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Data-driven monetary policy: Evidence from the Bank of Japan's equity purchase program

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ABSTRACT

Central banks' monetary policies are increasingly data-driven. To assess the consequences of such monetary policies, we study the equity ETF purchase program of the Bank of Japan (BOJ). We find that BOJ interventions under this program are highly predictable. To exploit this predictability, we design a portfolio strategy that buys (sells) stocks that are more (less) exposed to these interventions. Adjusting for known risk factors, this strategy earns a return of 12.90% per annum. BOJ interventions have a more positive impact on riskier stocks. Thus, the ETF purchase program aligns with the BOJ's goals of reducing equity risk premium by offering downside protection during periods of market uncertainty.

> Data dependence is, and always has been, at the heart of policymaking at the Federal Reserve.
>
> [Jerome H. Powell, Chair of the Federal Reserve]

1. Introduction

With the recent emergence of digitalization, central banks have increasingly adopted data-driven monetary policies (Powell, 2019; Lagarde, 2023). Such monetary policies refer to policy decision making by central banks based on the ever-growing pool of available economic data. These data sources aim to measure financial impacts and offer strategic solutions to overcome uncertainties associated with different economic conditions.[2] Measuring the consequences of data-driven monetary policies, however, is challenging due to the scarcity of real-time data (Orphanides, 2001; Orphanides and van Norden, 2002) and limited information exploitation (Bernanke and Boivin, 2003). To overcome these challenges, we examine the effects of data-driven monetary policies by exploiting the Bank of Japan's (BOJ) ETF purchase program.

The BOJ's ETF purchase program provides an ideal setting to study the effects of data-driven monetary policies for two reasons: first, the BOJ's equity purchase policy is highly mechanical. This suggests that the BOJ bases its policy decisions on financial market data rather than on subjective information. In fact, empirical studies reveal that the decision making of the BOJ intervention is

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[2] For example, in response to the economic downturn during the COVID pandemic, the Federal Reserve purchased $500 billion in treasury bonds in March 2020. See https://www.federalreserve.gov/newsevents/pressreleases/monetary20200315a.htm

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closely related to the returns of the overnight and morning sessions (Nangle and Yates, 2017; Hattori and Yoshida, 2023; Harada and Okimoto, 2021; Fukui and Yagasaki, 2023). Second, the BOJ publishes monthly policy discussions and discloses daily intervention decisions at the end of each trading day.[3] As part of the Qualitative and Quantitative Easing monetary policy, the BOJ has been directly injecting capital into the equity market since late 2010 (BOJ, 2010, 2013). Until the end of 2019, the BOJ has purchased more than 15 trillion yen in Japanese large-cap stocks. These frequent and large interventions motivate our investigation into their price impact on equity markets.

In theory, transparent information should be factored into the price of financial products (Timmermann and Granger, 2004). In other words, price movement derives not from trade itself but from information flow. Thus, the BOJ's frequent and large interventions in the stock market should have no impact on prices. However, recent studies (Coval and Stafford, 2007; Gabaix and Koijen, 2021; Hartzmark and Solomon, 2022a) challenge this idea by isolating price impact from market information. In that case, the BOJ's interventions may give rise to demand and supply imbalances, leading to temporary price dislocations in the stock market.

Moreover, because BOJ interventions are highly mechanical and predictable, they could also serve as a signal to synchronize the actions of market participants (Abreu and Brunnermeier, 2003). This signal has the potential to reduce the divergence of opinions in the market, which is a major cause of market uncertainty (Miller, 1977). Thus, even though the BOJ's interventions are highly transparent and predictable, they can generate price movements that are unrelated to fundamentals.

To exploit the predictability of BOJ's interventions, we use logit regressions to predict those interventions on a daily basis. Following Harada and Okimoto (2021), we assume that BOJ interventions begin in the afternoon session of the intervention days. To avoid any look-ahead bias, all the inputs in the prediction model are publicly available before the afternoon session on each trading day. We use 2011–2013 data as our training set for our logit prediction model. From the beginning of 2014, we start to use our trained model to predict the BOJ's intervention. To keep our model updated, we add the actual BOJ's action result into our sample and retrain our model after each trading day. In the six-year testing sample, we find that the model accurately predicts the likelihood of BOJ interventions for 1,272 of 1,466 trading days. The overall prediction accuracy rate is 86.77% with a sensitivity rate of 88.42% and a specificity rate of 85.97%. These patterns suggest that the timing of BOJ interventions is highly predictable.

We construct an independent double-sorted portfolio strategy to exploit the predictable nature of the BOJ interventions. The two sorting factors are the BOJ's purchase amount and a liquidity factor. Stocks are divided into five equal groups for each factor, which generates a 5×5 portfolio matrix. On each predicted intervention day, we go long (short) in stocks that are most (least) influenced by BOJ interventions if we predict that an intervention will occur. The long-short corner portfolio of this matrix indicates an average return of 13.31 basis points for each predicted BOJ intervention. This suggests a potential trading strategy: constructing a long-short portfolio during forecasted interventions and holding risk-free securities during nonintervention days. By doing so, investors in the Japanese equity market can achieve an average annual return of 10.58% relying solely on publicly available information. Furthermore, we find that the BOJ's interventions have a larger price impact on less liquid stocks. In the portfolio matrix, we determine that less liquid stocks tend to generate a higher return during the predicted intervention days. Overall, our results suggest that the BOJ's interventions align with its objective to reduce risk premiums in equity markets and to manage economic uncertainties.

The profitability of our long-short strategy is robust to risk adjustment. Controlling for the Fama–French five factors with momentum factor, we find an abnormal return of 5.12 basis points per trading day, or 12.90% per year, from the long-short strategy. Negative loadings on the market and size factors suggest that our strategy is biased towards larger stocks with less market risk premium. Consequently, the results indicate that the BOJ interventions could have a significant price impact on the Japanese equity market.

Additionally, we examine whether BOJ interventions represent unexplained risk factors by performing Fama–Macbeth two-step regressions. Controlling for Fama–French factors and firm characteristics, we find that the BOJ's interventions continue to attract a positive premium in stocks. The BOJ has thus far not sold its holdings and acts as a significant source of demand for the exposed stocks. Therefore, we conjecture that strategies that lean against these price dislocations are likely to be risky, supporting a persistent "BOJ intervention" premium in exposed stocks.

To further support our findings, we perform several robustness tests. First, we assess the effectiveness of the double-sorted portfolio by considering an alternative frequency for the average transaction value. Second, we change the prediction model from the logit model (in the baseline result) to other machine learning models, including random forest. We also conduct a prediction analysis on different subsamples of our dataset. These prediction models provide similar results to those of the logit model, which implies that key inputs – rather than the prediction model or the sample period used – contribute to the accuracy of the prediction results. Third, we evaluate the robustness of the long-short strategy by longing the BOJ affected index (TOPIX) and shorting the BOJ unaffected index (MOTHERS). The abnormal return is also significantly positive. Although this strategy is not feasible, it shows that BOJ interventions can potentially generate positive price pressure. Fourth, we examine the cross-sectional impact of BOJ interventions on indices not directly targeted, like JASDAQ, and demonstrate the limited BOJ impact on unaffected indices. Lastly, we assess potential macroeconomic impacts on BOJ interventions to control for the global economic and market performance on BOJ's decision making and our prediction model. After adding the high-frequency data Atlanta Fed GDPNow into the Fama–Macbeth regression model and incorporating the returns of international stock market indices into a logit prediction model, we find quantitatively similar results to our baseline findings.

[3] Data regarding these interventions can be accessed via the following link: https://www3.boj.or.jp\/market\/en\/menu_etf.htm

This study contributes to the literature related to the BOJ purchase price pressure generated on intervention days (Charoenwong et al., 2021) and to the non-information-driven price pressure. There is empirical evidence that mutual fund and ETF flows could lead to underlying asset price changes (Ben-Rephael et al., 2011). These flows can be caused by mutual fund fire sales (Coval and Stafford, 2007; Lou, 2012) or by the creation and redemptions of ETF shares (Brown et al., 2021). Furthermore, these flows into mutual funds are potentially predictable (Dyakov and Verbeek, 2013). Dividend payments can also create price pressure on the stock level (Ogden, 1994; Berkman and Koch, 2017; Hartzmark and Solomon, 2022b). The price pressure of dividend reinvestment can also be predicted even several weeks before the payment date (Hartzmark and Solomon, 2022a). In particular, (Dang et al., 2021) find that the government's direct capital injection in the equity market could lead to both a trading effect and an announcement effect. In line with (Dyakov and Verbeek, 2013), we offer a prediction model anticipating the BOJ's intervention by using public information to design the model inputs.

This study also aims to shed light on the existence and impact of unconventional monetary policy. Unconventional monetary policy, especially direct capital injection into the equity market, has been controversial in recent decades. Studies such as Bernanke et al. (1999), Bernanke and Gertler (2001), Rigobon and Sack (2003) state that central banks are not effective in responding to shocks in the equity market. As a result, most central banks have not implemented monetary policy by directly injecting capital into the equity market in recent decades. Central banks are more concerned with expected inflation and changes in the yield curve. However, there are some central banks that have implemented an unconventional monetary policy by purchasing equities. In most cases, a price impact is observed (Charoenwong et al., 2021; Dang et al., 2021; Harada and Okimoto, 2021), although it has some side effects (Chen et al., 2019; Charoenwong et al., 2021). We demonstrate that BOJ interventions have a positive price impact on low-liquidity stocks, implying the efficacy of unconventional monetary policy in mitigating risk.

