying interventions. It is zero otherwise. The estimation method is the OLS.

The candidate explanatory variables are the current exchange rate, the change in exchange rate from the previous month, and the PER index.[15] The estimated results are shown in Table 3. In the first three columns, the ternary intervention indicator is regressed on each explanatory variable. All of them, each in an individual regression, are statistically significant at the five percent level. However, the fitness of regression differs substantially: 0.17 for PER_t, 0.12 for e_t, and 0.01 for Δe_t. Column (5) includes all three explanatory variables together. The effect of PER remains statistically significant. As a robustness check, we re-estimate the specification in Table 3 with lagged explanatory variables. The results remain qualitatively the same in Appendix Table A.2. Considering the intervention variable as the categorical dependent variable, we re-estimated the models using the ordered logit, and the estimated results are shown in Appendix Table A.3. The effect of the lagged PER remains the most important among the three explanatory variables. We can calculate the increased probability of the MOF intervening from the estimated results. The MOF is more likely to intervene in the foreign exchange market by buying the JPY by 7.1 percent when the PER index reaches 40. [16]

[14]The MOF-BOJ often intervened on multiple days within the month. The directions of interventions were always consistent within the month.

[15]For the survey of the Japanese interventions, see Takagi (2014). The empirical analysis of Guyot and Montgomery (2025) includes the recent episodes of the Japanese yen buying interventions after September 2022. Here in this section, we do not aim to explore all the possible explanatory variables in the foreign exchange intervention literature.

[16]From the estimated value of 3.332 cutoff point, the probability of buying the JPY intervention is 3.5

As the last robustness check, we included the lagged intervention indicator as an explanatory variable. To avoid the endogeneity problem, the other explanatory variables are lagged two periods. The inclusion of the lagged intervention improves the fitness of regression substantially due to the large number of consecutive months with no interventions in the sample. Still, the PER index remains statistically significant, see Appendix Table A.4.

Table 4: signed value intervention regression

	signed value intervention variable				
	(1)	(2)	(3)	(4)	(5)
PER_t	78.238**				62.590**
	(11.613)				(15.873)
e_t		157.652**		153.370**	62.772
		(28.725)		(28.884)	(36.513)
Δe_t			274.847	188.708	-18.500
			(147.486)	(143.700)	(150.648)
Intercept	-787.910	-18980.87**	-1266.249*	-18503.49**	-7937.792
	(472.708)	(3263.541)	(490.826)	(3280.835)	(4191.705)
NOB	408	408	408	408	408
Adjusted R-squared	0.10	0.07	0.01	0.07	0.10

Note: Standard errors in parentheses. ** p<.01, * p<.05 The dependent variable is the signed intervention values, which take the negative sign in the JPY selling interventions and the positive sign in the JPY buying interventions. It is zero otherwise. The estimation method is the OLS.

Instead of using indicator as dependent variable, we also used the value amount of monthly interventions with the positive sign indicating the JPY buying. Table 4 shows that the estimated signs and statistical significance are qualitatively similar to the results in Table 3. In terms of the fitness of regression, the PER index has the largest explanatory power.

6.2 Exchange rate uncertainty

Uncertainty PER index

The PER index constructed in this study is not claimed to be optimal, but rather a mere starting point for examining the relevant information possibly contained in publicly available news sources. Fortunately for researchers, the simple methodology adopted in this study proves to be useful, as shown in the previous sections. Yet, in this subsection, we attempt to extend the PER index in one of the many possible dimensions.

percent, i.e., $1 - 1/(1 + e^{-}3.332)$, for PER=0. With the estimated coefficient of 0.03 for the PER, the probability of the JPY buying intervention is 10.6 percent, i.e., $1 - 1/(1 + e^{-}2.132)$.

The uncertainty affects the behavior of economic agents' decision-making and thus the economy's outcome. The economic policy uncertainty index of Baker et al. (2016), geopolitical risk index of Caldara and Iacoviello (2022), and the VIX of financial markets have proved be relevant factors in many applied studies. Following the methodology described in section 2.1, we search the articles containing both of the Japanese words "yen-daka (yen appreciation)" and "fukakujitsu (uncertainty)". Similarly, for the set of words "yen-yasu (yen depreciation)" and "fukakujitsu (uncertainty)". The PER index modified for uncertainty is constructed for the period between January 1985 and March 2025.

