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# State-dependent effects of the unconventional monetary policy in stock markets☆

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A B S T R A C T

This study analyzes the state-dependent effect of the Bank of Japan (BoJ)'s intervention in stock markets from 2013 to 2017. A causal inference on such intervention is difficult because of the self-selective behavior of central banks. To address this problem, I apply the propensity score method in a time series context, exploiting stock price information of a single day. The key finding is that the effects are state-dependent and stronger during market downturns.

## 1. Introduction

This study examines the effects of the stock purchasing program, which the Bank of Japan (BoJ) has conducted as part of its unconventional monetary policy. In the aftermath of the Great Recession, major central banks lost conventional monetary policy tools near the effective lower bound of nominal interest rates and adopted asset purchasing programs. They have purchased public and private bonds but not private stocks, except for the BoJ, which has been in a liquidity trap since before the Great Recession. This study conducts a causal inference on this stock purchasing program.

The causal inference of stock purchases is, however, complicated by the presence of potential endogeneity. The central bank's interventions are not arbitrary. The BoJ is apt to purchase stocks when the market is likely to be in a downturn. Treatments (days with interventions) and controls (days without interventions) are not randomly assigned. Thus, on average, the market situation on a day of intervention is probably worse than on a day without it. A simple comparison of stock prices between days with intervention and days without could lead to a biased estimate of the intervention effect. The estimation bias caused by the above potential endogeneity is called as self-selection bias.

To address the self-selection bias, this study applies the cross-sectional propensity score method in a time series context. In particular, after specifying the policy reaction function of the BoJ's trading desk, I use the remaining policy variations to "re-randomize" days with intervention and days without it. I can then non-parametrically estimate the intervention effect as if stock market interventions are randomized experiments. The propensity score method is part of Rubin's potential-outcome approach, which was originally developed in statistical science and is relatively new in the impact evaluation of macroeconomic policy. A few exceptions include Angrist and Kuersteiner (2011) and Angrist et al. (2013) who examine the state-dependent effects of (conventional) monetary policy and Jorda and Taylor (2016) who examine the effects of fiscal austerity in booms and recessions. This study is an application of the approach to the research on the use of unconventional monetary policy in stock markets.

The empirical results are summarized as follows. First, there is a demand pressure effect in stock markets. Second, the effects are different depending on the state of stock markets. In other words, stock market interventions in market downturns can boost stock prices up while those in market upturn cannot. I call this property as a

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state-dependency of intervention effect. The above findings have an important policy implication: the BoJ can be fully effective by intervening only when stock prices fall considerably.

Several studies have examined the effects of BoJ's stock purchasing program. Matsuki et al. (2015) is one of earliest studies. It reports that the stock purchasing program has a statistically significant impact on the stock price index, using daily data and a standard VAR model. Although Matsuki et al. (2015) is an important first step, it does not consider the state dependency of the intervention effect.[1]

More specifically, this study is closely related to the literature on the causal inference on the BoJ's stock purchasing program. Charoenwong et al. (2021), Harada and Okimoto (2021), and Adachi et al. (2021) find the causal effects in individual stock prices of stock purchasing program by employing the difference-in-difference (DiD) method.[2] This paper is different from these three studies in several respects. First, Charoenwong et al. (2021) and Harada and Okimoto (2021) do not examine state-dependency of intervention effects. Second, these studies do not consider the self-selection bias. Specifically, if market intervention is anticipated in advance, market prices will incorporate the information about the intervention. So, it is necessary to identify the policy shock that is unanticipated. My methodology can address the self-selection bias and identifies unanticipated market interventions.[3] Consequently, this study complements those previous studies and examines the state-dependent effects of the stock purchasing program.