The remainder of the paper is structured as follows. Section 2 describes the data and methodology. Section 3 discusses the findings of the liquidity impact and the price impact in relation to BOJ's unconventional monetary policy. Robustness tests are presented in Section 4 and Section 5 concludes.

2. Data and methodology

2.1. Data

The sample period for this study is from 1 January 2011 to 31 December 2019. Note that during BOJ's monthly monetary policy meeting in October 2010, BOJ decided to launch the unconventional monetary program known as the BOJ ETF purchase program. As only two purchases were made from October 2010 to December 2010, we ignore them and start on January 1, 2011. The sample period ends on December 30, 2019 to intentionally avoid the impact of COVID-19 and associated financial market movements. Furthermore, shortly after the initial shock of the COVID pandemic, the BOJ lowered its frequency of purchases. From 2011 to 2019, the BOJ intervened in roughly 20%–30% of total trading days on average. However, the BOJ only intervened less than 10 times during 2022. Thus, these policy changes in recent years may impair the quality of empirical conclusions.

We collect our data from several databases. BOJ daily intervention decisions are downloaded from its official website.[4] On the BOJ website, the updates on the intervention decision for each day and the purchase amount of each index-linked ETF are reported on each trading day. A null transaction in the spreadsheet means that there is no intervention on this trading day. The BOJ updates the file on a daily basis. Normally, the BOJ file is uploaded between 4:00 and 5:00 pm in the Japanese time zone, which is one to two hours after the closing of the Japanese equity market. Therefore, investors can only obtain information on any BOJ intervention after the market closes. Furthermore, the BOJ also discloses its ETF purchase program policy on its official website. The useful data in these documents include the annual budget of the ETF purchase program and the approximate purchase proportion in each index. However, the official BOJ documents do not disclose the purchase mechanism. Therefore, the timing of BOJ purchases and BOJ mechanisms assumed in our article are based on empirical evidence and rational assumptions from relevant literature such as Harada and Okimoto (2021), Katagiri et al. (2022), Hattori and Yoshida (2023).

Table 1 shows the descriptive statistics of the Japanese TOPIX index from 2011 to 2019. In addition to the financial performance of the TOPIX index, the table also contains features of the BOJ intervention during this nine-year period. As summarized in Table 1, in the early years of the BOJ's ETF purchase program, the annual budget for purchase is around 600–800 billion yen per year, and the purchase frequency is approximately 20–50 times per year (once a week or fortnight). The average purchase amount per intervention is around 10–30 billion yen. However, in 2013 the BOJ introduced an unconventional monetary policy, called Qualitative and Quantitative Easing (QQE) (BOJ, 2013). As a result, the BOJ's equity ETF purchase program was merged with the large QQE program, and the annual purchase budget increased sharply from slightly more than one trillion yen to three trillion yen at the end of 2014. In addition, the frequency of purchases also increased rapidly, reaching 75–90 times per year. The annual purchase budget doubled in the middle of 2016, from three trillion yen to six trillion yen. However, instead of increasing the frequency of purchase, the BOJ increased the purchase amount per intervention from 35 billion yen to 70 billion yen.

From the Refinitiv Tick History (TRTH), we obtain 15–min intraday prices and transaction volumes of the TOPIX constituent stock (totaling 2045 component stocks). As there are no daily transaction value data disclosed in our database, we use the trading volume and stock price to approximate the daily transaction value of each stock. To estimate the daily transaction value of each stock, we use the last price of the stock times the trading volume of this stock within each 15–min interval and sum all intervals

[4] Data can be found at the following link: https://www3.boj.or.jp\/market\/en\/menu_etf.htm

Table 1
Descriptive statistics of variables.

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019
Mean	−0.08%	0.07%	0.18%	0.04%	0.05%	0.01%	0.08%	−0.07%	0.06%
Median	−0.01%	0.03%	0.12%	0.08%	0.15%	0.05%	0.07%	−0.01%	0.04%
Maximum	6.64%	2.75%	5.21%	4.28%	6.40%	8.02%	2.36%	4.90%	2.81%
Minimum	−9.47%	−2.89%	−6.87%	−4.77%	−5.86%	−7.26%	−2.12%	−4.88%	−2.45%
Standard Deviation	1.42%	1.00%	1.51%	1.19%	1.27%	1.67%	0.68%	1.12%	0.82%
Sample size	245	248	245	244	244	245	247	245	241
Total BOJ Purchase (billion)	800	640	1095	1285	3069	4382	5607	6210	4088
Number of BOJ Days	42	23	58	75	89	90	78	87	58

The table shows the TOPIX index daily return's mean, median, max, min, daily volatility, number of observations, annual Bank of Japan (BOJ) purchase amount, and number of BOJ intervention day.

Table 2
Four-session returns for BOJ days and non-BOJ days.

Sessions	Overnight	Morning	Lunch break	Afternoon
BOJ days	−63.36***	−41.38***	0.31	4.81**
	(2.61)	(2.74)	(0.94)	(2.43)
Non-BOJ days	29.73***	13.09***	0.36	−1.53
	(1.54)	(1.25)	(0.43)	(1.20)
Full sample	4.60***	−1.62	0.35	0.18
	(1.59)	(1.28)	(0.41)	(1.06)

This table shows the overnight, morning, lunch break and afternoon session performance on BOJ intervention days, non-BOJ intervention days, and in the full sample. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

within each trading day. In Asian equity markets, there is normally a lunch break in the middle of the trading session. Thus, in the Japanese equity market, the whole trading session is split into four subsessions: overnight session (previous afternoon close to current morning open), morning session (morning open to morning close), lunch break session (morning close to afternoon open), and afternoon session (afternoon open to the afternoon close). We then compute the return of the overnight session (day t 9:00 am opening price divided by day $t-1$ 15:00 pm closing price), morning session (11:30 am closing price divided by 9:00 am opening price), lunch break session (12:30pm opening price divided by 11:30 am closing price), and afternoon session (15:00 pm closing price divided by 12:30 pm opening price), based on the TRTH intraday prices of each stock.

We also winsorize the return by the top 0.1% and the bottom 0.1%, because the TRTH intraday price of individual stock data does not adjust for any stock split, stock dividend, or reverse stock split. Therefore, in these cases, the return on the stock will be extremely large or small. To mitigate the outliers, we winsorize these outliers to the bottom 0.1% and the top 0.1% of 15-min intraday returns.

We gather daily weights of TOPIX index stocks from Bloomberg. As we assume that the BOJ's purchase will be placed in TOPIX index-linked ETFs, the TOPIX index weight of each individual stock can be the estimation of BOJ's purchase portion on each intervention day. Therefore, we collected daily weights of TOPIX constituent stock weights from January 1, 2011 to December 30, 2019.

2.2. *Design of front-running strategy*

To design a front-running strategy, we first study the returns obtained in different trading sessions: overnight, morning, lunch break, and afternoon sessions, on both intervention days and non-intervention days.

Table 2 shows the performance of the TOPIX index in these four sessions. Results are also classified into BOJ intervention day, non-BOJ intervention day, and full sample. In this table, the returns on the BOJ days show that the overnight and morning session returns are significantly negative, while the afternoon session returns on BOJ days are significantly positive. This is probably because the BOJ tends to make intervention decisions based on how the Japanese stock market performs in the overnight and morning sessions and starts to undertake transactions in the afternoon session. It is well documented that the price pressure of the BOJ's purchase comes on the same day of that intervention, and the contemporaneous price impact is likely to come on the afternoon session (12:30 pm to 3:00 pm). Charoenwong et al. (2021) examine the intraday return difference between BOJ-affected stocks and non-BOJ-affected stocks. When the market performs poorly during these sessions, the BOJ is more likely to intervene to buy stocks and stabilize the equity market. Furthermore, Harada and Okimoto (2021) claim that BOJ purchases often begin during the afternoon session of the intervention day. This aligns with the findings in Table 2, where the afternoon session returns on BOJ days are significantly positive.

Although there is no official confirmation of the BOJ's buying process, these statistical findings suggest a probable pattern: if the BOJ observes that the overnight and morning sessions have performed poorly, it is likely to act to stabilize the Japanese market. This leads to purchases after the lunch break session, causing the afternoon session returns to become positive. Based on this mechanism, we assume that there is a potential front-running strategy to predict the BOJ's moves and profit from their purchases. Therefore, in Section 2.3 we determine the factors that are likely to trigger a BOJ intervention and build a model to predict the BOJ's actions before its actual purchases. Further, in Section 2.4 we create a long-short portfolio to derive the profits generated from predicting the BOJ's interventions.

2.3. Prediction model construction

To avoid look-ahead bias and make this strategy feasible, we use only publicly available information to predict the BOJ intervention in the afternoon session. This means that all the information collected should be no later than the end of the lunch break session. The first group of inputs that we consider are the overnight returns and the morning session returns, because they have been well discussed in several papers (Hattori and Yoshida, 2023; Harada and Okimoto, 2021; Katagiri et al., 2022). As discussed in Section 2.2, the returns in the overnight session and the morning session on BOJ days exhibit a significantly negative trend, whereas the returns in these sessions on non-BOJ days are positive. This discrepancy can be attributed to the fact that the BOJ is more inclined to make purchasing decisions when the performance of the overnight and morning sessions is unfavorable (Chen et al., 2019; Charoenwong et al., 2021). This implies that both the overnight return and the morning session return may contribute strongly to the predictive power when constructing the prediction model. Also, we add the lagged one-day return of the S&P 500 index to our model to capture the impact of worldwide equity market movements during the overnight session.

