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Abstract

In this paper, we develop a model to predict large currency swings using transaction-level data on foreign exchange options, collected by trade repositories (TRs). These data allow us to capture heterogeneous currency risk perceptions of individual market participants. By applying a quantile regression combined with machine learning for variable selection, we find that market participants' views extracted from trade repository data significantly improve the predictions of large currency swings.

Keywords: *Currency swing, granular data, trade repository, foreign exchange option, quantile regression, variable selection*

JEL classification: C22, C55, F31, G17.

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1. Introduction

Currency markets exhibit volatile price fluctuations, driven by changes in market participants' outlook for the real economy and financial conditions. In the recent episode of August 2024, a weaker-than-expected U.S. labor market indicator triggered a swift unwinding of carry-trade positions built up by investors who had been selling Japanese yen (JPY) and buying U.S. dollars (USD), resulting in sharp JPY appreciation.[1] Since such large currency swings can have adverse effects on financial conditions and business activities, financial authorities could benefit from a sophisticated monitoring tool to better forecast such large fluctuations.[2] Given the observation that JPY has experienced larger currency swings compared with other advanced economies,[3] we ask how swings in the USD/JPY rate can be predicted by using Japan's trade repository data on foreign exchange options (FX options).

Previous studies have employed macroeconomic variables, such as interest rate differentials, changes in financial conditions, and spikes in policy uncertainty to forecast currency movements in times of market stress (Cenedese et al., 2014; Eguren-Martin and Sokol, 2022; Ferrara and Yapi, 2022). Our paper empirically proposes that currency risk perceptions extracted from transaction-level trade repository (TR) data provide valuable information for forecasting the tails of currency return distribution.[4] This idea is in line with the market microstructure research focusing on the heterogeneity of market participants' views, for example, by using the transaction flows of different investor groups (Menkhoff et al., 2016), to

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[1] There are various forms of carry trades. Some foreign investors borrow low-interest-rate currencies to invest in high-yielding foreign assets, while others combine spot FX trades and currency swaps.

[2] Taylor et al. (2021) present international evidence from four thousand multinational firms in 44 countries that an unexpected increase in exchange rate volatility reduces real corporate investment, especially for firms that do not use currency derivatives for hedging purposes.

[3] In terms of the monthly realized volatility in nominal effective exchange rates during the period from January 2009 through August 2025, JPY ranks the second highest following Norwegian krone among advanced economy currencies.

[4] After the global financial crisis, transaction-level data on over-the-counter (OTC) derivatives have been collected by trade repositories in many jurisdictions to improve the transparency of OTC derivatives markets and reduce the systemic risk. Japan's Financial Services Agency (FSA) is legally authorized to request reports on OTC derivative transactions from financial instruments clearing organizations and financial instruments business operators (those conduct Type I Financial Instruments Business, all banks, Shoko Chukin Bank, Development Bank of Japan, the members of the Federation of Shinkin Banks operating nationwide, Norinchukin Bank, and insurance companies). This leads to the wide coverage of derivative transactions executed in Japan. FSA shares this granular confidential data with the Bank of Japan (BOJ) for its effective use (Bank of Japan and Financial Services Agency, 2021). Similarly, FSA and BOJ collaboratively collect and publish *Statistics on Securities Financing Transactions in Japan*, which is the highly detailed granular data on the Japanese repo market, to improve risk management in financial institutions and monitor their conformity with various regulations.

enhance the forecasting ability of currency movement models. While previous studies typically assume that economic agents share the same information reflected in macro fundamentals, market microstructure studies hypothesize that selected investors have information advantages and their transactions have richer implications for future currency returns (Evans and Lyons, 2005). We build on these studies by using transaction-level TR data of FX options in Japan to extract investors' heterogeneous views and use this information as predictors of large USD/JPY fluctuations. Since investors trade FX options to hedge against potential currency fluctuations, the currency risk perceptions extracted from these data reflect investors' expectations of future volatility. Such transaction-level data allow us to investigate heterogeneity in market participants' currency risk perceptions such as implied volatility (IV). We test the usefulness of such measures in predicting large currency swings.

Our prediction model uses weekly changes in the USD/JPY spot rate at time t as the dependent variable, with three types of predictors: (i) macro-financial variables at time t, namely (a) the changes in 2-year yield differentials between the United States and Japan and (b) the changes in VIX to capture broad market sentiment; (ii) individual investors' currency risk perceptions extracted from FX option data at time $t\text{-}1$; and (iii) the interlinkages between (i) and (ii). First, it is natural to assume that macro-financial conditions induce position adjustments and price fluctuations in the currency market. Second, as our distinctive contribution, we posit that investors' currency risk perceptions at time $t\text{-}1$ also affect subsequent positions and prices in the market. For example, if certain investor groups have information advantages, they may hedge against potential movements in advance through FX option trading. These groups' currency risk perceptions may therefore serve as early warning indicators of future currency swings. Third, we explore whether the interlinkages between macro-financial variables and investors' currency risk perceptions have additional forecasting power. Specifically, we hypothesize that currency risk perceptions can either amplify or dampen market responses to changes in macro-financial variables.

To characterize large currency swings, we use a variant of quantile regression to study the impacts of variables on different quantiles of currency return distribution. Given the large number of candidate predictors for currency fluctuations, variable selection is essential. We employ L1-penalized quantile regression, developed by Belloni and Chernozhukov (2011), which integrates a machine learning-based variable selection procedure into standard quantile regression. While many earlier studies, particularly those using macroeconomic variables, manually selected a small number of regressors based on researchers' discretion, we take a data-driven approach. The main benefit of this method is to penalize the L1-norm of regression coefficients; coefficients of variables with relatively lower explanatory power are shrunk to exactly zero and excluded from the model, while variables that meaningfully explain variation in the dependent variable retain non-zero coefficients.

We find that higher IVs for certain investor groups help predict large currency swings in the tails of the return distribution in the following week. This suggests that these investors possess informational advantages that are useful for forecasting future currency fluctuations.[5,6]

We acknowledge some limitations. First, our analysis assumes a partial overlap in the composition of market participants in the spot FX and FX option markets. Investors active in the spot FX market but not regularly trading FX options with Japanese financial institutions (e.g., some hedge funds) may be underrepresented. Second, the impact of macro-financial variables on exchange rates is time-varying and influenced by prevailing market "narratives." Hence, the selected variables should not be interpreted as universally dominant drivers across all market conditions. Third, it is important to note that the LASSO-based method accounts for correlations among explanatory variables and selects a parsimonious subset from highly correlated candidates. Since currency risk perceptions across sectors are strongly correlated, caution is warranted in interpreting the selected variables as definitive determinants of currency swings; rather, they serve as useful predictors.

The rest of this paper is organized as follows. Section 2 reviews related studies. Section 3 presents our empirical strategy and data. Section 4 reports our empirical results, and Section 5 concludes.

2. Related Literature

The first strand of literature relevant to our study concerns the prediction of currency movements with macroeconomic variables (e.g., Meese and Rogoff, 1983; Engel and Wu, 2024;

[5] These information advantages in the over-the-counter markets are consistent with the market microstructure literature. For example, Czech and Monroe (2025) find that dealers initially reduce liquidity costs for informed investors and subsequently reduce liquidity for the broader market under market stress. They interpret this pattern as dealers "chasing information" from other investors with information advantages in interdealer markets.

[6] Information advantages can result from either larger information sets due to private information, or different ways of processing information due to investors' institutional arrangements, although it is difficult to disentangle one from the other.

Ikkatai et al., 2024).[7] Ikkatai et al. (2024) studies the impact of Japanese interest rate changes after the Bank of Japan's major monetary policy meetings.[8] While their paper examines the "average" impact of interest rate changes on exchange rates using the method of local projection, this paper uses quantile regressions to focus on the "tails" of the currency distribution, i.e. the large degrees of currency appreciation and depreciation.

This paper is most closely related to the literature which examines large currency swings, by employing quantile regressions with a particular focus on the tails of the currency return distribution. Prior research has studied the impact of market volatility, global financial conditions, and economic policy uncertainty (Cenedese et al., 2014; Eguren-Martin and Sokol, 2022; Ferrara and Yapi, 2022).[9] Another line of research links large currency movements to episodes of sudden carry-trade unwinding, in which investors take long positions in high-interest-rate currencies and short positions in low-interest-rate currencies (for example, Brunnermeier et al., 2008). Our paper contributes to this line of research while deviates by using transaction-level data to extract the currency risk perceptions for different groups and showing that the perceptions of a specific set of investors matter in improving the prediction of large currency swings. In other words, while prior research uses macroeconomic variables, we show that the information distilled from granular data provides valuable information, in line with the market microstructure literature, which we refer to in the next paragraph.