This modified PER did not substantially differ from the original PER. The correlation between them is 0.968. Therefore, we revised the formulation slightly as follows.

$$UPER = \left[\frac{No.(\text{depreciation \& uncertainty})}{No.(\text{depreciation})} - \frac{No.(\text{appreciation \& uncertainty})}{No.(\text{appreciation})} \right] \times 100 \tag{10}$$

No. indicates the number of articles containing words inside a parenthesis. Each fraction term in the bracket ranges between 0 and 1; therefore, the UPER index ranges from -100 to +100. The UPER index is still substantially correlated with PER, but it can be expected to have its own driving factor. The correlation between UPER and PER is 0.4968.

First, we run the same regression as equation (2). The AIC determines that the optimal lag length is 11, much smaller than 29 lag length of PER in Table 1. A surprising finding is the negative coefficient on the current change of exchange rate, Δe_t. The coefficients of the rest of the lag terms, except for the seventh, are all positive and statistically significant, see the online appendix.

Second, we compared the forecasting accuracies against AR(12) and lagged-ER TAR(12) models. For rolling windows of 60-month forecasts, the DM tests are worse for UPER than PER. The UPER-TAR(12) model has outperformed the lagged ER-TAR(12) model in 76 (112, henceforth, the PER result in parentheses) times and underperformed 7 (1) times with statistical significance at the five percent level, out of 145 different forecast starting months. Against AR(12), the UPER-TAR(12) model has outperformed in 57 (104) times and underperformed in 23 (1) times.

Third, against the professional forecasts, the dynamic forecasts of UPER are estimated according to equation 9. The DM test with the Bartlett kernel for the six-month forecast comparison between January 2018 and April 2024 indicates that the dynamic forecast of UPER performs worse than the professional forecasts at the ten percent significance level. The results are the same for 3-month and 1-month forecasts.

7 Conclusion

In this paper, we constructed the perceived exchange rate (PER) index based on the frequencies of relevant keywords appearing in the newspaper articles. By augmenting a simple time-series model of the exchange rate with the PER index as a threshold variable in a TAR model, we showed that the dynamic forecasts significantly improved. In addition, the PER TAR model is shown to be as good as the professional forecasters for horizons longer than three months.

We conclude this paper by listing a few future agendas for the PER index. First, the PER index may be modified by combining more relevant phrases/words in addition to the phrases/words used in this study. In section 6.2, we combined the phrase 'uncertainty' with depreciation and appreciation. The other candidate phrases possibly interesting include 'unexpectedly' and 'suddenly', among others. These refinements are left for future work. Second, we may refine the index by a higher frequency, such as weekly. In this case, manually collecting the counts of words via the Nikkei Inc. platform is too labor-intensive. We need to resort to applying the large language model directly to the original database. Third, if the PER index is proven to be a critical indicator, researchers in other countries can construct the PER index for their countries. Eventually, we can access all kinds of EPR indices with international cooperation.[17] Finally and most importantly, the PER index can be used as a threshold variable in the regression models that include an exchange rate as a dependent variable or one of the explanatory variables. For example, in an exchange rate pass-through analysis, we can analyse the nonlinear pricing behavior of exporters and importers with respect to exchange rate changes, see for example Nguyen and Sato (2019) for a study using a survey forecast as a threshold variable.

So far, we interpreted the PER index as the collective and subjective opinions of market participants, and more broadly, it reflects the perception of the general public. Their professional opinions in the newspaper articles may have a ripple effect on a much wider range of market participants, government officials, and consumers in general. Social learning is the updating of beliefs based on observations of the actions of others, Bikhchandani et al. (2024). The PER may cause an information cascade to the general public. Those influenced by the trend of the newspaper articles stop processing their own private information.

[17]For the country with the dominant currency, such as the US or the Euro area, the appropriate exchange rate is likely to be the nominal effective exchange rate.