Although this study focuses on the effects of stock purchasing program, previous studies such as Haitsma et al. (2016) and Kontonikas et al. (2013) have examined the link between the unconventional monetary policy of fixed-income-asset purchasing program and stock prices.[4]

This study also contributes to the literature by examining whether there is a demand pressure effect in stock markets. If markets are efficient, intrinsic values are the primary determinants of stock prices. An exogenous intervention in stock markets would not affect equilibrium prices. However, if markets are not efficient enough or other factors such as the limit of arbitrage (Shleifer and Vishny, 1997), transaction costs (Amihud and Mendelson, 1986), or inventory costs of market makers (Stoll, 1978) prevent the achievement of efficient equilibrium prices, a demand pressure effect could emerge. To capture this effect, it is necessary to identify exogenous variations in demand for stocks. Market interventions by a central bank are a typical example of exogenous changes in demand. I exploit this opportunity as a natural experiment and attempt to identify the demand pressure effect in aggregate stock markets.[5,6]

The rest of the paper is organized as follows. Section 2 provides an overview of the stock purchasing program. Section 3 presents the conceptual framework for the causal inference and my identification strategy. Section 4 reports the policy reaction function of the BoJ's trading desk and calculates the propensity score as a probability of intervention. Section 5 presents the estimation results and the counterfactual simulations. Section 6 concludes the study.

## 2. Stock purchases as an unconventional monetary policy tool

This section summarizes the experience of the stock purchasing program conducted by the BoJ and presents the stylized facts of this program.

### 2.1. Overview of the stock purchasing program

In October 2010, the BoJ decided to start purchasing stock-based exchange-traded funds (ETFs),[7] which are linked to major stock market indices, as part of its asset purchasing program "with the aim of encouraging the decline in risk premiums to further enhance monetary easing" (Bank of Japan, 2010). The purchased ETFs are the ones that are listed on a financial instruments exchange licensed in Japan.[8] The Bank has continued its ETF purchase even after shifting to a more aggressive monetary policy regime of "quantitative and qualitative easing" (QQE) in April 2013.[9] Although all major central banks have adopted unconventional policies after the Great Recession, the assets purchased are limited to fixed-income securities, except for the BoJ's stock purchases. Thus, intervention in stock markets may be one of the most unconventional policies among them.[10]

The BoJ has modified the program in several respects over the sample period. First, the Bank expanded the target amount of purchases six times to enhance monetary easing. Second, when switching to the QQE policy regime, the Bank transformed the program from a closed-end type to an open-end type by committing to continue asset purchases without further notification.

The chronology of stock purchases is summarized as follows. The Bank started the program on December 15, 2010.[11] At that time, the target amount was 0.45 trillion yen. After the program was introduced, the BoJ raised the target four times.[12] On April 4, 2013, the Bank decided to adopt the QQE and announced that it would purchase ETFs

[1] Ide and Minami (2013) and Harada (2017) examine the statistical relationship between individual stock prices and market interventions.

[2] Precisely, Adachi et al. (2021) investigates the effects on risk premium.

[3] In the meanwhile, Fukuda and Tanaka (2022) studies the effect of BoJ's ETF purchases paying special attention to the period during the Covid-19 crisis. My study shares the same sprits with Fukuda and Tanaka (2022) because both studies stress the necessity of making a distinction between anticipated and unanticipated interventions.

[4] Bhattarai and Neely (2022) provides the comprehensive survey on the efficacy of unconventional monetary policy.

[5] Harris and Gurel (1986) explore demand pressure effects in individual stock prices, using natural experimental opportunities of additions and deletions from market indices. Other studies that examine this topic include (Lynch and Mendenhall, 1997), Beneish and Whaley (1996), Wurgler and Zhuravskaya (2002), and Okada et al. (2006). Garleanu et al. (2009) estimate the demand pressure effects in derivatives markets.

[6] Certainly, asset market interventions by government officials are not limited to stock market intervention by the BoJ. Studies on foreign exchange intervention have a long tradition of identification issues on this subject. Fischer and Zurlinden (1999), Dominguez (2003), Dominguez (2006), and Fatum and Hutchison (2003) are well known studies. Taylor and Sarno (2001) provide a comprehensive summary of this literature. Furthermore, asset purchases in bond markets by central banks are another important and relatively new asset market intervention. As summarized in Williams (2013), many studies have analyzed the effects of asset purchasing programs in bond markets. Among others, D'Amico and King (2013), Kandrac and Schlusche (2013), and Meaning and Zhu (2011) find statistically significant demand pressure effects of bond purchases.

[7] A stock-based ETF is a security traded in securities exchanges and tracks a stock market index such as the *Nikkei225* and *TOPIX*.

[8] As of 2017, all the *Nikkei225*-, *TOPIX*-, and *JPX400*-indexed ETFs listed on the Tokyo Stock Exchange are physical ETFs and not synthetic ones.