Additionally, our work contributes to the literature on market microstructure, which emphasizes that transactions from different market participants can have distinct implications for future currency returns.[10] Osler and Vandrovych (2009) analyze transaction-level data and

[7] Instead of studying the nominal exchange rates, papers such as Hogen and Kishi (2024) study the drivers of real effective exchange rates, for example the productivity differentials in the tradable sector between two economies.

[8] Specifically, they empirically examine the response of the nominal exchange rate to the monetary policy changes, focusing on 14 major monetary policy meetings of the Bank of Japan. They find that JPY depreciated against USD in response to Japan's expansionary monetary policy shocks. They also find that the non-interest rate differential channel, captured by the changes of USD/JPY orthogonal to the changes in US-Japan yield differentials and presumably representing the shifts in future exchange rate expectations, played a major role in driving the nominal exchange rate.

[9] Brunnermeier et al. (2008) document that carry-trade returns are negatively skewed, implying that rapid appreciation of low-interest-rate currencies corresponds to the onset of the unwinding of investor positions. Relatedly, Farhi and Gabaix (2016) develop a model in which the possibility of rare but extreme shocks in the currency market is an important factor of risk premia in asset markets with their signals embedded in option prices. These papers support the idea that the second moment of currency returns (volatility) could have a predictive power for the first moment of currency returns.

[10] The literature builds on the empirical finding that currency order flows, as signals of net buying pressure in currency markets, improve predictive accuracy even after controlling for macro variables (Evans and Lyons, 2005; King et al., 2013). To explain the observation that exchange rate volatility at short- to medium-term horizons is

find that currency order flows from leveraged investors (e.g., hedge funds) and banks have predictive power for future returns, whereas those from non-leveraged customers (e.g., corporations) do not. Similarly, Menkhoff et al. (2016) show that order flows of long-term investors such as pension funds are associated with persistent shifts in exchange rates—reflecting superior processing of fundamental information—while flows from short-term investors such as hedge funds have only temporary effects, arising from gains in short-term liquidity provisions. Our paper aligns with this strand of literature by showing that the currency risk perceptions of investors situated in the center of FX option transaction networks play an important role in explaining future currency movements.

This paper is also related to Czech et al. (2025) and Hacioglu Hoke et al. (2026). Czech et al. (2025) show that larger transaction volumes of FX options predict depreciation of the foreign currency against USD the next day, especially when transactions by hedge funds or real money investors increase. Similarly, Hacioglu Hoke et al. (2026), using trade repository data in the United Kingdom, find that the changes in FX derivatives positions of hedge funds and pension funds have a predictive power for the weekly changes in USD/JPY. Our work differs from theirs in two points. First, while prior studies focus on transaction volumes, our main variables of interest are currency risk perceptions derived from FX option transactions and their interlinkages with macro-financial variables. This allows us to explicitly consider the possibility that traders' responses to macro-financial variables depend on prevailing currency risk perceptions before macro shocks hit—a relationship that has not been studied in the literature. Second, whereas the prior study examines the "average" impact on currency returns, we analyze effects on both the median and the tails of the return distribution. This approach allows us to capture not only the "central" scenario but also the "tail risks" that may potentially emerge. Thus, the heterogeneous perceptions on currency volatility extracted from granular data provide valuable information for authorities seeking to monitor hidden tail risks in the currency market.

The final strand of related research uses granular data to study the interlinkages between the foreign exchange derivatives market and the underlying financial markets such as spot FX, or other markets such as bond markets. Anderegg et al. (2022) demonstrate that volatility in the spot FX market is correlated with the positions of FX option market makers, owing to their

related to order flows but not to macroeconomic variables, Bacchetta and Wincoop (2006) introduce the concept of dispersed information about future macroeconomic fundamentals. Along this line, Cespa et al. (2022) show that FX transaction volume arising from hedging demand unrelated to fundamentals has a mean reverting impact on future returns, whereas transaction volume driven by fundamental shocks has a persistent impact.

hedging activities across the two markets. Relatedly, Kubitza et al. (2025) show that a widening in the USD/EUR cross-currency basis, i.e., a larger deviation from covered interest parity, induces Euro-area investors to rebalance their portfolios away from USD-denominated bonds.

3. Empirical Strategy and Data

This section describes our econometric method and data. Our data sources are summarized in Table 1. Subsection 3.1 introduces the L1-penalized quantile regression and explain our motivation for employing this approach. Subsection 3.2 describes how we extract measures of currency risk perceptions from granular data of FX options.

Figure 1 shows the time series of weekly USD/JPY changes, along with its histogram, which serves as the dependent variable in our estimation.[11] Positive values indicate JPY depreciation against the USD. Our estimation sample spans January 2016 to March 2025. The solid red line marks the median of weekly changes, while the dashed red lines denote the 10th and 90th percentiles (approximately -1.2 % and +1.3%, respectively). Although the median change is close to zero, the figure illustrates that the USD/JPY spot rate has experienced notable swings, by more than 1 percent change within a week.

Several episodes stand out. In early 2016, the JPY appreciated as a relatively safe asset amid a deteriorating global economic outlook. By late 2016, it depreciated following the U.S. presidential election. In early 2020, currency market volatility increased sharply during the onset of Covid-19-related uncertainty. In late 2022 through 2023, the Federal Reserve's rapid policy rate tightening led to sustained JPY depreciation. More recently, in August 2024, a weaker-than-expected U.S. labor market indicator worsened economic outlooks, triggering the unwinding of carry-trades and a sharp JPY appreciation. These episodes highlight the importance of closely monitoring currency swings.

3.1 Econometric Method

Our objective is to characterize the conditional quantiles of USD/JPY changes, with a particular focus on the tails that capture large currency swings. We especially focus on the tails of the currency return (JPY appreciation and depreciation tails) with our quantile regression. We are especially interested in whether the currency risk perceptions have additional forecasting power

[11] We use the daily series of USD/JPY spot rate at 5 p.m. in Tokyo, which is released from the Bank of Japan and calculate the log differences between the average spot rates in a specific week and those in its previous week.

in explaining tail events after controlling for macro-financial variables. Quantile regressions are suitable in evaluating the entire distribution of currency returns and are employed to explain the tail risks of economic growth or inflation (Adrian et al, 2019; Makabe and Norimasa, 2022).

In the first half of this subsection, we begin by describing our candidate regressors. Currency markets are highly complex, and the number of potential explanatory variables may exceed the length of our dependent variable's time series, making it difficult to determine ex-ante which variables are important. While previous studies—particularly those relying on macroeconomic variables—often select a small number of regressors based on researchers' discretion, our approach is to let the data guide variable selection. For this reason, we employ L1-penalized quantile regression, which combines quantile regression with a machine-learning-based variable selection mechanism. In the latter half of this subsection, we explain the motivation for and the mechanics of this methodology.

We aim to explain USD/JPY changes in week t using three groups of explanatory variables: (i) macro-financial variables in the week t, (ii) investors' currency risk perceptions in the preceding week *t-1*, and (iii) interaction terms between (i) and (ii). We use two macro-financial variables: the weekly changes in 2-year yield differentials between the United States and Japan, and the changes in VIX. The changes in macro-financial conditions can prompt position adjustments in the currency market. Next, we control for lagged currency risk perceptions, as certain sectors may possess informational advantages—such as signals of forthcoming currency swings and may hedge in advance through FX option trades. In this case, their currency risk perceptions could serve as early warning indicators for future currency swings. The construction of these variables is explained in subsection 3.2. Finally, the inclusion of interaction terms allows us to capture the interlinkages between macro-financial variables and currency risk perceptions and thus assess whether these early warning indicators amplify or dampen the effects of macro-financial variables.

A key feature of our dataset is that the number of candidate explanatory variables (p) is large with respect to the sample size (n): in our baseline specification, the former is $p = 218$ (excluding the intercept) while the latter is $n = 481$. This represents a classical high-dimensional "n<<p" problem, where naive estimation can become unstable or even ill-defined when $p \geq n$.

To address this, we adopt a machine-learning framework for variable selection that identifies variables with relatively high explanatory power while excluding less informative ones from the model in a data-driven way. Specifically, we employ the L1-penalized quantile regression (L1-QR) method proposed by Belloni and Chernozhukov (2011), which integrates quantile regression with LASSO-type regularization (Tibshirani, 1996).