References

Asako, Kazumi, Yasuyuki Komaki, Yosuke Takeda, Toshiki Jinushi, and Yasushi Hayashi (2007) "Comparative Statistical Analyses of the Foreign Exchange Rate Survey Data -JCIF and WEIS-," *The Economic Review*, 58 (2), 163–186.

Bacchetta, Philippe and Eric Van Wincoop (2004) "A Scapegoat Model of Exchange-Rate Fluctuations," *American Economic Review*, 94 (2), 114–118.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis (2016) "Measuring Economic Policy Uncertainty," *The Quarterly Journal of Economics*, 131 (4), 1593–1636, 10.1093/qje/qjw024.

Baldwin, Richard E. and Richard K. Lyons (1994) "Exchange rate hysteresis? Large versus small policy misalignments," *European Economic Review*, 38 (1), 1–22, 10.1016/0014-2921(94)90002-7.

Bikhchandani, Sushil, David Hirshleifer, Omer Tamuz, and Ivo Welch (2024) "Information Cascades and Social Learning," *Journal of Economic Literature*, 62 (3), 1040–1093, 10.1257/jel.20241472.

Binetti, Alberto, Francesco Nuzzi, and Stefanie Stantcheva (2024) "People's understanding of inflation," *Journal of Monetary Economics*, 148, 103652, 10.1016/j.jmoneco.2024.103652.

Boero, Gianna and Emanuela Marrocu (2002) "The performance of non-linear exchange rate models: a forecasting comparison," *Journal of Forecasting*, 21 (7), 513–542, 10.1002/for.837.

Caldara, Dario and Matteo Iacoviello (2022) "Measuring Geopolitical Risk," *American Economic Review*, 112 (4), 1194–1225, 10.1257/aer.20191823.

Cheung, Yin-Wong, Wenhao Wang, and Frank Westermann (2025) "An In-Sample Evaluation of Exchange Rate Models: In Search of Scapegoats," *CESifo Working Papers* (11852).

Clements, Michael P and Jeremy Smith (1999) "A Monte Carlo Study of the Forecasting Performance of Empirical Setar Models," *J. Appl. Econ.*

Dick, Christian D., Ronald MacDonald, and Lukas Menkhoff (2015) "Exchange rate forecasts and expected fundamentals," *Journal of International Money and Finance*, 53, 235–256, 10.1016/j.jimonfin.2015.02.002.

Diebold, Francis X. (2015) "Comparing Predictive Accuracy, Twenty Years Later: A Personal Perspective on the Use and Abuse of Diebold–Mariano Tests," *Journal of Business & Economic Statistics*, 33 (1), 1–1, 10.1080/07350015.2014.983236.

Diebold, Francis X and Roberto S Mariano (1995) "Comparing Predictive Accuracy," *Journal of Business & Economic Statistics*, 13 (3), 253–263.

Ferrara, Laurent, Massimiliano Marcellino, and Matteo Mogliani (2015) "Macroeconomic forecasting during the Great Recession: The return of non-linearity?" *International Journal of Forecasting*, 31 (3), 664–679, 10.1016/j.ijforecast.2014.11.005.

Frankel, Jeffrey A and Kenneth A Froot (1990) "Chartists, Fundamentalists, and Trading in the Foreign Exchange Market," *American Economic Review*, 80 (2), 181–185.

Guyot, Opale and Heather A. Montgomery (2025) "Against the wind or with it? The intraday and daily dynamics of yen interventions," *Journal of the Japanese and International Economies*, 78, 101392, 10.1016/j.jjie.2025.101392.

Hansen, Stephen, Michael McMahon, and Andrea Prat (2018) "Transparency and Deliberation Within the FOMC: A Computational Linguistics Approach*," *The Quarterly Journal of Economics*, 133 (2), 801–870, 10.1093/qje/qjx045.

Huber, Florian (2016) "Forecasting exchange rates using multivariate threshold models," *The B.E. Journal of Macroeconomics*, 16 (1), 10.1515/bejm-2015-0032.

Ito, Takatoshi (1990) "Foreign Exchange Rate Expectations: Micro Survey Data," *The American Economic Review*, 80 (3), 434–449.

Ito, Takatoshi and Tomoyoshi Yabu (2007) "What prompts Japan to intervene in the Forex market? A new approach to a reaction function," *Journal of International Money and Finance*, 26 (2), 193–212.