[9] The QQE was an policy package that the BoJ introduced in April 2013 to achieve the 2% inflation target. The QQE consists of the quantitative easing that aims to increase the amount of monetary base and the qualitative easing that aims to affect asset prices. The stock purchasing program is a part of the qualitative easing measures.

[10] Several central banks have purchased private stocks. The Swiss National Bank purchases foreign stocks as part of its foreign exchange rate policy. The Hong Kong Monetary Authority temporarily intervened in stock markets during the Asian financial crisis in the late 1990s to fight speculators. The Czech National Bank and the Bank of Israel also hold private stocks.

[11] The decision to start the stock purchasing program was made at the Monetary Policy Meeting in October 2010; the Bank was engaged in legislative and administrative preparations until December 15, 2010.

[12] On March 14, 2012, the BoJ decided to add 0.45 trillion yen to the target and announced that it would meet this target by the end of June 2012. Further, the Bank raised the target by 0.2 trillion yen on April 27, 2012 and by 0.5 trillion yen on October 30, 2012.

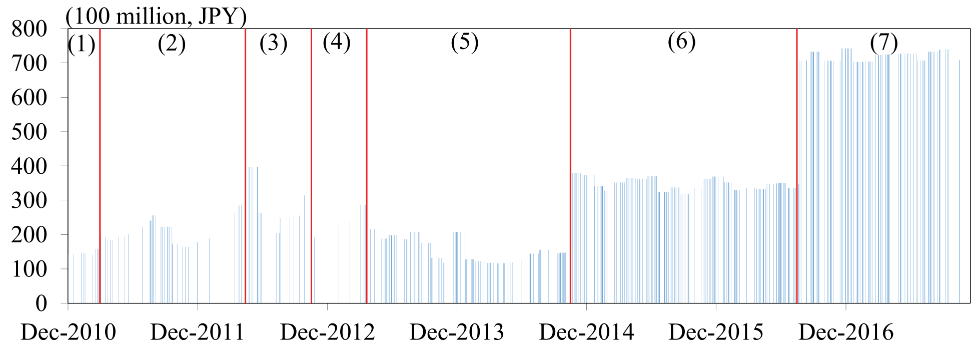


**Fig. 1.** Stock Market Interventions.
Note: The blue bars and vertical red lines represent the purchases of stocks and policy changes described in the text, respectively. Non-business days are excluded.

**Table 1**
Summary statistics of Stock Market Interventions.

| | (a) Interventions (days) | (b) Business days (days) | (c) a/b (%) | (d) Average purchases (100 mil. yen) | (e) S.D. of purchases |
|---|---|---|---|---|---|
| Full sample Dec. 15, 2010–Nov. 30, 2017 | 436 | 1708 | 25.5 | 361.6 | 209.2 |
| (I) *pre-QQE* period Dec. 15, 2010–Apr. 4, 2013 | 71 | 566 | 12.5 | 230.2 | 68.5 |
| Subsample (1): *pre-QQE 1* Dec. 15, 2010–Mar. 14, 2011 | 10 | 59 | 16.9 | 149.9 | 8.0 |
| Subsample (2): *pre-QQE 2* Mar. 15, 2011–Apr. 27, 2012 | 38 | 278 | 13.7 | 213.0 | 36.7 |
| Subsample (3): *pre-QQE 3* May 1, 2012–Oct. 30, 2012 | 16 | 126 | 12.7 | 306.3 | 76.5 |
| Subsample (4): *pre-QQE 4* Oct. 31, 2012–Apr. 4, 2013 | 7 | 103 | 6.8 | 264.0 | 47.3 |
| (II) *QQE* period Apr. 5, 2013–Nov. 30, 2017 | 365 | 1142 | 32.0 | 387.2 | 217.7 |
| Subsample (5): *QQE 1* Apr. 5, 2013–Oct. 31, 2014 | 113 | 387 | 29.2 | 155.9 | 34.2 |
| Subsample (6): *QQE 2* Nov. 1, 2014–Jul. 29, 2016 | 154 | 426 | 36.2 | 348.5 | 17.3 |
| Subsample (7): *QQE 3* Aug. 1, 2016–Nov. 30, 2017 | 98 | 329 | 29.8 | 712.5 | 55.1 |

Note: On the basis of the policy decisions that changed the target amount of stocks, I split the entire sample into seven subsamples. *QQE* stands for the "quantitative and qualitative easing" policy regime introduced on April 4, 2013.

worth 1 trillion yen per year. It then proceeded to triple the target (to 3 trillion yen per year) on October 31, 2014 and again raised this target to 6 trillion yen per year on July 27, 2016.