Formally, the L1-QR estimator solves:

$$\min_{\beta \in \mathbb{R}_p} \mathbb{E}_n[\rho_\tau(y_t - x_t'\beta)] + \frac{\lambda\sqrt{\tau(1-\tau)}}{n}\sum_{j=1}^{p} \hat{\sigma}_j|\beta_j| \tag{1}$$

where $\rho_\tau(u) = (\tau - \mathbb{I}\{u \leq 0\})u$ is the tilted absolute deviation loss function for the τth quantile, $\mathbb{I}$ is an indicator function which equals 1 only if the deviation loss $u = y_t - x_t'\beta$ is negative, $\hat{\sigma}_j^2$ is the estimated variance of regressor j, β is the coefficient vector, λ is the penalty parameter, and n, p and t are the sample size, the number of regressors and the length of our data time-series, respectively. In our case, y_t is the weekly change in the USD/JPY spot rate, and x_t contains (i) macro-financial variables in the week t, (ii) investors' currency risk perceptions in the preceding week *t-1*, and (iii) interaction terms between (i) and (ii).

The first term corresponds to the standard quantile regression objective function (Koenker and Hallock, 2001). While the sample mean minimizes the sum of squared residuals, the median minimizes the sum of absolute residuals. More generally, conditional quantiles are obtained by minimizing asymmetrically weighted absolute residuals, assigning different weights to positive and negative deviations via the tilted absolute deviation loss function ρ_τ.[12]

The second term introduces an L1-norm-penalty on coefficients, shrinking them toward zero and setting some as exactly zero. This performs variable selection alongside estimation, enabling stable estimation even when p exceeds n.[13,14] The penalty introduces bias relative

[12] Minimizing the sum of absolute residuals equates the number of positive and negative residuals and ensures that there are the same number of observations above and below the median. Similarly, giving different weights to positive and negative residuals yield the quantiles (Koenker and Hallock, 2001).

[13] This estimation is consistent provided that, for each conditional quantile of the dependent variable, when at most s out of the p candidate regressors have a nonzero effect, where s increases at a slower rate than the sample size n, along with the other technical assumptions discussed in the original paper.

[14] Technically, the penalty-level hyperparameter λ is chosen to achieve the optimal convergence rates for L1-penalized quantile regression, following Belloni and Chernozhukov (2011). Specifically, λ is set based on the supremum norm of the rescaled gradient of the sample objective function evaluated at the true parameter value. For further technical details, see Section 2.3 of the original paper.

to unpenalized estimation, but this bias can be mitigated by a two-step procedure: first applying L1-QR to select variables, and then re-estimating an unpenalized quantile regression using only the selected variables ("post-L1-QR"). Belloni and Chernozhukov (2011) show that this approach retains favorable convergence properties while reducing regularization bias. We therefore report post-L1-QR estimates in Section 4.

3.2 Currency risk perceptions

We define currency risk perceptions based on the idea that greater uncertainty in the FX market increases demand for FX options as hedging tools. Consequently, higher FX option prices imply higher expected currency risk among market participants. Prior studies, such as Brunnermeier et al. (2008), which link large currency swings to episodes of sudden stops of carry-trades support the idea that the second moment of currency returns (volatility), or more general information embedded in option prices, could have a predictive power for the first moment of currency returns. High volatility dampens the return of carry-trades, which requires investors to unwind their accumulated positions and causes the appreciation of low-interest-rate currencies. Under this rationale, implied volatility (IV)—obtained as the inverse of the Black-Scholes option pricing formula—serves as a key indicator of expected future currency volatility. A related measure, risk reversal (RR)—the difference between the IV of call and put options—captures directional bias in risk perceptions. A higher RR indicates greater caution among investors about JPY depreciation relative to appreciation.

To estimate these indicators, we use transaction-level data on over-the-counter derivatives (TR data) provided by Japan's Financial Services Agency. We select data on FX options that meet the following four criteria: (i) USD/JPY currency pair, (ii) maturities of 1 week, 1 month, or 3 months, (iii) European-style contracts, (iv) vanilla options with no special terms or conditions.[15,16] For each transaction, IV is estimated using six inputs: (i) option premium (contract price), (ii) strike price, (iii) maturity, (iv) USD/JPY spot rate, (v) U.S. interest rate

[15] Washimi (2020) and Takizuka and Suzuki (2022) also use this granular FX option data.

[16] To remove outliers, we exclude contracts whose option strike prices are outside the reasonable range of 50 and 200 JPY per USD. We also discard contracts lacking the necessary data to calculate IV, as well as those with notional amounts which are likely to be misreported (exceeding the 99.9997th percentile).

expectations, and (vi) Japanese interest rate expectations.[17,18,19] We estimate IV for each executed FX option contract by minimizing the deviation between the theoretical Black-Scholes price and the observed price. Outliers—those with IV below 0.1 or above the historical maximum since 2008 (based on Bloomberg data)—are removed, leaving roughly 260 thousand contracts.[20]

Weekly aggregates are then computed for the median values of IV across all contracts executed in each week. To capture heterogeneity, we also compute the medians for each buyer-seller sectoral pairs (e.g., the implied volatility of options which large domestic banks sold to foreign securities firms).[21] RR is similarly calculated as the difference between the median IV of call and put options executed in each week.[22]

We retain series with less than 50% missing values, filling remaining gaps via a Kalman filter while preserving observed values.[23,24] Each IV and RR series is classified into three states—high, low, or normal—based on whether the value deviates from its historical mean by more than one standard deviation from January 2016 to March 2025. For example, the "high IV" state corresponds to periods of unusually elevated expected volatility. We use high and low states of these currency risk perceptions as dummy variables in our quantile regressions.

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[17] Option maturities are calculated as the difference between the expiration and trade dates. To measure risk perceptions over 1 week, 1 month, and 3 months, contracts are matched with maturities of 7-8 days, 14-42 days, and 61-121 days, respectively.

[18] Specifically, we use the USD/JPY spot rate at 5:00 p.m. New York time on the business day prior to the option trade date (i.e., early morning in Tokyo on the trade date), which we take as the benchmark exchange rate for option traders on that day.

[19] We assume that all market participants share the prevailing interest rate outlooks. For the U.S., we linearly interpolate between the effective Federal Funds Rate and 15 grid points of U.S. OIS rates (spanning maturities from 1 month to 3 years) to obtain the rate corresponding to each contract's maturity. For Japan, we apply the same method, interpolating between the Tokyo Over Night Average Rate (TONA) and 9 grid points of Japanese OIS rates (spanning maturities from 1 month to 3 years).

[20] The purpose of this preprocessing step is to exclude contracts with unrealistically high or low estimated IV. Note that Bloomberg's IV did not reach the extreme levels observed during the global financial crisis throughout our estimation period (January 2016-March 2025). Moreover, the maximum realized IV since 2008 exceeds the historical average during our sample period by more than six standard deviations.

[21] We calculate the 25th and 75th percentiles only when at least two relevant contracts are available.

[22] We compare call and put options with similar product characteristics by matching those whose absolute delta values—a measure of the sensitivity of the option price to changes in the underlying USD/JPY spot rate—fall between 0.15 and 0.35.

[23] Note that missing values occur when no transactions take place between specific FX option seller and buyer groups during a given week.

[24] Our rationale is that weekly data series with 50% or more missing values over the sample period are unlikely to serve as useful monitoring indicators in practice, due to their infrequent availability.

Figure 2 shows that our weekly median IV closely tracks Bloomberg's series, confirming our estimation's plausibility. Figure 3 compares 11 crosse-sector series of IV from different pairs of option buyer and seller sectors, revealing similar overall dynamics but differences in the timing and frequency of volatility spikes, suggesting the heterogeneity of information contained in the transactions across market participants. Figure 4 displays the summary statistics of these 11 series in Figure 3 and the results of statistical tests whether a pair of series have equal means or variances. The upper panel shows that each series has a different level of summary statistics, especially the number of outliers (spikes in the time-series), as shown in Figure 3.[25] In the lower panel, we conduct statistical tests that a pair of series have different means or variances to check for the heterogeneity of currency risk perceptions. We find that out of 55 combinations resulting from 11 series, 42 pairs have different means and 28 pairs have different variances, respectively. This shows there exists heterogeneity in currency risk perceptions across sectors.