In addition to the overnight return, morning session return, and S&P 500 index lagged one-day return, we introduce the BOJ's annual purchase budget constraint to capture the impacts of that limit on the BOJ's market operations. The BOJ's monetary policy sets an upper limit on the annual purchase amount, which means that the total purchase amount within a year is unlikely to go beyond this target (although the total spending in 2018 exceeded the annual budget). Therefore, we introduce two factors to measure the impact of budget constraints on BOJ's purchase operation: hard limit and soft limit. The hard limit means that spending on ETF purchases has already exceeded its annual budget amount. In this case, BOJ officials are not likely to purchase shares aggressively due to budget constraints. This is likely to happen at the end of each year, as did occur in 2016 and 2018. After 1 January, the budget amount is refreshed. The soft limit means that spending on ETF purchases is faster than on a pro rata basis. For example, if the BOJ purchases ETF at high frequency at the beginning of the year, even though it does not reach the hard limit, it is still exceeding its expected year-to-date spend on a pro rata basis. Therefore, it is likely that the BOJ's spending will be lower for the rest of the year.

To quantify the impact of BOJ budget constraints on purchase operations, we first find several key dates on which the BOJ changes its annual budget amount. We then accumulate the BOJ's annual purchase amount yearly. The difference between the BOJ's annual budget amount on a specific date and the actual BOJ accumulated purchase value is the hard limit value (we use the % term here by dividing by the budget amount). The soft limit measure, on the other hand, is based on the remaining budget and the remaining days. We calculate the remaining budget proportion and remaining days (%) within each year and obtain the ratio of these two numbers minus one. For example, if the remaining budget is 80% and the remaining days are 60%, then we a ratio of 1.33, and the actual number we get is 0.33 by deducting 1. This ratio indicates that the remaining budget is probably sufficient for the remaining days of the year. If the number is below zero, that means that the money is being spent faster than on a pro-rata basis, and the BOJ is likely to reduce the frequency of purchase. However, it is worth noting that the impacts of hard limit and soft limit is not symmetrical. This is because the BOJ is likely to leave some budget untouched, but it is not likely that it would often exceed the budget constraint. Because of this lack of symmetry, we focus only on the negative side and set positive figures as zero. In addition, as there is an inclusion relation between the hard limit and soft limit, we set the soft limit to zero when the hard limit has been reached.

The logit model is shown below:

$$P_{Intervention=1} = \frac{1}{1+e^{-Z_t}},$$

$$\begin{aligned} Z_t = \alpha &+ \beta_1 \times Overnight\ return_t + \beta_2 \times Morning\ return_t \\ &+ \beta_3 \times S\&P500\ return_{t-1} + \beta_4 \times Hard\ Limit_{t-1} \\ &+ \beta_5 \times Soft\ Limit_{t-1} \end{aligned} \tag{1}$$

where $Overnight\ return_t$ refers to the overnight return on day t, $Morning\ return_t$ refers to the morning return at day t, $S\&P500\ return_{t-1}$ refers to the SP500 index on day $t-1$, $Hard\ Limit_{t-1}$ refers to the hard limit of the previous trading day, and $Soft\ Limit_{t-1}$ refers to the soft limit.[5]

To avoid look-ahead bias and make our trading strategy feasible, we design a prediction strategy. First, we use the first three-year data as the initial training set to train the logit model and use that model to predict the next trading day operation (intervention or not). Second, on each trading day, we can observe the actual results of any BOJ operation. We compare the prediction result

[5] There are potential concerns about an endogeneity issue between the morning session returns and the possibility of BOJ intervention in the morning session. In our prediction model, we have introduced five predicting factors, four of which are free from the endogeneity issue. In addition, the Shapley value indicates that the contribution power of the morning session return in the prediction model is around 25%, which means that the impact of any potential endogeneity would be modest. Furthermore, research has shown evidence that the poor performance of the equity market in the morning session triggers the BOJ intervention, including (Nangle and Yates, 2017; Hattori and Yoshida, 2023; Fukui and Yagasaki, 2023). There is empirical evidence that the price impact from BOJ's intervention begins in the afternoon session of the intervention day (Harada and Okimoto, 2021; Katagiri et al., 2022).

Table 3
Logit model coefficients and prediction results.

Panel A: logit Model Coefficients			
	Coefficients	Standard Error	t-stat
Overnight return	2.60	0.151	−17.17***
Morning return	−2.71	0.161	−16.82***
S&P 500 lag 1-day return	−0.02	0.01	−2.98***
Soft limit	−0.01	0.001	−8.10***
Hard limit	−0.31	0.101	−3.05***

Panel B: logit Model Prediction Results			
Prediction	True	False	Accuracy
Full Sample	1272	194	86.77%
Subsample 2014–2016	358	69	83.84%
Subsample 2016–2019	724	110	86.81%

Panel A of the table shows the coefficients of five variables in logit prediction model. Panel B of the table shows the look-ahead-bias-free prediction result based on the logit model. Subsample 2014–2016 starts from November 4, 2014 when the BOJ tripled the annual budget of ETF purchase program from one trillion yen to three trillion yen, and subsample 2016–2019 starts from August 5, 2016, when the BOJ further doubled the annual budget from three trillion yen to six trillion yen. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

and the actual result and record them in the table. Third, after each trading day, we add the actual result of this trading day to the training set and use the new training set to retrain the logit model. For example, if we are on day t (the sample starts from day zero), we have t samples in the training set. We use these samples to train the logit model and predict the BOJ operation at $t+1$ day. After the prediction, we add $t+1$ to the training set and retrain the model to predict BOJ operation $t+2$ days.

In this predicting strategy, we start to introduce dynamic Youden J statistics in each trading day to determine the threshold of the logit model, because the threshold default of 0.5 is not necessarily the default value. To find the optimal threshold, we use Youden's J statistics (Youden, 1950), which is the sensitivity rate plus the specificity rate minus one. Maximizing Youden's J statistic can give us the optimal threshold of the logit model. Before the prediction in each trading day, we calculate the optimal threshold using Youden's J statistics and fit the logit model with the latest optimal threshold. So, in our strategy, the threshold changes every day.

The prediction result and summary statistics for each sample period are shown in Table 3. The findings show that the model provides a very good accuracy ratio. The prediction accuracy (true prediction rate) is 88.26% for the full sample result, and the prediction model performs well in each subsample group. This indicates that the logit prediction model we construct in this section could effectively anticipate the BOJ's intervention in advance of its announcement after the market closes on each trading day. Furthermore, the inputs in the logit model are free of any look-ahead bias. In other words, all the information collected is publicly available in this logit model. We could claim that this prediction model makes it feasible for market participants to predict the BOJ's operation and potentially front-run. These highly accurate prediction results provide confidence to build a portfolio based on the front-running strategy.

2.4. Constructing the long-short portfolio

After the promising prediction results on BOJ interventions, we next identify the stocks that are most likely to be affected by a BOJ intervention. Here, we introduce two sorting factors when constructing our long-short portfolio: the dollar amount of the BOJ purchase of each TOPIX stock and the proportion of the amount of the BOJ purchase to the total daily trading value. We assume that the BOJ only purchases stocks in the TOPIX index based on the weights of stocks within the TOPIX.[6] Therefore, each stock's BOJ purchase dollar amount is calculated as

$$DA_{i,t} = BOJ_t \times w_{i,t}, \tag{2}$$

where BOJ_t represents the BOJ purchase amount on day t, and $w_{i,t}$ refers to the weight of stock i in TOPIX index on day t. The logic behind this is relatively simple: a higher purchase amount is likely to shift the demand curve towards the right and cause price pressure on stocks.

However, $DA_{i,t}$ may not be the perfect sorting factor because price pressure caused by interventions can be limited when there is sufficient market liquidity to absorb purchase orders. Therefore, we also introduce another sorting factor $RF_{i,t}$ calculated as the

[6] Based on the BOJ's official documents, the BOJ's daily intervention is split into TOPIX, Nikkei225, and Nikkei400 index-linked ETFs. Due to the lack of weights of the Nikkei225 and Nikkei400 constituent stocks, we cannot proceed with the calculations like Charoenwong et al. (2021). However, as the BOJ's interventions are mostly allocated to the TOPIX index in later years, TOPIX constituent stock weights can be viewed as a good representation of weight allocation.

proportion of the BOJ purchase amount to the total daily trading value to represent the liquidity impact of the BOJ purchase. Thus,

$$RF_{i,t} = \frac{DA_{i,t}}{Trading\ Value_{i,t}} = BOJ_t \times \frac{w_{i,t}}{Trading\ Value_{i,t}}, \tag{3}$$

where, $Trading\ Value_{i,t}$ refers to the transaction value of the stock i on day t. It can also refer to the moving average of the trading value in the previous 5 trading days (one week period) and 22 trading days (one month period). Here $RF_{i,t}$ effectively captures the impact of liquidity and market depth. Although high DA may cause high price pressure, a high daily transaction value may indicate that the stock has strong liquidity and market depth. Accordingly, BOJ interventions can be quickly absorbed without a strong price impact.