Jackson, Karen and Georgios Magkonis (2024) "Exchange rate predictability: Fact or fiction?" *Journal of International Money and Finance*, 142, 103026, 10.1016/j.jimonfin.2024.103026.

Jongen, Ron, Willem F.C. Verschoor, Christian C.P. Wolff, and Remco C.J. Zwinkels (2012) "Explaining dispersion in foreign exchange expectations: A heterogeneous agent approach," *Journal of Economic Dynamics and Control*, 36 (5), 719–735, 10.1016/j.jedc.2012.01.005.

Knetter, Michael M. (1994) "Is export price adjustment asymmetric?: evaluating the market share and marketing bottlenecks hypotheses," *Journal of International Money and Finance*, 13 (1), 55–70, 10.1016/0261-5606(94)90024-8.

Kräger, Horst and Peter Kugler (1993) "Non-linearities in foreign exchange markets: a different perspective," *Journal of International Money and Finance*, 12 (2), 195–208, 10.1016/0261-5606(93)90024-6.

Kuziemko, Ilyana, Michael I. Norton, Emmanuel Saez, and Stefanie Stantcheva (2015) "How Elastic Are Preferences for Redistribution? Evidence from Randomized Survey Experiments," *American Economic Review*, 105 (4), 1478–1508, 10.1257/aer.20130360.

Meese, Richard A. and Kenneth Rogoff (1983) "Empirical exchange rate models of the seventies," *Journal of International Economics*, 14 (1-2), 3–24, 10.1016/0022-1996(83)90017-X.

Menkhoff, Lukas, Rafael R. Rebitzky, and Michael Schröder (2009) "Heterogeneity in exchange rate expectations: Evidence on the chartist–fundamentalist approach," *Journal of Economic Behavior & Organization*, 70 (1-2), 241–252, 10.1016/j.jebo.2009.01.007.

Nguyen, Thi-Ngoc Anh and Kiyotaka Sato (2019) "Firm predicted exchange rates and nonlinearities in pricing-to-market," *Journal of the Japanese and International Economies*, 53, 101035, 10.1016/j.jjie.2019.101035.

Obstfeld, Maurice and Alan M. Taylor (1997) "Nonlinear Aspects of Goods-Market Arbitrage and Adjustment: Heckscher's Commodity Points REvisited," *Journal of the Japanese and International Economies*, 11, 441–479.

Pippenger, Michael K and Gregory E Goering (1998) "Exchange Rate Forecasting: Results from a Threshold Autoregressive Model," *Open Economies Review*, 9, 157–170.

Rapach, David E. and Mark E. Wohar (2006) "The out-of-sample forecasting performance of nonlinear models of real exchange rate behavior," *International Journal of Forecasting*, 22 (2), 341–361, 10.1016/j.ijforecast.2005.09.006.

Rossi, Barbara (2013) "Exchange Rate Predictability," *Journal of Economic Literature*, 51 (4), 1063–1119, 10.1257/jel.51.4.1063.

Shapiro, Adam Hale and Daniel J Wilson (2022) "Taking the Fed at its Word: A New Approach to Estimating Central Bank Objectives using Text Analysis," *The Review of Economic Studies*, 89 (5), 2768–2805, 10.1093/restud/rdab094.

Takagi, Shinji (1991) "Exchange Rate Expectations: A Survey of Survey Studies," *Staff Papers - International Monetary Fund*, 38 (1), 156–183, 10.2307/3867039.

——— (2014) "The Effectiveness of Foreign Exchange Market Intervention: A Review of Post-2001 Studies on Japan," *Journal of Reviews on Global Economics*, 3, 84–100, 10.6000/1929-7092.2014.03.07.

Yoon, Gawon (2010) "Do real exchange rates really follow threshold autoregressive or exponential smooth transition autoregressive models?" *Economic Modelling*, 27 (2), 605–612, 10.1016/j.econmod.2009.11.015.