4. Empirical Results

In this section, we present our primary empirical findings. Table 2 reports the coefficients from the post-L1-QR estimation, given equation (1), for the 10th percentile (JPY appreciation tail), 50th percentile (median), and 90th percentile (JPY depreciation tail) of weekly USD/JPY changes. The explanatory variables are grouped into three categories: (i) macro-financial variables in week *t*, (ii) currency risk perceptions derived from FX option data in week *t-1*, and (iii) interaction terms between (i) and (ii). We especially focus on the tails of the currency return (JPY appreciation and depreciation tails) with our quantile regression. We are especially interested in whether the currency risk perceptions have additional forecasting power after we control for macro-financial variables.

First, we examine the effect of macro-financial variables. A widening of the yield differentials between the United States and Japan leads to JPY depreciation.[26] The weekly change in VIX is not selected as an explanatory variable with relatively higher explanatory power.[27]

Regarding the JPY appreciation tail (10th percentile), higher IV of options purchased by domestic securities companies from foreign securities companies predicts JPY appreciation in

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[25] For each series, we count how many data points exceed the historical average by more than 3 standard deviations.

[26] A widening of US-JP yield differentials means that US 2-year yield rises more than JP yield in the corresponding week, or JP 2-year yield lowers more than US yield.

[27] The empirical results do not change if we exclude the changes in VIX from our set of explanatory variables.

the following week in a statistically significant manner. For the JPY depreciation tail (90th percentile), higher IV of options bought by foreign banks from domestic large banks and elevated RR—reflecting stronger hedging needs for JPY depreciation—predict JPY depreciation next week in a statistically significant way. These findings indicate that elevated IV in specific sectors signals forthcoming currency movements in the tails of the USD/JPY return distribution.

Figure 5 illustrates the FX option transaction network, showing that foreign banks, domestic large banks, and securities companies—commonly referred to as "market makers"—occupy central positions in the network. The statistically significant coefficients associated with these sectors' currency risk perceptions in Table 2, especially in the tails, suggest these well-connected market makers possess superior information about market sentiments. This aligns with prior microstructure research highlighting the informational advantages of certain market participants.

We evaluate model performance by comparing three specifications: (i) an unrestricted model including all variables from Table 2, (ii) a restricted model with an intercept and two macro-financial variables (3 variables in total), and (iii) an alternative model that adds lagged FX option volume growth, following Czech et al. (2025). Using the local goodness-of-fit measure for each quantile regression (Koenker and Machado (1999)), Figure 6 demonstrates that adding currency risk perceptions substantially improves fit in the tails of the currency return distribution, but not around the median.[28,29]

This suggests FX options, as hedging instruments, embed valuable information on tail risks expected by option market participants. This enhances our understanding that FX options contain information for extreme currency movements. Conversely, including lagged FX option volume yields limited improvement over macro-financial variables alone, indicating that the volume measure likely captures the same effects already explained by macro-financial variables.

[28] Specifically, we estimate both unrestricted and restricted quantile regression models and calculate one minus the ratio of their minimized sum of asymmetrically weighted absolute residuals. This measure serves as the natural analog of R-squared in a classical least squares regression when the restricted model includes only an intercept. Because it evaluates the relative fit of the quantile regression models at a specific quantile based on the weighted sum of absolute residuals, this measure reflects a local goodness of fit rather than a global fit across the entire conditional distribution.

[29] Specifically, for each pair of option buyer and seller categorized by business sector, we calculate the weekly growth rate of FX transaction volume relative to the average volume over the previous three weeks. Following Czech et al. (2025), we use the growth rate rather than the absolute level to control for long-term growth trends in the FX option market and to capture abnormal spikes in transaction volume.

This further underscores the superior informational content of currency risk perceptions extracted from granular data.

To further facilitate our interpretation, we next aggregate the implied volatility for call and put options separately and include them in our quantile regression. Dollar call (put) options are the rights for option buyers to purchase (sell) a defined notional amount of USD at a set rate on a set date in exchange for the payment of option prices.[30] It means dollar call (put) option buyers expect USD to appreciate (depreciate) against JPY in the future.

Table 3 shows the empirical result when we use the implied volatility disaggregated for call and put options in our quantile regression. Regarding the JPY appreciation tail (10th percentile), higher IV of *put* options purchased by foreign banks from domestic large banks predicts JPY appreciation in the following week in a statistically significant manner. Foreign banks as *put* options' buyers benefit from JPY appreciation against USD as their prior expectations come true. Similarly, for the JPY depreciation tail (90th percentile), higher IV of *call* options bought by foreign banks from domestic securities companies predict JPY depreciation next week. Again, foreign banks as *call* options' buyers benefit from JPY depreciation against USD as their expectation materializes. Thus, this result implies that foreign banks have superior predicting power for the future exchange rates, presumably because they are situated in the center of the options transaction network.[31]

The rest of the tables is devoted to robustness checks. In the Table 4, we change the maturity of yield differentials from 2-year to 10-year and find a similar result.[32] Table 5 presents results when we use the changes in the levels of currency risk perceptions to find a consistent result[33], instead of using dummy variables as we classify the level of currency risk perceptions into high, low and medium states as in our main specification.

In the Table 6, we predict the rise in volatility, which we define as the 95th percentile of realized volatility[34], by the lagged level of 1 week implied volatility from our granular data.

[30] As we noted in our data section, we limit our sample to European options and exclude American options.

[31] It is possible that if foreign banks purchase a portion of options for their clients such as hedge funds, hedge funds might have superior predicting power for the future exchange rates as well, consistent with prior studies (Osler and Vandrovych, 2009; Hacioglu Hoke et al., 2026).

[32] The result does not change if we use the US-Japanese differentials of OIS 3-month.

[33] For this robustness check, we scale each series with mean zero and unit standard deviation beforehand.

[34] We calculate realized volatility as the weekly variance of log daily changes in USD/JPY. In the Appendix Figure, 95th percentile of this indicator shows the large magnitude of currency depreciation or appreciation.

Specifically, we compare the fit of quantile regressions when we use each sector's 1w implied volatility and the Bloomberg series. We find that the implied volatility of foreign securities companies, domestic securities companies and large domestic banks have higher predictive powers for 1 week ahead realized volatility compared to the Bloomberg series. This result, consistent with our main result, shows that the currency risk perceptions of some sectors have relatively higher information values than those of other sectors in terms of the fitness of quantile regressions.

Finally, we acknowledge some limitations. First, our analysis assumes a partial overlap in market participant composition between spot FX and FX option markets. Investors active in spot FX but not regularly trading FX options with Japanese financial institutions (e.g., some hedge funds) may be underrepresented. Second, the impact of macro-financial variables on exchange rate is time-varying and influenced by prevailing market "narratives." Hence, variables selected by LASSO should not be interpreted as universally dominant drivers across all market conditions. Third, it is important to note that the LASSO-based method accounts for correlations among explanatory variables and selects a parsimonious subset from highly correlated candidates. Since currency risk perceptions across sectors are strongly correlated[35], caution is warranted in interpreting the selected variables as definitive determinants of currency swings; rather, they serve as useful predictors.

5. Conclusion

We develop a prediction model for currency swings using granular transaction records of FX options. This detailed data enables us to capture the heterogeneous views of market participants regarding currency risk. By applying L1-penalized quantile regression to a combination of macro-financial variables, currency risk perceptions and their interlinkages, we find that market participants' perceptions significantly improve the prediction of currency swings. Our findings suggest that large currency swings are closely linked to the diverse risk perceptions across market participants. From a policy perspective, currency risk perceptions derived from such granular data provide valuable insights for monitoring latent currency swing risks.

[35] Most correlations of implied volatility between different sectors fall within the range of 0.6 and 0.7 across the majority of FX option buyer-seller pairs.