However, if we use $DA_{i,t}$ and $RF_{i,t}$ to sort stocks on day t, there is a "look-ahead" issue because $w_{i,t}$ and $Trading\ Value_{i,t}$ can only be observed at the end of day t. Therefore, to make our trading strategy feasible, we must avoid look-ahead bias by using $DA_{i,t-1}$ and $RF_{i,t-1}$ to sort TOPIX stocks on day t. Another problem is that when day t or day $t-1$ is not a BOJ intervention day, BOJ_t or BOJ_{t-1} then becomes zero and both $DA_i, t-1$ and $RF_{i,t-1}$ turn zero for all stocks. To ignore this issue, we adjust the ranking factors as follows:

$$\widetilde{DA_{i,t}} = \frac{DA_{i,t}}{BOJ_t} = \frac{BOJ_t \times w_{i,t}}{BOJ_t} = w_{i,t}, \tag{4}$$

$$\widetilde{RF_{i,t}} = \frac{RF_{i,t}}{BOJ_t} = \frac{BOJ_t \times w_{i,t}}{BOJ_t \times Trading\ Value_{i,t}} = \frac{w_{i,t}}{Trading\ Value_{i,t}}. \tag{5}$$

We divide BOJ_t for both factors because BOJ_t is fixed for all stocks in the TOPIX index and when we do sorting for stocks, only $w_{i,t}$ and $\frac{w_{i,t}}{Trading\ Value_{i,t}}$ affect the sorting results. In this case, we could also sort when day t or day $t-1$ is not a BOJ day without being affected by the absence of the BOJ intervention dollar amount ($BOJ_t = 0$).

After computing $\widetilde{DA_{i,t}}$ and $\widetilde{RF_{i,t}}$, we use the TOPIX weight at day $t-1$ and each of the three ranking factors (1-day lagged, 5-day moving average, and 22-day moving average ranking factors) to construct double-sorted tables. On each trading day t, we sort the stocks by TOPIX weight $t-1$ and each of the three ranking factors one by one (results are shown separately) by quantiles. These two sorting processes are performed independently. This means that each group's number of stocks can be different — it is possible that some groups have more stocks, and some groups have less. For example, for group $(5,5)$ — that is, the highest ranking factor ratio and the highest TOPIX weight — contains approximately 50k stocks, while group $(1,1)$ may contain only 40k stocks. Using this double-sorting result, we calculate the mean, standard error, and t−stat for each group. Calculating the mean of each cell in this table means that we construct an equal weighted portfolio by purchasing all stocks within this cell with the same amount of money.

We add one more column (RF_LS) and one more raw (Weight_LS) to show the L-S portfolio result. The RF_LS is the long-short portfolio constructed by the long highest ranking factor and the short lowest ranking factor to realize the price impact generated by the liquidity issue. The Weight_LS is the Long-Short portfolio constructed by long highest TOPIX weight stocks and short lowest TOPIX weight stocks. As in our analysis, TOPIX weight is the representation of the dollar amount of the BOJ purchase, this long-short portfolio aims to capture the price pressure generated by the BOJ purchase. The intersection of RF_LS and Weight_LS (bottom right cell) is the corner portfolio of the long (DA5, RF5) and short (DA1, RF1) portfolio. This portfolio aims to capture both the BOJ purchase price pressure and the liquidity factor. Thus, the objective is to predict BOJ's behavior and invest in the days of predicted BOJ purchase at the closing time of the morning session to take advantage of the BOJ purchase in the afternoon session. Meanwhile, in the rest of the time (non-BOJ days shown by the model or the morning session during predicted BOJ days), we invest the portfolio in the Japanese 10−year government bond.

3. Empirical results

In this section, we present the findings of the long-short portfolio constructed based on our prediction model and the sorting method outlined in Section 2 to derive the potential profits from both the long leg and the short leg. Furthermore, we assess the performance of the long-short portfolio using the Fama–French five-factor model to calculate the abnormal return derived from our trading strategy. Fama–Macbeth two-step regression is introduced to test the BOJ's intervention as a risk factor and identify its impact on stock returns.

3.1. Long-short portfolio return

Table 4 presents a 5 × 5 matrix of portfolio return capturing the BOJ's impact from two fundamental dimensions of investment characteristics: stock weights in the TOPIX index and stock illiquidity. We investigate the returns of the portfolio matrix, which are generated by independently ranking the data based on these two factors and dividing them into quintiles. The vertical axis denotes the level of influence of the BOJ purchase amount on the portfolio. The top (bottom) row of the matrix indicates the average return of a portfolio constructed from stocks that are least (most) affected by the BOJ's intervention. The vertical axis illustrates decreasing stock liquidity from top to bottom, indicating the ease of buying or selling stocks without significantly affecting market prices. The far left (right) of the matrix represents the return of the portfolio with the least (highest) liquidity among all stocks, according to our liquidity indicator. Therefore, each cell in the matrix represents the return associated with a specific combination of purchase amount and stock liquidity. The top left (bottom right) corner portfolio represents the least (most) affected stock portfolio return.

Table 4
Portfolio results sorted by risk factor (RF) and dollar amount (DA).

	RF1	RF2	RF3	RF4	RF5	RF5-RF1
DA1	−5.92***	−8.45***	−8.59***	−7.64***	−2.83***	3.09***
	(0.62)	(0.54)	(0.53)	(0.61)	(0.73)	(0.95)
DA2	−2.58***	−5.13***	−5.61***	−3.97***	−0.56	2.03**
	(0.58)	(0.50)	(0.49)	(0.55)	(0.67)	(0.88)
DA3	−0.19	−1.51***	−2.13***	−0.05	0.99*	1.18
	(0.53)	(0.51)	(0.51)	(0.45)	(0.56)	(0.77)
DA4	1.24***	1.58***	1.64***	1.12**	6.29***	5.05***
	(0.45)	(0.47)	(0.48)	(0.46)	(0.44)	(0.63)
DA5	3.58***	3.34***	3.63***	5.10***	4.56***	0.97*
	(0.40)	(0.40)	(0.43)	(0.41)	(0.38)	(0.55)
DA5-DA1	9.51***	12.08***	12.22***	12.74***	7.39***	
	(0.74)	(0.73)	(0.72)	(0.73)	(0.75)	

The table shows portfolio return results sorted by DA and RF (DA and RF are divided into five equal parts). DA1 means the stock group with lowest weights in the TOPIX index, and DA5 means the stock group with highest weights in the TOPIX index. Similarly, RF1 means the stock group with lowest RF ratio, and RF5 means the stock group with the highest RF ratio. RF5-RF1 is the portfolio that shorts RF1 and longs RF5, and DA5-DA1 is the portfolio that shorts DA1 and longs DA5. The bottom right portfolio is the corner portfolio obtained by longing (DA5, RF5) and shorting (DA1, RF1). *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

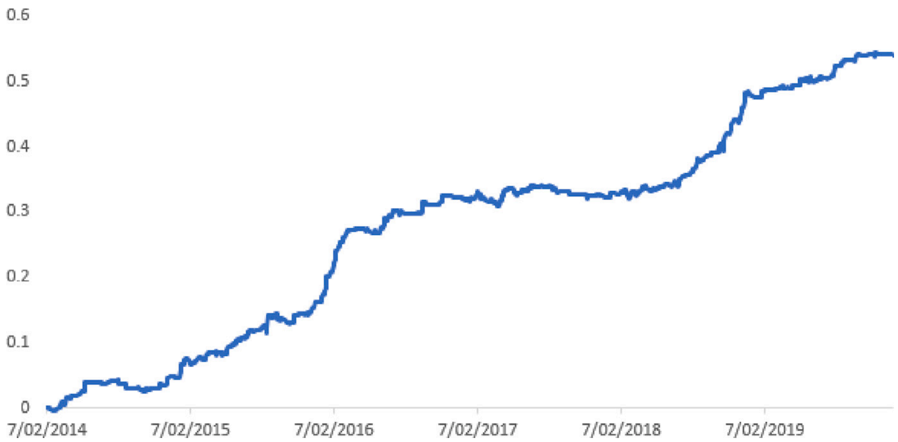

Fig. 1. Accumulated long-short portfolio return. The figure shows the accumulated return generated from the long-short portfolio strategy from 2014 to 2019.

Table 4 reveals that the impact of BOJ interventions is uneven across stocks. More specifically, the impact of BOJ interventions is more pronounced on stocks with higher weights and less liquidity. Portfolios characterized by high intervention amounts (top to bottom) and less liquidity (left to right) tend to yield superior returns. In contrast, portfolios with low BOJ purchase amounts and higher stock liquidity exhibit lower returns.

Based on these results, we construct the long-short portfolio as follows. The long portfolio with the most affected position is (DA5, RF5), and the short portfolio with the least affected position is (DA1, RF1). The return of the corner portfolio is 13.31 basis points and is significantly below the 1% level. Taking into account that the number of intervention days per year is up to 90, the annual return generated based on this long-short strategy is as high as 11.97% per year. This result indicates a high potential for profit from such trading strategies. The accumulated portfolio return is shown in Fig. 1. We perform the same analysis on the long-short strategy using the sorting factors of TOPIX weight and Amihud liquidity ratio to account for liquidity impact of the BOJ's intervention. The Amihud liquidity ratio provides quantitatively similar results that are presented in Appendix.

Furthermore, the long-leg and short-leg portfolio return patterns show that the trading strategy captures the price pressure from the BOJ interventions. The short-leg portfolio generates −5.92 basis points return for each BOJ intervention prediction. This result is consistent with the work of Gao et al. (2018) and Zhang et al. (2019), which show that there is a strong momentum within a trading day. As the BOJ usually intervenes on trading days with poor performance in the overnight and morning sessions, poor performance in the overnight and morning sessions tends to incur a negative return in the afternoon session through the momentum effect. However, the long-leg portfolio shows a positive significant return result, suggesting that the BOJ's intervention could potentially overcome intraday momentum from the overnight and morning sessions and place strong and positive price pressure on affected stocks.

The long-short portfolio strategy strongly supports the hypothesis that BOJ's interventions could cause price pressure. Furthermore, the long-short portfolio is an extension of Harada and Okimoto (2021) opinion that the BOJ is likely to start an intervention in the afternoon session of the intervention day. The BOJ's intervention has a significant impact on the afternoon session of the

Table 5
Fama–Macbeth cross-sectional regression.