A Appendix:

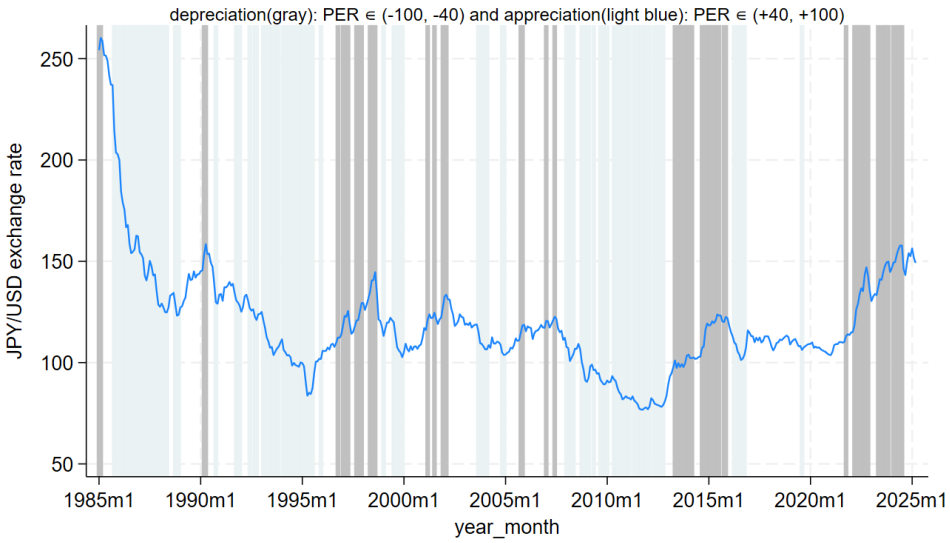

Figure A.1: The depreciation and appreciation regimes by perceived exchange rates

Note: The depreciation regime is defined as PER $\geqq$ +40 and shaded with gray color. The appreciation regime is defined as PER $\leqq$ -40 and shaded with light blue.

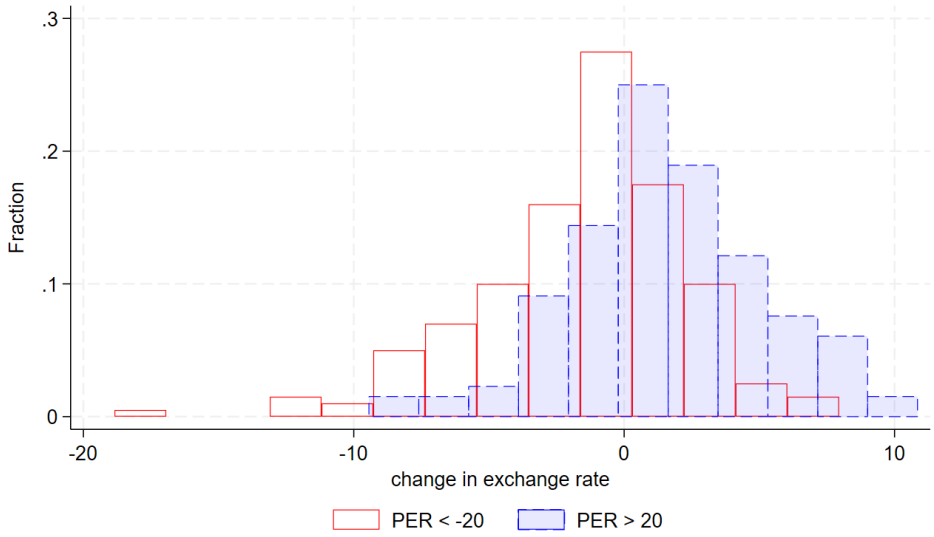

Figure A.2: The distribution of exchange rate changes by PER index

Note: The distributions of exchange rate changes are shown for when $PER < -20$ and when $PER > 20$. The 142 months are associated with $PER > 20$. Positive changes in the exchange rate, indicating depreciation, occur 99 months, and negative changes occur in 43 months. The 200 months are associated with $PER < -20$. Positive changes in the exchange rate, indicating depreciation, occur 69 months, and negative changes occur in 131 months.