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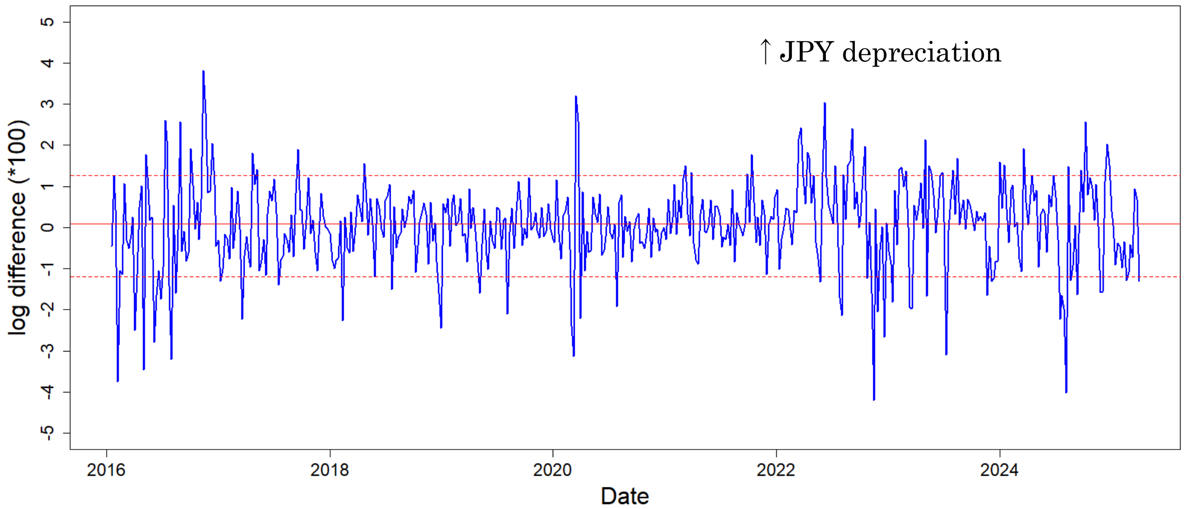
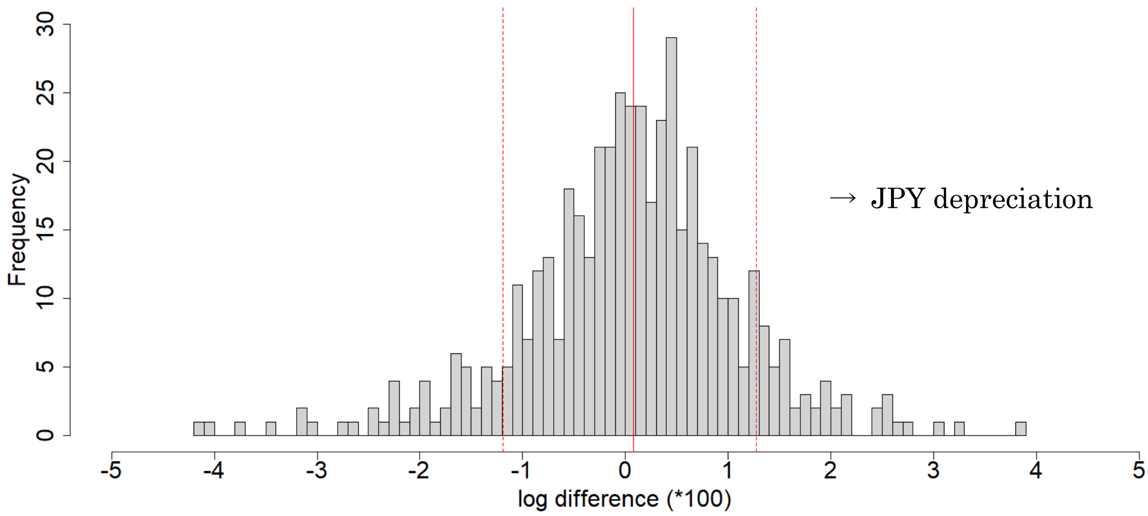
Figure 1. Time-series and histogram of USD/JPY weekly changes

Panel A: Time-series of USD/JPY weekly changes



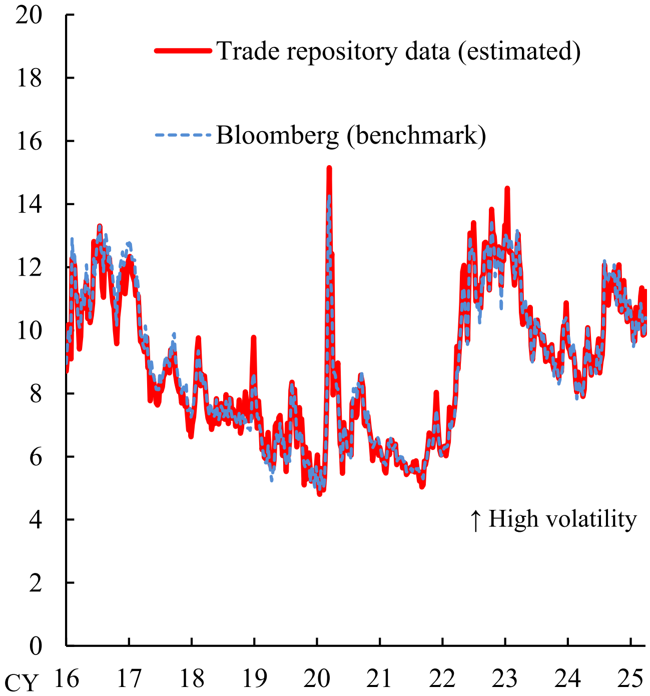
Panel B: Histogram of USD/JPY weekly changes



Note: Log differences between the average spot rates in a specific week and those in its previous week. The positive values of the weekly changes mean the JPY depreciation against USD. Latest data as of the week that starts from March 31, 2025. The red solid line denotes the median value of the weekly changes, and the red dashed lines denote their 10 and 90 percentiles.

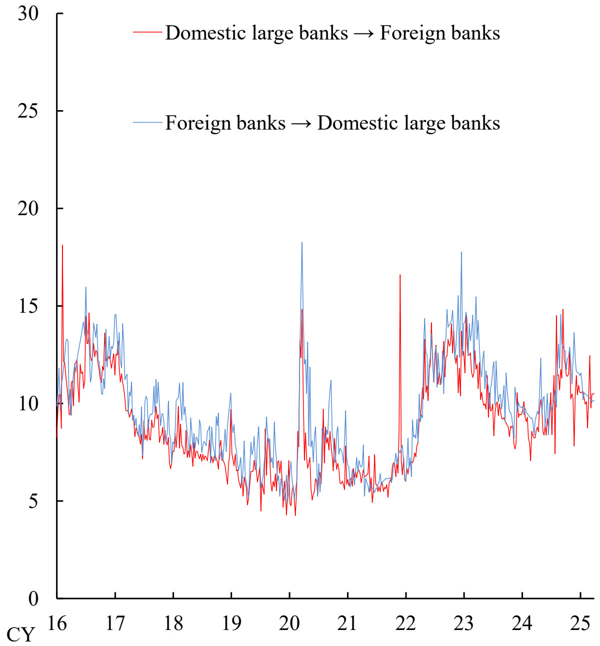
Source: Bank of Japan.

Figure 2. Comparison of the median IV estimated from trade repository data and the published IV from Bloomberg



Note: Latest data as of March 31, 2025.

Figure 3. Variation in currency risk perceptions across sectors
Weekly series of the median value for each pair of FX option buyer and seller on the unit of business secotrs