Risk factors	I	II	III
BOJ Dummy	0.038***	0.027***	0.027***
	(0.005)	(0.004)	(0.004)
MRP	−0.039	−0.009	−0.012
	(0.029)	(0.033)	(0.032)
SMB	−0.016	−0.014	−0.013
	(0.013)	(0.014)	(0.014)
HML	0.016	0.011	0.009
	(0.015)	(0.016)	(0.016)
RMV	−0.008	−0.006	−0.006
	(0.009)	(0.009)	(0.009)
CMA	0.012	0.004	0.005
	(0.009)	(0.009)	(0.009)
Ret 1-day lag[a]		0.017***	0.018***
		(0.003)	(0.003)
Ret 22-day lag[b]		0.012***	0.018***
		(0.000)	(0.001)
Vol 22-day lag[c]		−0.003	−0.003
		(0.006)	(0.006)
Profit margin			−0.015**
			(0.006)
D/E ratio			0.002
			(0.002)
ROA			0.072***
			(0.014)
Growth rate			0.007
			(0.012)

The table shows the Fama–Macbeth two-step regression results. The first step of the Fama–Macbeth regression is running time series regressions for each individual stock against five Fama–French pricing factors. The second step of the Fama–Macbeth regression is running cross-sectional regressions between the afternoon session return of each individual stock and betas derived from step one of the regression with the BOJ dummy variable and control variables. The second-step regression result is shown in the table in %. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

[a] Lagged one-day individual stock afternoon-return.

[b] Lagged 22-day accumulated individual stock afternoon-return.

[c] Lagged 22-day volatility.

Japanese equity market on intervention days, and by predicting the BOJ's intervention, we can potentially construct a feasible trading strategy to generate profits based on this feature. Similarly, the 5 × 5 portfolio matrix shows that the BOJ's intervention creates higher price pressure on less liquid stocks. The results shown in the $RF5-RF1$ column indicate long-short portfolio results by longing the least liquid stocks and shorting the most liquid stocks. Four of five long-short portfolios show positive significant returns, providing empirical evidence for the notion that the BOJ's intervention has higher positive impacts on high-risk stocks. As those interventions are likely to come when market performance is poor, BOJ's equity purchase works as a kind of "insurance" for market participants. Considering the BOJ's predictable mechanism and its downside-risk protection on high-risk stocks, the intervention can be treated as a signal to synchronize the market. The opinion convergence from synchronization can also reduce the level of market uncertainties (Miller, 1977).

3.2. Fama–Macbeth regression analysis

To further test the significance of BOJ's intervention in the afternoon session of the TOPIX index, we implement Fama–Macbeth regressions to test the consequences of BOJ's intervention as a pricing factor on stock returns.

For each of the stock listed in the sample, we run time series regressions between the afternoon returns of the stock and Fama–French five pricing factors, using a 30-day rolling window to calculate the estimated betas. After running time-series regressions, we obtain the estimated betas of all five Fama–French factors for each stock in the sample. Meanwhile, we add one more factor to the cross-sectional return, the "BOJ Dummy".[7] After running the regression between asset returns and six loadings (and three control variables), we perform a time series analysis containing 1,450 trading days' risk premiums of six loading factors.

This analysis is presented in Table 5. The significant BOJ dummy variable suggests that BOJ interventions have an impact on the afternoon session returns of stocks in the TOPIX index. As we use a rolling 30-day window to generate beta loadings, there is no look-ahead bias. The Fama–Macbeth regression result indicates a feasible trading strategy by generating a return from the

[7] The BOJ dummy equals one when there is a BOJ intervention on that trading day and zero when the BOJ does not intervene on that trading day.

Table 6
Abnormal return results from Fama–French model.

Panel A: Fama–French three factors with momentum

	Alpha	MKT	SMB	HML	MOM	R^2
Long-only	1.18*	4.66***	−5.82***	−5.69***	0.97	0.052
	(0.71)	(1.26)	(2.16)	(1.75)	(1.89)	
Short-only	−4.01***	10.04***	7.78***	−3.44*	1.79	0.116
	(0.80)	(1.26)	(2.42)	(1.75)	(1.65)	
Long-short	5.19***	−5.38***	−13.60***	−2.25*	−0.82	0.102
	(0.61)	(0.74)	(1.91)	(1.24)	(0.93)	

Panel B: Fama–French five factors with momentum

	Alpha	MKT	SMB	HML	RMW	CMA	MOM	R^2
Long-only	1.17*	5.12***	−5.77***	−6.14***	1.53	4.50	0.92	0.054
	(0.68)	(1.28)	(2.18)	(2.57)	(4.69)	(3.40)	(1.86)	
Short-only	−3.91***	9.85***	7.74***	−3.99	−1.94	−1.23	1.79	0.116
	(0.79)	(1.28)	(2.43)	(2.47)	(4.58)	(3.58)	(1.66)	
Long-short	5.15***	−4.73***	−13.51***	−2.15	3.47	5.71**	−0.90	0.108
	(0.60)	(0.72)	(1.87)	(1.81)	(3.29)	(2.44)	(0.92)	

The table shows the classic Fama–French three and five factors with momentum on the long-short portfolio constructed in Section 2.4. The long leg and short leg panels show the performance of long leg-only and short leg-only portfolio performances under these pricing model, while long short panel contains the performance of long-short portfolio under pricing models. Results are in basis points. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

BOJ intervention factor. This suggests that market participants could generate excess returns by predicting the BOJ's intervention operations, as the BOJ can potentially influence stock market movements in the afternoon session.

3.3. Performance of long-short trading strategy

Driven by the significant and positive returns generated on BOJ's intervention days and the positive BOJ factor from the Fama–Macbeth model, we construct the trading strategy using the following steps. First, we construct a long-short portfolio at the beginning of the afternoon session of predicted BOJ intervention days and liquidate the portfolio at the end of the trading day. Second, for the rest of the trading days, we invest our capital in risk-free securities. Note that the predicted BOJ interventions are based on the results of the prediction model shown in Section 2.3.

We use the Fama–French three- and five-factor models with momentum factor, which include market excess return, SMB, HML, RMW, CMA, and MOM to assess the performance of our strategy based on the anticipated BOJ interventions. The results are reported in Table 6. We find that, in general, the abnormal returns based on the three- and five-factor pricing models are positive, including the long leg-only portfolio, the short-leg only portfolio, and the long-short portfolio. Specifically, the short leg (DA1,RF1) portfolio shows −2.90 basis points abnormal returns per each prediction, and the long leg (DA5, RF5) portfolio shows 1.17 basis points abnormal returns on average. Furthermore, the SMB loading for long (short) leg portfolio is −5.77 (7.26) basis points. These results comply with the feature of the long (short) leg portfolio because the long (short) leg portfolio contains the highest (lowest) market cap stocks in the TOPIX index. Therefore, the SMB loading for the long-short portfolio is −13.02 basis points and indicates that the portfolio is titled towards large stocks. All other factors, except MKT and SMB, are largely hedged out when using the long-short strategy.

These findings imply that it is possible to benefit from anticipating the BOJ's interventions in advance by using only publicly available information. In other words, the ex ante view used in the prediction model and the long-short portfolio provides a feasible trading strategy for market participants.

3.4. Three-index long-short results

We incorporate three indices representing BOJ interventions into the analysis. According to BOJ disclosures, the bank intervenes by purchasing ETFs linked to three indices: the Nikkei 225, Nikkei 400, and TOPIX. Prior to 2014, BOJ interventions were limited to Nikkei 225 and TOPIX ETFs. However, following policy adjustments in 2014, the Nikkei 400 index was included in the intervention targets. In 2016 and again in 2018, the BOJ significantly increased its purchases of TOPIX-linked ETFs, with approximately 75%–80% of its holdings in TOPIX ETFs by the end of 2019. To estimate the BOJ's intervention across these indices more accurately, we use disclosed allocation ratios for the published portions and, for the undisclosed portions, rely on the market capitalization of the Nikkei 225, Nikkei 400, and TOPIX ETFs to assign the intervention amounts proportionally.

Table 7
Double-sorted portfolio results by three indices.

	RF1	RF2	RF3	RF4	RF5	RF5-RF1
DA1	−11.85***	−10.87***	−10.35***	−6.59***	−1.95***	9.90***
	(0.60)	(0.50)	(0.50)	(0.59)	(0.75)	(0.96)
DA2	−7.55***	−8.32***	−7.09***	−2.92***	3.21***	10.76***
	(0.56)	(0.48)	(0.48)	(0.54)	(0.67)	(0.73)
DA3	−3.86***	−3.98***	−3.62***	−0.47	3.82***	7.68***
	(0.53)	(0.50)	(0.50)	(0.51)	(0.57)	(0.78)
DA4	−0.93**	−1.36***	0.81*	2.15***	4.13***	5.06***
	(0.45)	(0.45)	(0.46)	(0.45)	(0.44)	(0.63)
DA5	2.46***	1.60***	3.52***	3.75***	4.88***	2.42
	(0.41)	(0.42)	(0.42)	(0.39)	(0.36)	(0.54)
DA5-DA1	14.31***	12.47***	13.87***	10.34***	6.83***	
	(0.73)	(0.65)	(0.65)	(0.71)	(0.83)	

The table shows the portfolio return results sorted by absolute dollar amount (DA) and the liquidity-like risk factor (RF). The stocks are sorted by average weights (representing the Bank of Japan's [BOJ's] stock purchase dollar amount) of three indices, and the BOJ intervention days are predicted results from logit model. The liquidity-like risk factor is computed by the dollar amount divided by 22-day lagged average transaction value. In the table, DA and RF ratios are divided in five equal parts. DA1 means the stock group with lowest weights in the TOPIX index, and DA5 means the stock group with highest weights in the TOPIX index. Similarly, RF1 means the stock group with lowest RF ratio, and RF5 means the stock group with the highest RF ratio. RF5-RF1 is the portfolio that shorts RF1 and longs RF5, and DA5-DA1 is the portfolio that shorts DA1 and longs DA5. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

Table 8
Fama–French regression results by TOPIX index only and by three indices.