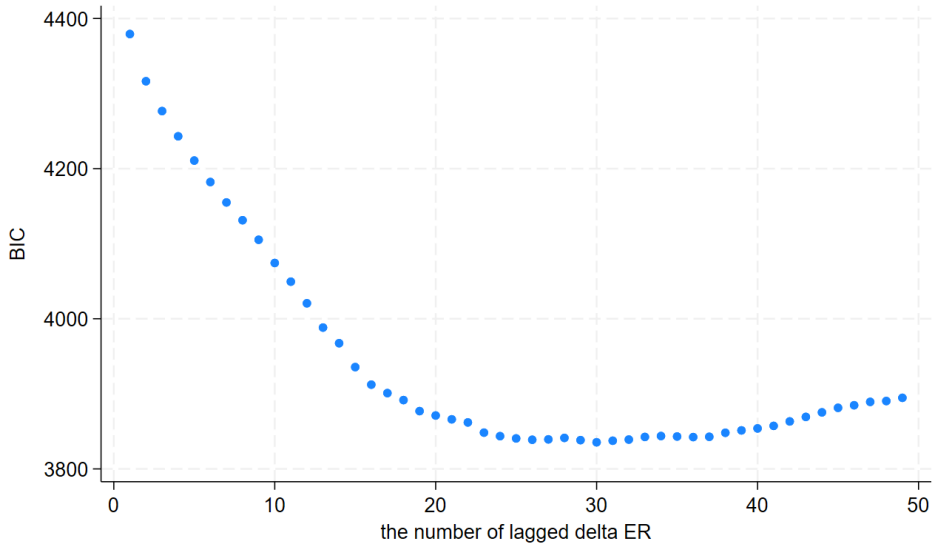

Figure A.3: The optimal number of exchange rate lag terms for the PER regression model

Note: The PER index is regressed on the current and the lagged terms of exchange rate changes, Δe. The horizontal axis represents the number of lagged terms of exchange rate changes plus the current exchange rate change. The vertical axis indicates the corresponding Bayesian information criteria. The minimum BIC is obtained with 29 lags specification.

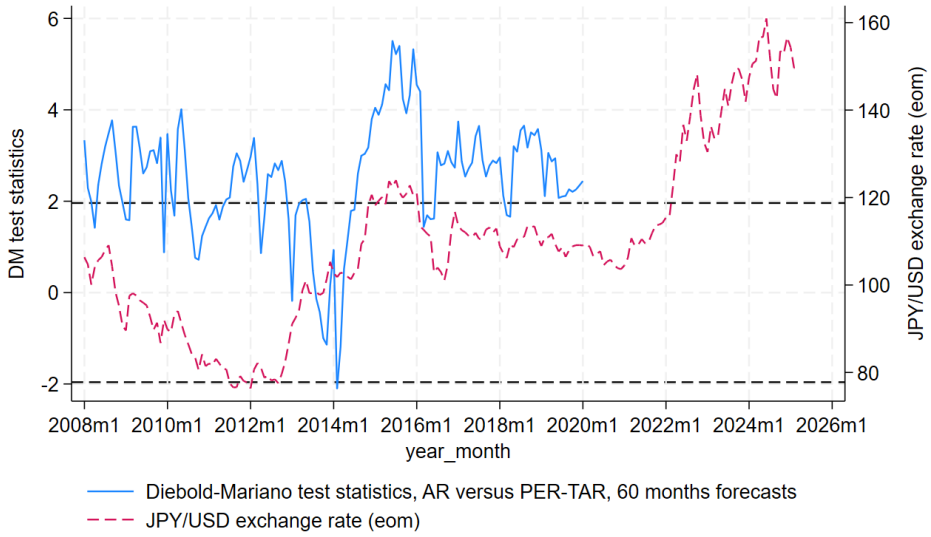

Figure A.4: The comparison of forecast models: the AR(12) versus the PER-TAR(12)

Note: The forecast intervals are 60 months. The starting month for forecasts is from January 2008 to January 2020. Positive DM test statistics indicate that the PER-TAR(12) model has better forecast accuracy. The horizontal dashed lines indicate statistical significance at the five percent level. The PER-TAR(12) model has outperformed the AR(12) model in 104 times with statistical significance at the five percent level, out of 145 different forecast starting months. Only one for vice versa.