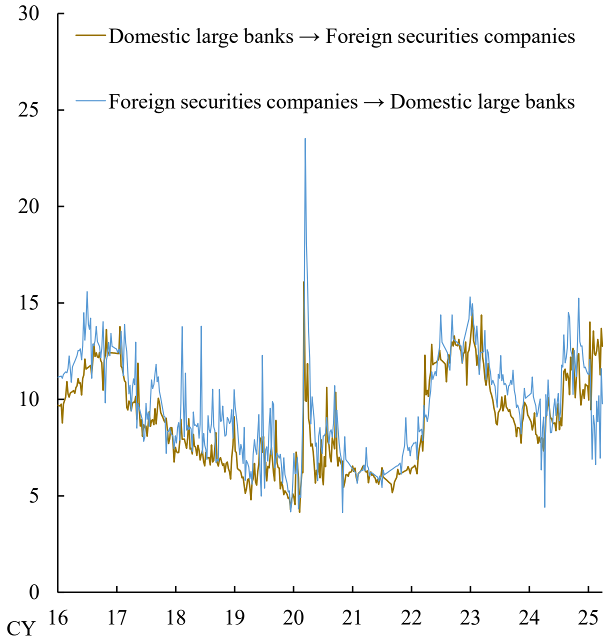
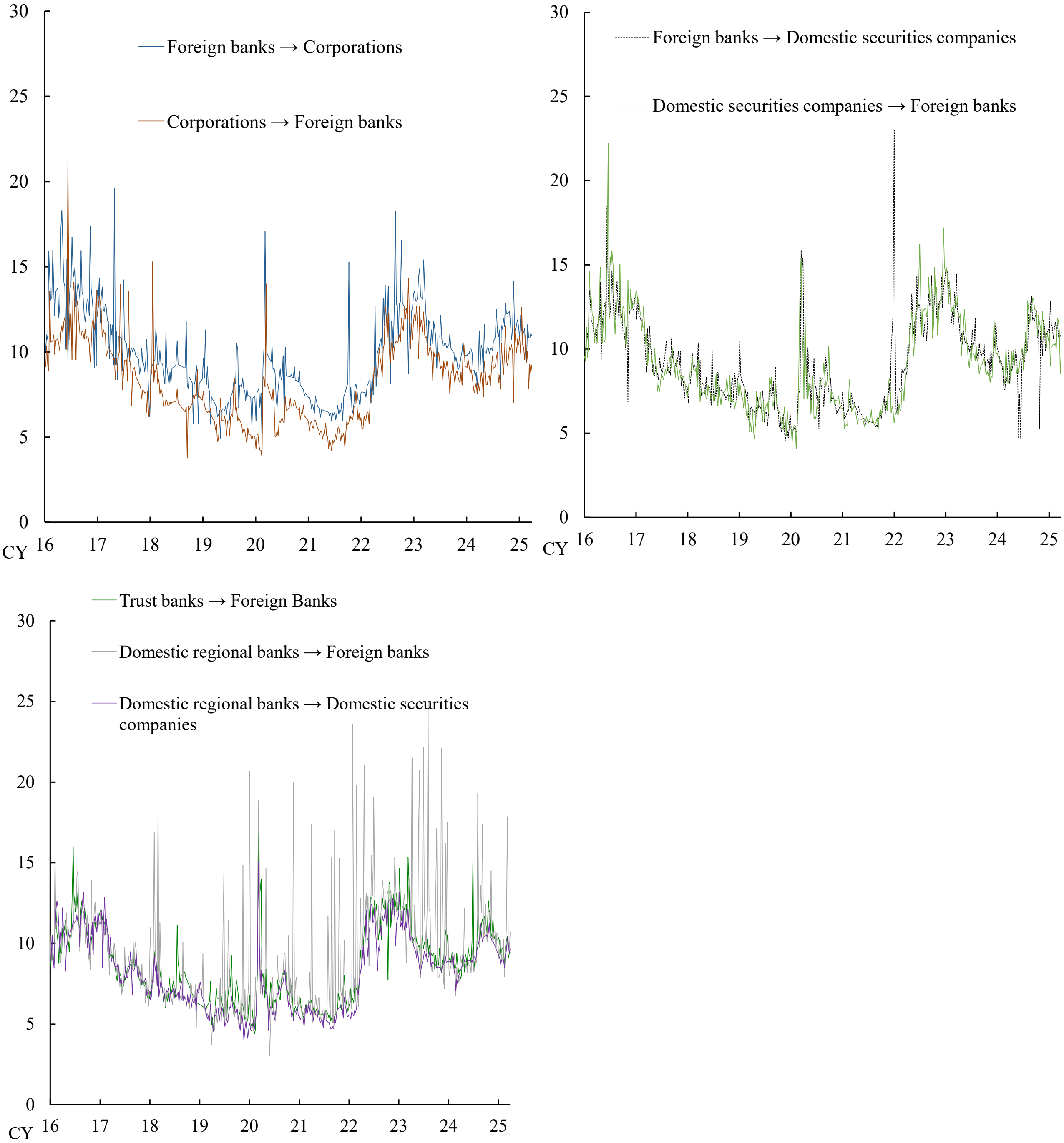


Figure 3. Variation in currency risk perceptions across sectors (continued)



Note: Latest data as of March 31, 2025. We classify each market participant into different business sectors by checking their names from our trade repository. We mean "foreign" when an entity's headquarter is located overseas. The legend "Sector A → Sector B" denotes the median value of implied volatility extracted from options which a market participant in sector A sold to a market participant in sector B.

Sources: Trade repository data; Bloomberg; Bank of Japan; FRED.

Figure 4. Summary statistics of currency risk perceptions in different sectors (shown in Figure 3)

Summary statistics

	(1) Domestic large banks → Foreign banks	(2) Foreign banks → Domestic large banks	(3) Domestic large banks → Foreign securities companies	(4) Foreign securities companies → Domestic large banks	(5) Foreign banks → Corporations	(6) Corporations → Foreign banks	(7) Foreign banks → Domestic securities companies	(8) Domestic securities companies → Foreign banks	(9) Trust banks → Foreign Banks	(10) Domestic regional banks → Foreign banks	(11) Domestic regional banks → Domestic securities companies
Mean	8.8	9.7	8.8	9.7	9.9	8.4	9.2	9.1	8.6	9.2	8.1
Standard deviation	2.5	2.6	2.4	2.6	2.5	2.4	2.6	2.7	2.3	3.4	2.2
Max	18.1	18.3	16.1	23.5	19.6	21.4	23.0	22.2	17.1	25.0	15.0
Min	4.3	4.9	4.2	4.1	4.8	3.8	4.5	4.1	4.4	3.0	4.0
Number of outliers	2	2	0	2	8	1	1	2	1	18	1

Differences in Means

	1	2	3	4	5	6	7	8	9	10	11
1											
2	✔										
3		✔									
4	✔		✔								
5	✔		✔								
6	✔	✔	✔	✔	✔						
7	✔	✔	✔	✔	✔	✔					
8		✔		✔	✔	✔					
9		✔		✔	✔		✔	✔			
10	✔	✔	✔	✔	✔	✔			✔		
11	✔	✔	✔	✔	✔		✔	✔	✔	✔	

Differences in Variances

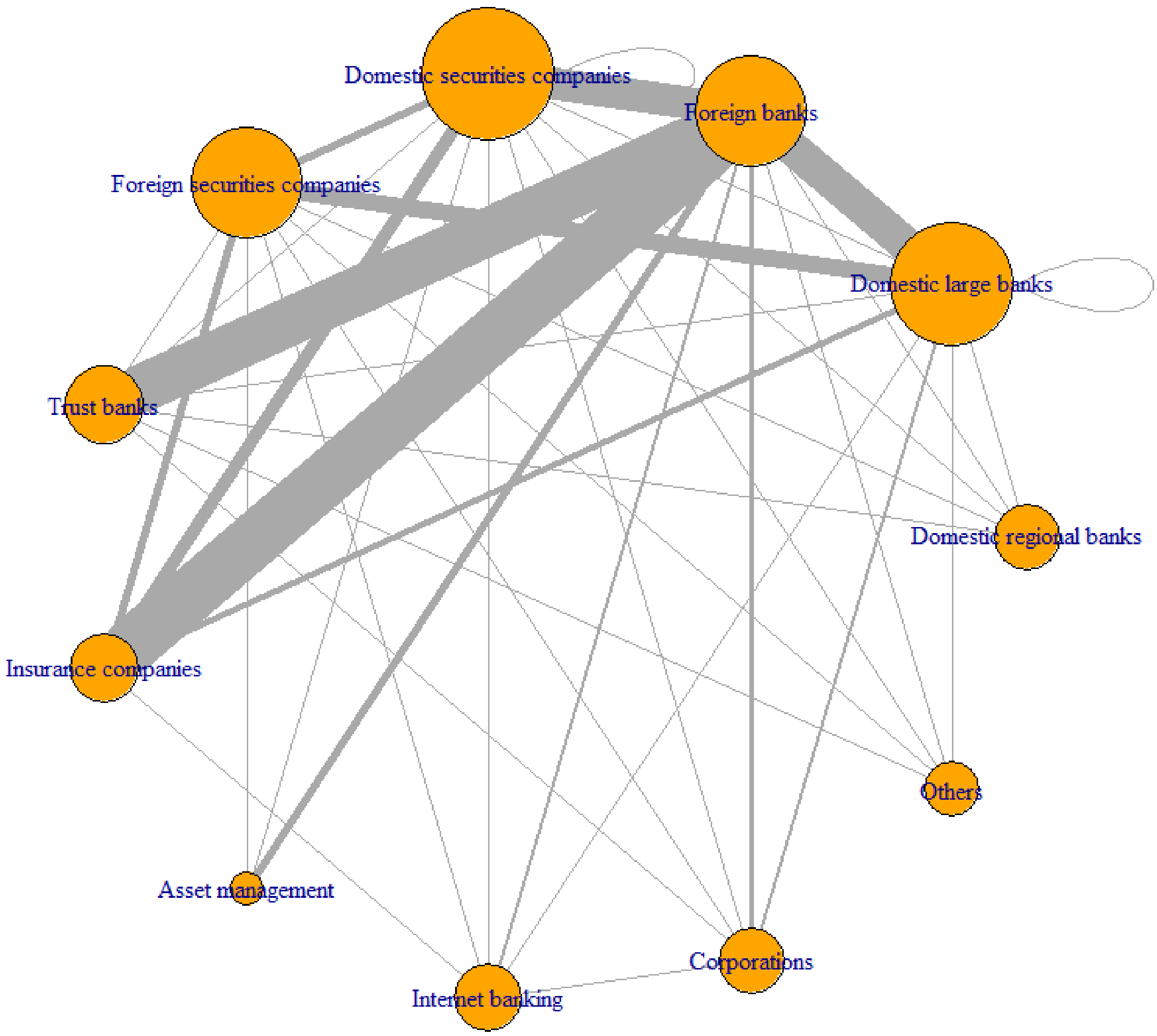
	1	2	3	4	5	6	7	8	9	10	11
1											
2											
3											
4											
5											
6				✔							
7											
8			✔			✔					
9		✔		✔			✔	✔			
10	✔	✔	✔	✔	✔			✔	✔		
11	✔	✔		✔	✔				✔		