Fama–French five-factor regression by TOPIX and three indices								
	Alpha	MKT	SMB	HML	RMW	CMA	MOM	R^2
TOPIX 3-factor	5.12***	−5.57***	−13.47***	−3.34***			−0.40	0.100
	(0.59)	(0.81)	(1.76)	(1.26)			(0.89)	
TOPIX 5-factor	5.12***	−5.17***	−13.45***	−4.37**	0.22	4.47**	−0.43	0.103
	(0.58)	(0.79)	(1.74)	(1.86)	(3.39)	(2.26)	(0.88)	
3-index 3-factor	5.19***	−5.38***	−13.60***	−2.25*			−0.82	0.102
	(0.61)	(0.74)	(1.91)	(1.24)			(0.93)	
3-index 5-factor	5.15***	−4.73***	−13.51***	−2.15	3.47	5.71**	−0.90	0.108
	(0.60)	(0.72)	(1.87)	(1.81)	(3.29)	(2.44)	(0.92)	

The table presents the results of the classic Fama–French three- and five-factor regressions applied to the long-short portfolio constructed in Section 2.4. The first two rows display the regression results using only the weights of TOPIX constituent stocks, while the last two rows show the results based on the weighted average method from Charoenwong et al. (2021), which incorporates the weights of three indices. The regression outcomes are expressed in basis points. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

Following the methodology of Charoenwong et al. (2021), we calculate a weighted average of stock weights to test whether the long-short portfolio designed in the previous section continues to exhibit abnormal returns for these three indices.[8] Table 7 presents the portfolio return results sorted by absolute dollar amount (DA) and the liquidity-like RF for the weighted average holdings of each stock across the three indices. We find that by going long on the highest quintile (55) and short on the lowest quintile (11), we achieve a zero-cost corner portfolio with an average return of 16.73 basis points per trade. This indicates that the inclusion of weighted stocks from the three indices continues to yield similar results to those derived from using the TOPIX index alone in the baseline results.

We further test the portfolio strategy based on the three-index weighting method by using Fama–French multi-factor regressions to assess whether abnormal returns persist after controlling for different factor loadings. Table 8 lists the results of Fama–French regressions using TOPIX index weight only and the weighted average of the three indices' weights. We find that both methods yield similar results. Even after controlling for the five Fama–French pricing factors plus the momentum factor, the portfolios based on both the TOPIX index and the three-index weighted average generate abnormal returns exceeding 5 basis points per trading day. The similar performance of both portfolios is likely due to the substantial weight of BOJ purchases in TOPIX ETFs. Additionally, a significant portion of the BOJ's purchases target Nikkei 225 ETFs, whose constituents are the largest-cap stocks in the market. Under the three-index weighted average approach, these large-cap stocks receive a higher proportion of BOJ purchases, thereby boosting the portfolio's excess returns.

Furthermore, we apply a Fama–Macbeth regression to examine the premium associated with BOJ interventions as a factor loading in the three-index portfolio. The results are shown in Table 9 and indicate that the BOJ dummy variable significantly impacts stock

[8] While Charoenwong et al. (2021) approach offers a more precise estimate of BOJ intervention in individual stocks, the lack of historical data on the weightings of Nikkei 225 components prevents us from accurately calculating the weighted averages. Consequently, we do not use these results as our baseline but rely on calculations based on the TOPIX index. However, the conclusions drawn from both approaches are highly consistent.

Table 9
Fama–Macbeth cross-sectional regression results: Three indices.

Risk factors	I	II	III	IV	V	VI
BOJ Dummy	0.038***	0.027***	0.038***	0.027***	0.090**	0.0079**
	(0.005)	(0.004)	(0.005)	(0.004)	(0.036)	(0.037)
MRP	−0.039	−0.012	−0.042	−0.014	−0.040	−0.014
	(0.029)	(0.032)	(0.030)	(0.032)	(0.029)	(0.032)
SMB	−0.016	−0.013	−0.015	−0.013	−0.015	−0.013
	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)
HML	0.016	0.009	0.014	0.009	0.016	0.009
	(0.015)	(0.016)	(0.009)	(0.016)	(0.015)	(0.016)
RMV	−0.008	−0.006	−0.009	−0.006	−0.009	−0.005
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
CMA	0.012	0.005	0.009	0.005	0.012	0.005
	(0.009)	(0.009)	(0.011)	(0.009)	(0.009)	(0.009)
Ret 1-day lag[a]		0.018***		0.018***		0.018***
		(0.003)		(0.003)		(0.003)
Ret 22-day lag[b]		0.011***		0.011***		0.011***
		(0.000)		(0.000)		(0.000)
Vol 22-day lag[c]		−0.003		−0.003		−0.003
		(0.006)		(0.006)		(0.006)
Profit margin		−0.015**		−0.015***		−0.015***
		(0.006)		(0.006)		(0.006)
D/E ratio		0.002		0.002		0.003
		(0.002)		(0.002)		(0.003)
ROA		0.072***		0.072***		0.072***
		(0.014)		(0.014)		(0.014)
Growth rate		0.007		0.007		0.007
		(0.012)		(0.012)		(0.012)
lagged GDP[d]					1.28	1.17
					(1.166)	(1.224)

The table shows the Fama–Macbeth two-step regression results. The first two columns contain the baseline results using TOPIX constituent stocks. Column 3–6 are regression results using (Charoenwong et al., 2021)'s weighting method to compute the weighted average of three indices (TOPIX, Nikkei 225, and Nikkei 400), where columns 3 and 4 are baseline Fama–Macbeth results and columns 5-6 are Fama–Macbeth results with macro control. The Fama–French Japanese market pricing factors are downloaded from the Kenneth French Data Library. The fundamental factors are collected from the Refinitiv Workstation. The daily GDP control is from the Federal Reserve Bank of Atlanta. The regression results are shown in %. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

[a] Lagged one-day individual stock afternoon-return.
[b] Lagged 22-day accumulated individual stock afternoon-return.
[c] Lagged 22-day volatility.
[d] Lagged 1-day change of GDP growth rate.

Table 10
Portfolio results sorted by dollar amount (DA) and 5-day risk factor (RF)

	RF1	RF2	RF3	RF4	RF5	RF5-RF1
DA1	−8.97***	−6.86***	−4.55***	−0.16	3.49	12.47***
	(0.33)	(0.52)	(0.81)	(1.49)	(4.39)	(2.35)
DA2	−7.11***	−5.07***	−1.52***	1.32	−4.27	2.84
	(0.39)	(0.41)	(0.54)	(0.88)	(2.61)	(1.69)
DA3	−4.39***	−1.76***	−0.29	0.88	−4.39***	−0.01
	(0.62)	(0.41)	(0.41)	(0.53)	(1.48)	(1.38)
DA4	−1.66	0.22	1.30***	1.49***	1.38**	3.04
	(1.65)	(0.59)	(0.36)	(0.31)	(0.58)	(1.92)
DA5	−6.38	2.15	3.34***	3.26***	4.00***	10.38
	(–)	(6.00)	(1.15)	(0.38)	(0.21)	(–)
DA5-DA1	2.59	9.01	7.89***	3.42***	0.50	
	(–)	(9.15)	(2.09)	(1.07)	(1.82)	

The table shows the portfolio return results sorted by DA and RF with 5-day lagged average transaction value as denominator. In the table, DA and RF ratios are divided into five equal parts. DA1 means the stock group with lowest weights in the TOPIX index, and DA5 means the stock group with highest weights in the TOPIX index. Similarly, RF1 means the stock group with lowest RF ratio, and RF5 means the stock group with the highest RF ratio. RF5-RF1 is the portfolio that shorts RF1 and longs RF5, and DA5-DA1 is the portfolio that shorts DA1 and longs DA5. The bottom right portfolio is the corner portfolio by longing (DA5, RF5) and shorting (DA1, RF1). *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

returns, whether or not control variables are included. This result demonstrates that our findings remain valid under the methodology of Charoenwong et al. (2021).

Table 11
Logit model coefficients and prediction results.

Prediction	True	False	Accuracy
Full Sample	1265	201	86.29%
Subsample 2014–2016	375	52	87.82%
Subsample 2016–2019	717	117	85.97%

The table shows the coefficients of five variables in random forest prediction model. Subsample 2014–2016 starts from November 4, 2014 when the Bank of Japan (BOJ) tripled the annual budget of ETF purchase program from one trillion yen to three trillion yen, and subsample 2016–2019 starts from August 5, 2016, when the BOJ further doubled the annual budget from three trillion yen to six trillion yen.

Table 12
Fama–French multi-factor model results in subsamples.