### 2.2. Stylized facts about the stock purchasing program

Fig. 1 presents the daily purchases of stocks by the BoJ; non-business days are excluded. The vertical lines represent the changes in the target and segment the whole sample into seven subsamples. Fig. 1 suggests that (i) interventions are frequently and irregularly executed, (ii) variations in the daily intervention amount in each subsample are not large, and (iii) when the policy target is changed, the daily intervention amount is apt to be adjusted. This tendency is more evident under the QQE regime (subsamples (5), (6), and (7)).

Table 1 details the summary statistics. Columns (a) and (b) report the frequencies of interventions and the number of business days, respectively. Column (c), which shows the ratio of interventions to total business days, suggests that in any subsample, interventions took place in 6.8%–36.2% of business days. Columns (d) and (e) present the average amount of interventions and their standard deviations, respectively. These two columns suggest that the variations are not large within each subsample period.

Per these findings, in the econometric analysis in the subsequent section, I will focus on the interventions in subsamples under the *QQE* policy regime because the number of interventions in the subsamples of the *pre-QQE* period is so small that it is difficult to ensure enough observations to make empirical causal inferences. Further, the inferences for the *QQE* subsamples have the advantage of being comparable under the same policy framework.[13]

It is also worth mentioning that the amount purchased is considerably large relative to the total trading volume; the average amount of intervention in the *QQE* period is equal to 1.5 percent of the daily trading volume. In detail, it is equal to 0.6, 1.2, and 2.6 percent in the *QQE 1*, *QQE 2*, and *QQE 3* periods, respectively.[14]

## 3. Causal inference of stock market interventions

To begin with the empirical inferences, I lay out a linear parametric system of stock prices and interventions for the exposition of my problem.

$$\Delta EP_t = \alpha \cdot I_t + \nu_{1,t}, \tag{1}$$

[13] The framework of the stock purchasing program is different in the *pre-QQE* and *QQE* periods. It was a closed-end form in the *pre-QQE* period but was transformed into an open-end form in the *QQE* period.

[14] The trading volume per day in Section I of Tokyo Stock Exchange is 2.47, 2,80, and 2.70 trillion yen for the *QQE 1*, *QQE 2*, and *QQE 3* periods, respectively.

$$I_t = -\beta \cdot \Delta EP_t + \nu_{2,t}, \tag{2}$$

where $\Delta EP_t$, and $I_t$ are daily returns in stock prices and intervention amounts, respectively. $\nu_{i\in\{1,2\},t}$ are *i.i.d.* stochastic shocks with standard deviations $\sigma_{\nu_i}$. In this subsection, I tentatively postulate that the intervention is a continuous variable, for the sake of simplicity.

Without additional identification assumptions, this system of equations is under-identified because the number of parameters ($\alpha$, $\beta$, $\sigma_{\nu_1}$, and $\sigma_{\nu_2}$) are greater than the available moments of data (variance and covariance of $\Delta EP_t$ and $I_t$). For the estimation of the model, one may impose a timing assumption, which states that the BoJ's trading desk decides whether to intervene on the basis of the information in the previous period such as $\Delta EP_{t-1}$ and by restricting the coefficient of $\Delta EP_t$ to zero in the policy reaction function.

In addition to the identification assumption, the above parametric approach has several prerequisites. First, all the variables are included in the system. This is not an easy one to suffice for models of daily or intra-daily stock prices. Many factors such as macroeconomic news, market microstructure, or trading activities of noisy traders could affect stock prices in high frequencies. Wrong specifications would distort coefficients because of the omitted variable bias. Second, another presumption is the linear specification. In stock markets, the intervention effects may be state-dependent and nonlinear. For example, the intervention effects may be asymmetric and stronger in market downturns or may be a concave function of intervention amounts. Standard linear parametric models are not suitable where such potential misspecifications are present.

This study adopts a flexible semi-parametric approach to avoid the issues that could emerge when applying linear parametric models to the examination of the daily stock market intervention. The approach adopted in this study does not specify the price formation mechanism in stock markets by switching the focus of identification from a model of the stock price determination to a model of the policy intervention determination.