Note 1: In the upper panel, Note in Figure 3 applies. In calculating the number of outliers for each series, we regard data points as outliers if the value exceeds the historical averages by more than 3 times of standard deviations.

Note 2: In the lower panel, we conduct tests whether two different series of implied volatility have same means or variances, and show ✔ if the null hypotheses that the pair of implied volatility series have equal means or variances are rejected at the 5% significance level. The numbers of 1-11 correspond to the series numbers shown in the upper panel.

Sources: Trade repository data; Bloomberg; Bank of Japan; FRED.

Figure 5: Transaction network in the FX option market



Note: The calculation is based on the pooled data of FX options executed during January 2016 and March 2025. The width of lines are proportional to the notional amounts of FX options. The sizes of circles for each sector corresponds to the network centrality indicator (the PageRank indicator).
Source: Trade repository data.
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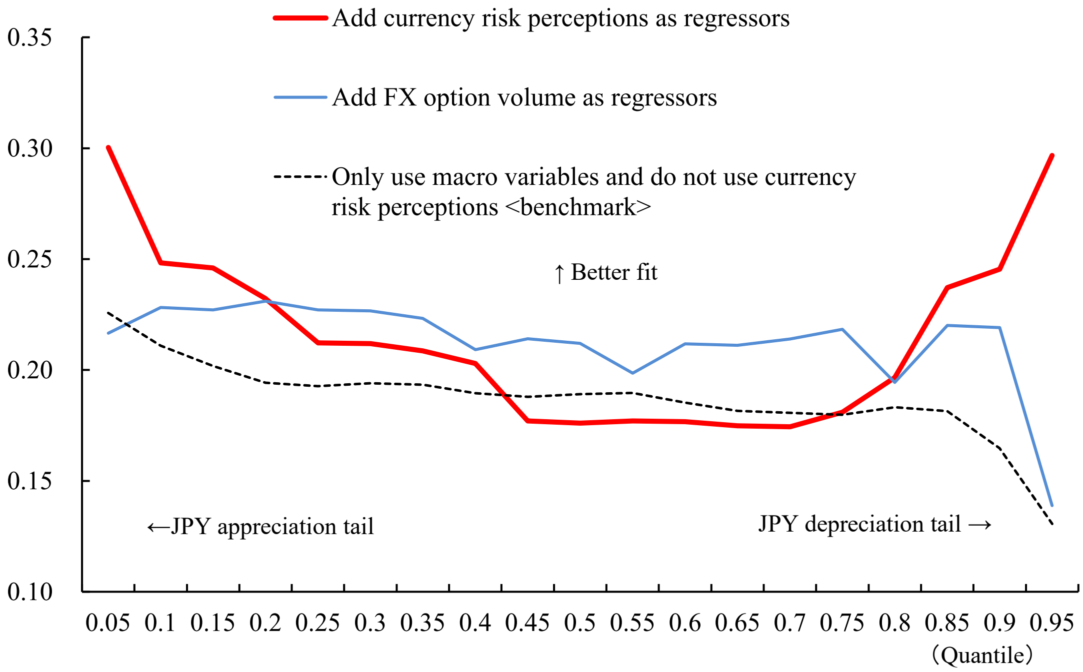
Figure 6: Comparison in the goodness of fit for each quantile whether the currency risk perceptions are included in quantile regressions



Note: We calculate a local measure of goodness of fit for each quantile based on Koenker and Machado (1999). The benchmark is when the quantile regression uses only 3 variables (an intercept, the weekly changes in the yield differentials between the US and Japan, the weekly changes in VIX). The black dashed line represents the restricted model in which we only include an intercept and two macro-financial variables. The red bold line represents the unrestricted model in our main result shown in Table 2, while the blue solid line represents the alternative model in which we include an intercept, two macro-financial variables, and the lagged growth of FX option volume, following Czech et al. (2025).

Sources: Trade repository data; Bloomberg; Bank of Japan; FRED.

Table 1: Data Sources

Type of variable	Input data for calculation	Data sources
Dependent Variable	USD/JPY spot rate at 5 p.m. in Tokyo (the mid rates of the bid and offer rates)	Bank of Japan
Explanatory Variable (1) Macro-financial variables	US-Japan yield differentials (2-year US treasury rate, closing price 2-year Japanese Government Bond rate, closing price)	Bloomberg
	VIX	Bloomberg
Explanatory Variable (2) Currency risk perceptions (Implied volatility / Risk reversal)	Option contracted price (for each executed contract)	Financial Services Agency "Trade repository data"
	Option strike price (for each executed contract)	
	Maturity (for each executed contract) (difference between expiration and trade dates)	
	USD/JPY spot rate (at 5 p.m. in New York on the previous business day, i.e., early morning in Tokyo on the trade date)	Bloomberg
	US interest rate expectations (interpolate between FF rate and US OIS rates)	FRED, Bloomberg
	Japanese interest rate expectations (interpolate between TONA and Japanese OIS rates)	Bank of Japan, Bloomberg

Table 2: Estimation results of Post-L1-quantile regression

Variables				JPY appreciation tail ← 10 percentile	Median	JPY depreciation tail → 90 percentile
Intercept				-0.842 ***		0.760 ***
Changes in US-Japan Interest Rates Differentials (2-year)				6.267 ***	6.079 ***	5.547 ***
	IV1w	Domestic large banks→Foreign banks	High			0.963 **
	IV1m	Foreign securities corp.→Domestic securities corp.	High	-0.787 ***		
	RR1m		High			0.586 **

Note 1: The dependent variable is the USD/JPY weekly changes. *** and ** denote statistical significance at 1% and 5% confidence levels based on the bootstrapped standard errors, respectively. Our estimation sample period is between January 2016 and March 2025.

Note 2: The legend "Sector A → Sector B" denotes the summary statistics of implied volatility extracted from options which a market participant in sector A sold to a market participant in sector B. The coefficients without any sectors specified denote the summary statistics of currency risk perceptions of all market participants.

Note 3: "IV" means the median value of implied volatility extracted from options. "RR" denotes the risk reversal (the difference between the implied volatility of call and that of put options), i.e., the major indicator of the bias in investors' risk perceptions. Higher RR means market participants are more cautious for JPY depreciation than for JPY appreciation. For all currency risk perceptions, we classify the sample period into three states, whether the IV or RR is higher or lower by more than 1 historical standard deviation relative to the historical average during our sample period, and we use them as dummy variables as "High" and "Low" states in the quantile regression estimation. "1w," "1m" and "3m" mean the maturity of options. "Macro-financial variables * Currency risk perceptions" mean the interaction terms between the two indicators.

Note 4: We do not show the variables that are not statistically significant at 5% confidence level.

Sources: Trade repository data; Bloomberg; Bank of Japan; FRED.

Table 3: Estimation results of Post-L1-quantile regression (disaggregating the implied volatility for put and call options separately)

Variables					JPY appreciation tail ←		JPY depreciation tail →
					10 percentile	**Median**	**90 percentile**
Intercept					-0.824 ***	0.109 **	0.777 ***
Changes in US-Japan Interest Rates Differentials (2-year)					5.636 ***	4.901 ***	5.002 ***
	IV1m	Domestic large banks → Foreign banks	Put	High	-0.521 **		
	IV3m	Domestic securities companies → Foreign banks	Call	High			0.863 ***
Yield differentials *	IV1w	Domestic large banks → Foreign banks	Put	High		3.172 **	

Note 1: The dependent variable is the USD/JPY weekly changes. *** and ** denote statistical significance at 1% and 5% confidence levels based on the bootstrapped standard errors, respectively. Our estimation sample period is between January 2016 and March 2025.