	2014–2019		2014–2016		2016–2019	
	3-factor	5-factor	3-factor	5-factor	3-factor	5-factor
Alpha	5.12***	5.12***	5.99***	5.93***	4.26***	4.27***
	(0.59)	(0.58)	(0.94)	(0.70)	(0.71)	(0.71)
MRP	−5.57***	5.17***	−4.66***	−3.93***	−5.89***	−6.02***
	(0.81)	(0.79)	(1.11)	(0.60)	(1.24)	(1.17)
SMB	−13.47***	−13.45***	−9.21***	−9.14***	−18.48***	−18.56***
	(1.76)	(1.74)	(2.26)	(1.27)	(2.68)	(2.66)
HML	−3.34	−4.37**	−3.29	−3.74	−3.73**	−4.24*
	(1.26)	(1.86)	(2.01)	(3.15)	(1.65)	(2.52)
RMV		0.22		1.02		−1.81
		(3.39)		(0.97)		(4.61)
CMA		4.47**		7.77***		−0.88
		(2.26)		(3.00)		(3.33)
MOM	−0.40	−0.43	0.79	−0.86	−0.05	−0.04
	(0.89)	(0.88)	(1.29)	(0.88)	(1.16)	(1.18)

The table shows the Fama–French multi-factor regression results. The first two columns present the baseline results from full sample size (2014–2019). Columns 3–4 contain the results of the first subsample period from 2014 to 2016, and columns 5–6 contain the results of the second subsample period from 2016 to 2019. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

4. Robustness tests

In this section, we perform several robustness tests to further support the validity of the results.

4.1. Alternative frequency of average transaction value

To test the effectiveness of the ranking factor model, or specifically the denominator of our RF ratio, we test alternative frequencies of the average transaction value. In the baseline analysis, we use the average of the 22-day lagged transaction value to capture the average trading value in the previous month. The main benefit of using long-term average trading value is that it reduces short-term volatility and provides a more stable outcome.

We rerun the analysis using the average five-day lagged transaction value to capture a shorter frequency of the transaction value and determine whether the length of the transaction value has an impact on the results. The results of this analysis are summarized in Table 10 and are quantitatively similar to the baseline analysis. The corner portfolio generates 12.97 basis points return on average for each BOJ intervention compared to 13.31 basis points return from the baseline models. However, the average of the five-day lagged transaction value can be more volatile.[9]

4.2. Alternative prediction models and subsample tests

We further investigate the validity of our results by using an alternative prediction model (random forest model) and by performing the analysis over two sub-sample periods in our sample.

Apart from the logit model used in Section 2.3, we also consider other prediction models including random forest. Unlike the linear logit model, the random forest model is a nonlinear prediction model. Such model can capture more complex relationships than linear models, and thus may provide more robust results. The results of the random forest analysis are shown in Table 11 and reveal similar findings compared to the logit prediction analysis. The prediction accuracy rate is around 85%, and the performance in both sub sample periods is similar to the logit model. Therefore, linear and nonlinear models provide similar predictive performance.

[9] Some of the cells in the 5 × 5 matrix do not contain enough samples. For example, the portfolio (DA5, RF1) contains only one sample, so *t*–statistics do not work. However, the 22-day RF results have no such issue. All cells of the 22-day RF results contain 30,000–50,000 samples in the 5 × 5 matrix, which implies that the results obtained from our baseline model are robust.

Table 13
Portfolio results sorted by risk factor (RF) and dollar amount (DA): Mothers index.

	Alpha	MKT	SMB	HML	RMW	CMA	R^2
3-factor	0.18***	0.01	−0.37***	0.35***			0.18
	(0.04)	(0.04)	(0.09)	(0.07)			
4-factor	0.17***	0.02	−0.35***	0.57***	0.48		0.20
	(0.04)	(0.03)	(0.08)	(0.11)	(0.18)		
5-factor	0.17***	0.01	−0.35***	0.61***	0.46***	−0.17	0.20
	(0.04)	(0.04)	(0.08)	(0.10)	(0.18)	(0.12)	

The table shows the classic Fama–French three-, four- and five-factor evaluations on the long-short portfolio (the long BOJ-affected index [TOPIX] and the short BOJ-unaffected index [MOTHERS]). *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

Table 14
Four-session returns for BOJ days and non-BOJ days by TOPIX and JASDAQ.

Index	Sessions	Overnight	Morning	Lunch break	Afternoon
TOPIX	BOJ days	−63.36***	−41.38***	0.31	4.81**
		(2.61)	(2.74)	(0.94)	(2.43)
	Non-BOJ days	29.73***	13.09***	0.36	−1.53
		(1.54)	(1.25)	(0.43)	(1.20)
	Full sample	4.60***	−1.62	0.35	0.18
		(1.59)	(1.28)	(0.41)	(1.06)
JASDAQ	BOJ days	−42.03***	−35.47***	−2.30	−2.59
		(4.73)	(8.30)	(1.60)	(6.44)
	Non-BOJ days	29.02***	21.59***	0.63**	−1.94
		(3.14)	(5.72)	(0.87)	(4.10)
	Full sample	4.59	2.89	−0.16	−2.11
		(2.91)	(4.79)	(0.80)	(3.49)

This table presents the performance of TOPIX and JASDAQ constituent stocks across different trading sessions – overnight, morning, lunch break, and afternoon – on days with the Bank of Japan (BOJ) interventions (BOJ days), non-intervention days (non-BOJ days), and across the 2014–2019 entire sample period. The performance is measured in basis points. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

Following the prediction results of the logit model in panel B of Table 3, Table 12 shows the abnormal returns of the long-short portfolio strategy from Fama–French regression using two subsamples; January 2014 to August 2016 and August 2016 to December 2019. This subdivision is justified by the significant increases in the BOJ budget for stock purchases, and in daily purchase amounts, starting in August 2016.[10] The logit model achieves consistently high prediction accuracy in the full sample (2014–2019) and the two subperiods (2014–2016 and 2016–2019). Similarly, the performance of the long-short portfolio strategy remains comparatively strong in the two subperiods and the full sample, with a lower alpha after 2016. This finding is consistent with the results in Harada and Okimoto (2021), who also demonstrate that the abnormal returns generated by BOJ interventions gradually decline over their sample period. Overall, despite the adjustments in BOJ policy during this time, the underlying mechanisms and their impact on the market remain relatively stable.

4.3. Alternative long-short strategies

To realize the abnormal return based on BOJ's purchase, we construct the long-short portfolio using long TOPIX, a BOJ-affected index, and short MOTHERS, which is a Japanese start-up and small cap companies index that is not affected by BOJ interventions. To test the impact of BOJ interventions, we long the TOPIX index and short the MOTHERS index on BOJ intervention days. As the TOPIX index is the BOJ-affected index and MOTHERS is the unaffected index, if BOJ's purchase truly has a significant impact on index value, the risk-adjusted return of this long-short portfolio should be positive.

Table 13 presents the corresponding Fama–French five-factor analysis. Although it is not possible to trade the index, the results in Table 13 imply that the BOJ intervention has a significant positive impact on the value of the index and on stock prices involved in the affected index. After controlling for risk factors (the potential differences between the TOPIX index and the MOTHERS index in nature), risk-adjusted returns are significantly positive by longing the TOPIX index and shorting MOTHERS. The insignificant loading on MKT indicates that the market risk is mostly hedged out because both the long and short sides of the long-short portfolio are indices. The negative loading on SMB and positive loading on HML and RMW capture the major differences between TOPIX and MOTHERS: TOPIX contains large-cap, highly valued stocks with stable profitability, while MOTHERS contains small-cap start-ups that normally do not have stable cash flow. After controlling for these risk factors, the significant and positive results shown in Table 13 support the notion that BOJ interventions can have a significant price impact on stocks.

[10] The total annual budget was raised from three trillion yen to six trillion yen, and the daily purchase amount was increased from approximately 30 billion yen per day to 70 billion yen per day.

Table 15
Fama–French results with TOPIX and JASDAQ constituent stocks.

	Alpha	MKT	SMB	HML	RMW	CMA	MOM	R^2
TOPIX 3-factor	5.12***	−5.57***	−13.47***	−3.34***			−0.40	0.100
	(0.59)	(0.81)	(1.76)	(1.26)			(0.89)	
TOPIX 5-factor	5.12***	−5.17***	−13.45***	−4.37**	0.22	4.47**	−0.43	0.103
	(0.58)	(0.79)	(1.74)	(1.86)	(3.39)	(2.26)	(0.88)	
JASDAQ 3-factor	1.79	16.35	13.40	−40.01***			−0.48	0.090
	(0.76)	(10.50)	(19.56)	(15.38)			(8.76)	
JASDAQ 5-factor	0.78	12.45	6.21	−97.97***	−117.66***	7.83	−0.61	0.124
	(0.67)	(9.96)	(18.58)	(30.10)	(44.29)	(25.05)	(8.97)	

The table shows the classic Fama–French three- and five-factor regressions on long-short portfolio constructed by the logit prediction model. The first two rows contain TOPIX-constituent stock results, while the last two rows contain JASDAQ-constituent stock results. The Fama–French Japanese market factor loadings are from the Kenneth French Data Library. The results are in basis points. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

4.4. Cross-sectional impact on different indices

To explore the cross-sectional impact of BOJ interventions, we examine the impact on indices that are not directly targeted by the BOJ interventions, such as the JASDAQ index. We conduct a control experiment to compare the effects on TOPIX- and JASDAQ-constituent stocks in a long-short portfolio strategy. As the BOJ's intervention targets the Nikkei 225, Nikkei 400, and TOPIX, which encompass over 2,000 of Japan's largest stocks, small- and mid-cap indices like JASDAQ should theoretically remain unaffected.