Table A.1: Estimation results of two-threshold PER TAR model for JPY/USD exchange rates

	Regime 1	Regime 2	Regime 3
λ	<-25.73		17.53<
e_{t-1}	0.835 (0.076)	0.629 (0.090)	0.872 (0.121)
e_{t-2}	0.102 (0.093)	0.117 (0.112)	0.011 (0.179)
e_{t-3}	-0.137 (0.090)	0.112 (0.118)	0.105 (0.167)
e_{t-4}	0.026 (0.096)	-0.194 (0.105)	-0.005 (0.173)
e_{t-5}	-0.030 (0.093)	0.078 (0.106)	-0.080 (0.169)
e_{t-6}	-0.090 (0.087)	0.067 (0.113)	-0.111 (0.163)
e_{t-7}	0.227 (0.092)	0.067 (0.107)	-0.021 (0.162)
e_{t-8}	-0.040 (0.090)	0.102 (0.112)	0.264 (0.167)
e_{t-9}	0.047 (0.084)	-0.171 (0.125)	-0.123 (0.160)
e_{t-10}	-0.054 (0.084)	0.057 (0.124)	0.148 (0.159)
e_{t-11}	0.045 (0.081)	-0.009 (0.126)	-0.073 (0.167)
e_{t-12}	-0.009 (0.057)	0.091 (0.093)	0.035 (0.117)
constant	6.441 (1.290)	6.772 (2.362)	0.025 (3.043)

Note: Standard errors in parentheses. The estimates in column Regime 1 are shown for PER below -25.73. The Reigme 2 column shows estimates when PER is between -25.73 and 17.53. The last column shows estimates for PER being greater than 17.53.

Table A.2: ternary intervention indicator with the lagged explanatory variables

	ternary intervention indicator (-1, 0, +1)				
	(1a)	(2a)	(3a)	(4a)	(5a)
PER_{t-1}	0.004**				0.003**
	(0.000)				(0.001)
e_{t-1}		0.008**		0.008**	0.004*
		(0.001)		(0.001)	(0.002)
Δe_{t-1}			0.025**	0.021**	0.012
			(0.006)	(0.006)	(0.006)
Intercept	-0.064**	-1.020**	-0.089**	-0.964**	-0.505**
	(0.020)	(0.138)	(0.021)	(0.137)	(0.174)
Number of observations	409	409	409	409	409
Adjusted R-squared	0.14	0.10	0.04	0.12	0.16

Note: Standard errors in parentheses. ** p<.01, * p<.05 The dependent variable is the ternary intervention indicator variable, which takes the value of -1 in the JPY selling interventions and +1 in the JPY buying interventions. It is zero otherwise. The estimation method is the OLS.

Table A.3: ternary intervention indicator, ordered logit estimates

	ternary intervention indicator (-1, 0, +1)				
	(1b)	(2b)	(3b)	(4b)	(5b)
PER_{t-1}	0.030**				0.021**
	(0.004)				(0.005)
e_{t-1}		0.052**		0.050**	0.022*
		(0.008)		(0.008)	(0.010)
Δe_{t-1}			0.151**	0.137**	0.079
			(0.038)	(0.039)	(0.041)
Number of observations	409	409	409	409	409
Pseudo R-squared	0.14	0.09	0.03	0.11	0.15

Note: Standard errors in parentheses. ** p<.01, * p<.05 The dependent variable is the ternary intervention indicator variable, which takes the value of -1 in the JPY selling interventions and +1 in the JPY buying interventions. It is zero otherwise. The estimation method is the Ordered Logit.

Table A.4: ternary intervention indicator, ordered logit with the lagged intervention

	(6)	(7)
Int_{t-1}	3.708**	3.407**
	(0.308)	(0.332)
PER_{t-2}		0.014*
		(0.006)
e_{t-2}		0.008
		(0.013)
Δe_{t-2}		-0.062
		(0.050)
Number of observations	408	408
Pseudo R-squared	0.34	0.37

Note: Standard errors in parentheses. ** p<.01, * p<.05 The dependent variable is the ternary intervention indicator variable, which takes the value of -1 in the JPY selling interventions and +1 in the JPY buying interventions. It is zero otherwise. The estimation method is the Ordered Logit.