Note 2: The legend "Sector A → Sector B" denotes the summary statistics of implied volatility extracted from options which a market participant in sector A sold to a market participant in sector B. The coefficients without any sectors specified denote the summary statistics of currency risk perceptions of all market participants.

Note 3: "IV" means the median value of implied volatility extracted from options. "RR" denotes the risk reversal (the difference between the implied volatility of call and that of put options), i.e., the major indicator of the bias in investors' risk perceptions. Higher RR means market participants are more cautious for JPY depreciation than for JPY appreciation. For all currency risk perceptions, we classify the sample period into three states, whether the IV or RR is higher or lower by more than 1 historical standard deviation relative to the historical average during our sample period, and we use them as dummy variables as "High" and "Low" states in the quantile regression estimation. "1w," "1m" and "3m" mean the maturity of options. "Call" denotes the dollar call options, i.e. the rights to purchase a defined notional amount of USD at a set rate for option buyers. Similarly, "Put" denotes the dollar put options, i.e. the rights to sell a defined notional amount of USD at a set rate for option buyers. "Macro-financial variables * Currency risk perceptions" mean the interaction terms between the two indicators.

Note 4: We do not show the variables that are not statistically significant at 5% confidence level.

Sources: Trade repository data; Bloomberg; Bank of Japan; FRED.

Table 4: Estimation results of Post-L1-quantile regression (using the yield differentials of 10 year as the macro variable instead of 2-year as in Table 3)

Variables					JPY appreciation tail ← 10 percentile	Median	JPY depreciation tail → 90 percentile
Intercept					-0.689 ***		0.818 ***
Changes in US-Japan Interest Rates Differentials (10-year)					5.945 ***	8.012 ***	6.144 ***
	IV3m	Domestic large banks → Foreign banks	Put	High	-0.705 **		
	IV3m	Domestic securities companies → Foreign banks	Call	High			0.801 ***
Yield differentials *	IV1w	Domestic large banks → Foreign banks	Put	High	7.677 ***		

Note 1: The dependent variable is the USD/JPY weekly changes. *** and ** denote statistical significance at 1% and 5% confidence levels based on the bootstrapped standard errors, respectively. Our estimation sample period is between January 2016 and March 2025.

Note 2: The legend "Sector A → Sector B" denotes the summary statistics of implied volatility extracted from options which a market participant in sector A sold to a market participant in sector B. The coefficients without any sectors specified denote the summary statistics of currency risk perceptions of all market participants.

Note 3: "IV" means the median value of implied volatility extracted from options. "RR" denotes the risk reversal (the difference between the implied volatility of call and that of put options), i.e., the major indicator of the bias in investors' risk perceptions. Higher RR means market participants are more cautious for JPY depreciation than for JPY appreciation. For all currency risk perceptions, we classify the sample period into three states, whether the IV or RR is higher or lower by more than 1 historical standard deviation relative to the historical average during our sample period, and we use them as dummy variables as "High" and "Low" states in the quantile regression estimation. "1w," "1m" and "3m" mean the maturity of options. "Call" denotes the dollar call options, i.e. the rights to purchase a defined notional amount of USD at a set rate for option buyers. Similarly, "Put" denotes the dollar put options, i.e. the rights to sell a defined notional amount of USD at a set rate for option buyers. "Macro-financial variables * Currency risk perceptions" mean the interaction terms between the two indicators.

Note 4: We do not show the variables that are not statistically significant at 5% confidence level.

Sources: Trade repository data; Bloomberg; Bank of Japan; FRED.

Table 5: Estimation results of Post-L1-quantile regression (using the changes in the levels of currency risk perceptions instead of using dummy variables as in Table 2)

Variables		JPY appreciation tail ← 10 percentile	Median	JPY depreciation tail → 90 percentile
Intercept		-0.980 ***		0.991 ***
Changes in US-Japan Interest Rates Differentials (2-year)		6.542 ***	5.602 ***	5.475 ***
IV3m	Foreign banks→Domestic securities corp.	-0.258 **		
RR1m	Trust banks→Foreign banks		0.189 ***	

Note 1: The dependent variable is the USD/JPY weekly changes. *** and ** denote statistical significance at 1% and 5% confidence levels based on the bootstrapped standard errors, respectively. Our estimation sample period is between January 2016 and March 2025.

Note 2: The legend "Sector A → Sector B" denotes the summary statistics of implied volatility extracted from options which a market participant in sector A sold to a market participant in sector B. The coefficients without any sectors specified denote the summary statistics of currency risk perceptions of all market participants.

Note 3: "IV" means the median value of implied volatility extracted from options. "RR" denotes the risk reversal (the difference between the implied volatility of call and that of put options), i.e., the major indicator of the bias in investors' risk perceptions. Higher RR means market participants are more cautious for JPY depreciation than for JPY appreciation. We scale each currency risk perception with mean zero and unit standard deviation within the sample period and use the changes in the scaled levels of currency risk perceptions for our explanatory variables. "1w," "1m" and "3m" mean the maturity of options. "Macro-financial variables * Currency risk perceptions" mean the interaction terms between the two indicators.

Note 4: We do not show the variables that are not statistically significant at 5% confidence level.

Sources: Trade repository data; Bloomberg; Bank of Japan; FRED.

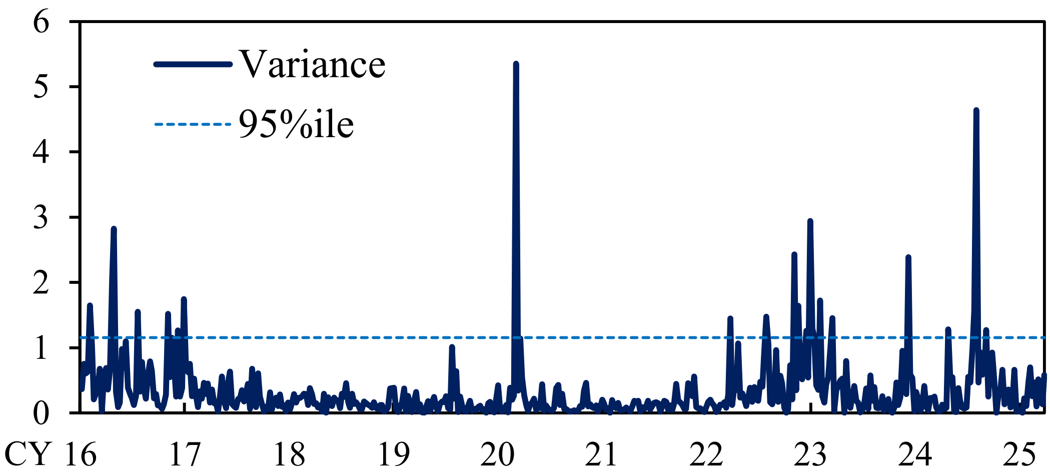
Table 6: Estimation results of realized volatility

	(Depedent variable: Realized volatility 1 week ahead)					
	(benchmark)	(Implied volatility level of each sector extracted from TR data)				
	Bloomberg	Domestic securities companies	Foreign securities companies	Large domestic banks	Foreign banks	Trust banks
IV	0.11 ***	0.11 ***	0.10 ***	0.11 ***	0.11 ***	0.11 ***
R-squared	0.20	0.21	0.25	0.20	0.18	0.17

Note 1: The dependent variable is the weekly variance of log daily changes in the USD/JPY spot rate. *** denote statistical significance at 1% confidence level based on the bootstrapped standard errors. Our estimation sample period is between January 2016 and March 2025.
Note 2: The legend "Sector A" denotes the summary statistics of implied volatility extracted from options which a market participant in sector A purchased from or sold to another market participant.
Note 3: "Bloomberg" means 1w implied volatility of USD/JPY publicly available from Bloomberg. IV for each sector means the median level of implied volatility extracted from trade repository data.

Sources: Trade repository data; Bloomberg; Bank of Japan; FRED.

Appendix Figure: Indicator of realized volatility



Note: The weekly variance of log daily changes in the USD/JPY spot rate. Latest data as of the week that starts from March 31, 2025. The dashed line denotes 95 percentile of the data series.
Source: Bank of Japan.