We use intraday stock price data for JASDAQ constituents from 2014 to 2019 and compare the returns of TOPIX and JASDAQ constituents in four periods (overnight, morning, lunch break, and afternoon) in Table 14. On BOJ intervention days, both TOPIX and JASDAQ show significant negative returns in the overnight and morning sessions, suggesting that the BOJ's decisions are driven by these periods. However, unlike TOPIX, JASDAQ does not display positive returns in the afternoon session, probably due to its higher volatility. We further use market capitalization data for JASDAQ stocks to estimate constituent weightings and use intraday price and volume data to compute a liquidity-like RF for each stock. The performance of the TOPIX and JASDAQ portfolios, as captured by the Fama–French regression, is compared in Table 15. We find that the JASDAQ portfolios do not show significant excess returns, unlike the TOPIX portfolio, which generates excess returns of over 5 basis points. Thus, BOJ interventions predominantly affect the three main indices, with limited impact on smaller, non-targeted indices such as the JASDAQ.

4.5. Macroeconomic impact on the boj's decision making

We add macroeconomic controls to demonstrate the robustness of our findings. Given that most macroeconomic indicators such as GDP, inflation, or unemployment rates, are released monthly or quarterly, they are not suitable for our daily long-short strategy. To address this, we choose the Atlanta Fed GDPNow as our control variable, as it is updated daily and provides real-time revisions to GDP estimates based on key economic data released throughout each day.[11] Thus, we include the lagged GDPNow growth rate to capture the impact of macroeconomic changes on BOJ intervention decisions. The results are shown in Table 16 and reveal that the significance of the BOJ dummy decreases from 1% to 5% after adding GDPNow as a control. However, the BOJ dummy remains significant overall, indicating that BOJ interventions continue to play a noteable role in Japanese stock returns, even after controlling for macroeconomic factors.

4.6. Global market performance and the boj's decision making

To address the potential impact of global market performance on the BOJ's decision making, we incorporate the return of the international stock market index as a proxy for global market performance into our logit prediction model. In the baseline model, we use the S&P 500 index to represent overnight stock market performance. To assess the influence of international factors, we replace the S&P 500 with six other major global indices: NASDAQ, Singapore SGX/STI30, Australia ASX200, Canada S&P/TSX, UK FTSE100, and China SH500. The precision of the prediction model and the excess returns from the trading strategy for these six indices are presented in Table 17. The results show no significant changes in the accuracy of the model prediction or the excess returns when replacing the S&P 500 with these other indices. This aligns with our expectations, as although international indices like the S&P 500 do reflect overnight global market trends, the overnight returns of the Japanese stock market are equally effective in capturing the impact of global market movements. Japanese investors may interpret overnight market information differently, and this local interpretation is more relevant to predict BOJ intervention.

[11] While GDPNow is updated about once or twice a week, it offers more frequent data than conventional quarterly GDP figures.

Table 16
Fama–Macbeth cross-sectional regression controlled by high-frequency GDP data.

Risk factors	BL1	BL2	Robust1	Robust2
BOJ Dummy	0.038***	0.027***	0.090**	0.079**
	(0.005)	(0.004)	(0.036)	(0.037)
MRP	−0.039	−0.012	−0.039	−0.013
	(0.029)	(0.032)	(0.029)	(0.032)
SMB	−0.016	−0.013	−0.02	−0.013
	(0.013)	(0.014)	(1.204)	(0.013)
HML	0.016	0.009	0.016	0.009
	(0.015)	(0.016)	(0.015)	(0.016)
RMV	−0.008	−0.006	−0.009	−0.006
	(0.009)	(0.009)	(0.009)	(0.009)
CMA	0.012	0.005	0.012	0.005
	(0.009)	(0.009)	(0.008)	(0.009)
Ret 1-day lag[a]		0.018***		0.018***
		(0.003)		(0.003)
Ret 22-day lag[b]		0.011***		0.011***
		(0.000)		(0.000)
Vol 22-day lag[c]		−0.003		−0.003
		(0.006)		(0.006)
Profit margin		−0.015**		−0.015***
		(0.006)		(0.006)
D/E ratio		0.002		0.003
		(0.002)		(0.003)
ROA		0.072***		0.072***
		(0.014)		(0.014)
Growth rate		0.007		0.007
		(0.012)		(0.012)
lagged GDP[d]			1.276	1.180
			(1.094)	(0.964)

The table presents the results of the Fama–Macbeth two-step regressions. The first two columns display the baseline results based on TOPIX-constituent stocks, while the last two columns show the results incorporating macroeconomic controls. The BOJ Dummy variable is set to one on days when the logit prediction model indicates that the Bank of Japan is likely to intervene in the market and zero on days when the model suggests no intervention. The regression outcomes are expressed as percentages in the table. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

[a] Lagged one-day individual stock afternoon-return.

[b] Lagged 22-day accumulated individual stock afternoon-return.

[c] Lagged 22-day volatility.

[d] Lagged one-day change of GDP growth rate.

Table 17
Logit model prediction results.

Prediction	True	False	Accuracy	Alpha
S&P 500	1272	194	86.77%	5.12%
NASDAQ	1262	204	86.08%	5.10%
SG	1222	244	83.36%	4.89%
AU	1245	221	84.92%	4.95%
CA	1221	245	83.29%	4.80%
UK	1247	219	85.06%	4.92%
CN	1209	257	82.47%	4.51%

The table contains the robustness check of using different global equity indices to replace the S&P 500 index in our baseline result. The alpha is the abnormal return generated from Fama–French five-factor with momentum regression, using TOPIX-only data and logit model for four fixed prediction factors (overnight TOPIX return, morning TOPIX return, hard budget limit, and soft budget limit) and one global index

5. Conclusion

This paper investigates the economic consequences of data-driven monetary policies by drawing conclusions from the Bank of Japan's ETF purchase program. Although predicting central bank policy actions is challenging, we design a logit prediction model that achieves a prediction accuracy of 86.77%. Thus, based on the fact that BOJ interventions are based on data and publicly available information, they can be highly predictable. Furthermore, the implementation of a long-short trading strategy based on the model's predictions further challenges the efficient market hypothesis and identifies profitable strategies with an average return of 13.31 basis points per BOJ intervention. Thus, BOJ actions can generate significant price pressure in the Japanese equity market. Therefore, we provide empirical evidence that data-driven monetary policies could cause price pressure, despite being highly predictable.

Table A.1
Portfolio results sorted by Amihud ratio & dollar amount (DA).

	ami1	ami2	ami3	ami4	ami5	ami5-ami1
DA1	−9.68***	−4.01***	0.60	0.01	7.36	17.04***
	(0.31)	(0.57)	(1.12)	(2.21)	(6.58)	(3.94)
DA2	−8.96***	−3.76***	−1.45***	−0.43	5.16**	14.12***
	(0.43)	(0.38)	(0.54)	(0.94)	(2.21)	(1.72)
DA3	−8.04***	−1.86***	−1.13***	−0.16	3.22***	11.27***
	(0.96)	(0.42)	(0.39)	(0.50)	(0.95)	(1.37)
DA4	−10.78***	0.48	0.72*	0.74**	2.81***	13.59***
	(3.86)	(0.71)	(0.38)	(0.33)	(0.42)	(3.82)
DA5	3.12	1.18	3.35***	2.55***	4.49***	1.37
	(7.03)	(1.74)	(0.59)	(0.33)	(0.23)	(7.66)
DA5-DA1	12.80	5.19*	2.75**	2.54**	−2.88	14.17***
	(10.28)	(2.99)	(1.27)	(1.30)	(2.96)	(0.39)

The table shows the portfolio return results sorted by DA and Amihud liquidity ratio. In the table, DA and Amihud ratio are divided in five equal parts. DA1 means the stock group with lowest weights in TOPIX index and DA5 means the stock group with highest weights in TOPIX index. Similarly, Amihud1 means the stock group with lowest Amihud ratio and Amihud5 means the stock group with the highest Amihud ratio. Ami5-Ami1 is the portfolio that short Amihud1 and long Amihud5, and DA5-DA1 is the portfolio that short DA1 and long DA5. The bottom-right portfolio is the corner portfolio by longing (DA5,Amihud5) and shorting (DA1,Amihud1). *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

This study assesses the consequences of unconventional monetary policy, particularly direct capital injections into the equity market. In contrast to some skepticism about the impact of such policies in responding to market shocks, the findings suggest that BOJ interventions have substantial price impacts (Charoenwong et al., 2021; Harada and Okimoto, 2021). Our results strongly support the view that BOJ interventions cause significant positive price pressure, especially in high-risk stocks. The downside protection works as "insurance" and helps market investors generate homogeneous expectations about stock prices, greatly reducing market uncertainties. In addition, non-fundamental price pressure is caused by exogenous forces, drawing parallels with studies on mutual fund and ETF flows, dividend payments, and government capital injections (Coval and Stafford, 2007; Dyakov and Verbeek, 2013; Hartzmark and Solomon, 2022a; Dang et al., 2023).

This study underscores the importance of data-driven policy-making in the central bank decision-making process and its potential implications for market participants. The insights drawn revealed in this study are valuable to central banks when adopting similar policies, as well as investors and analysts of financial markets.

CRediT authorship contribution statement

Zechu Liu: Writing – original draft, Methodology, Formal analysis, Data curation. **Christina Sklibosios Nikitopoulos:** Writing – review & editing, Supervision. **Kenny Phua:** Writing – review & editing, Supervision, Methodology. **Jianxin Wang:** Supervision, Methodology.

Appendix. Amihud liquidity ratio

To strengthen our results, we replace the ranking factor (RF) with the Amihud liquidity ratio and run the same long-short strategy. Table A.1 presents this analysis and reveals results similar to the baseline model. The corner portfolio of long (DA5, Amihud5) and short (DA1, Amihud1) generates 14.17 basis points return on each Bank of Japan (BOJ) intervention day. This indicates that the BOJ intervention has a strong influence on both large stocks and less liquid stocks. In addition, the results of the Amihud liquidity ratio further demonstrate that our ranking factor ratio contains a liquidity-like feature.

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