However, it should be noted that a semi-parametric approach is not free of problems. While being free of the issues of model misspecification in daily stock markets, it needs to deal with the self-selection problem of market interventions. In the following subsections, I first present the self-selection issue and propose a conceptual framework of the empirical analysis used to remedy it.

### 3.1. Self-selection bias

Table 2 reports daily returns in stock prices, conditional on whether interventions take place ($D_t = 1$) or not ($D_t = 0$). If the BoJ's interventions are randomly decided, the difference between these two figures would be the nonparametric estimates of the intervention effects.

Interestingly, columns 1 and 2 in Table 2 clearly show that stock prices dropped when the BoJ intervened in the market and increased when it did not. The average differences of treatments ($D_t = 1$) and controls ($D_t = 0$) in column 4 are statistically significant. These patterns hold irrespective of subsample periods.[15]

Table 2 does not necessarily suggest that the stock purchasing program is counter-productive. Considering that the policy objective is to encourage the decline in risk premiums to further enhance monetary easing, it is natural to find the BoJ buying stocks when stock markets are likely to experience a downturn. Rigobon and Sack (2003) find a similar pattern in the conventional monetary policy. Decisions regarding whether to intervene may not be arbitrary but self-selective. Thus, the simple group averages in Table 2 could be biased. I need a causal inference to separate the true causal effects from self-selection biases.

[15] These patterns also hold in the *pre-QQE* period and the different market index of the *Nikkei225* instead of the *TOPIX*.

**Table 2**
Changes in Stock Prices Conditional on Stock Market Interventions.

| | $\Delta EP_t \mid D_t = 1$ % | $\Delta EP_t \mid D_t = 0$ % | Difference % | $H_0$:Difference = 0 $t$-statistics |
|---|---|---|---|---|
| Full sample of *QQE* | −1.00 | 0.54 | −1.54 | 20.28 |
| Subsample *QQE 1* | −1.20 | 0.57 | −1.77 | 14.40 |
| Subsample *QQE 2* | −1.12 | 0.64 | −1.76 | 13.47 |
| Subsample *QQE 3* | −0.47 | 0.33 | −0.81 | 8.82 |

Note: $D_t = 1$ and $D_t = 0$ represent days with interventions and days without interventions, respectively. Figures represent daily returns of the Tokyo Stock Price Index (*TOPIX*).

### 3.2. Conceptual framework of the empirical analysis

This subsection sets out a formal framework to mitigate the self-selection bias and identify the causal effects of the stock purchasing program. Now, I define $\Delta EP_{t,l}$ as the percentage change in $\Delta EP_t$ between $t$ and $t+l$.

The analytical framework builds on the concept of potential outcomes. Potential outcomes in this study are realizations of stock prices in a parallel world with two states. In one state, a market intervention takes place and in the other state, it does not. Specifically, potential changes in stock prices $\{\Delta EP_{t,l}(d); d \in \{0,1\}\}$ are defined as a set of values that $\Delta EP_{t,l}$ would take, if $D_t = d$.[16] In this framework, the causal effect of an intervention is the differential of potential stock price changes, $\Delta EP_{t,l}(1) - \Delta EP_{t,l}(0)$.

Here, the problem is that I can observe realized stock prices only in one state and cannot observe them in the parallel world.[17] Therefore, I will estimate the intervention effects on an average instead of the effects on individual observations.

$$\theta_l \equiv E\left[\Delta EP_{t,l}(1) - \Delta EP_{t,l}(0)\right]. \tag{3}$$

Now, I can show why the differential of sample averages by group in Table 2 could be biased. The left-hand side of (4) is the differential of sample averages by group. The first term on the right-hand side of (4) is the average intervention effects, which is the differential between the realized stock price changes on the day of intervention and the unrealized potential stock price changes on the same day. The second term is the self-selection bias, which represents the differential of potential stock price changes between intervention days and no-intervention days.

$$\begin{aligned} E\left[\Delta EP_{t,l} \mid D_t = 1\right] - E\left[\Delta EP_{t,l} \mid D_t = 0\right] &= \underbrace{E\left[\Delta EP_{t,l}(1) \mid D_t = 1\right] - E\left[\Delta EP_{t,l}(0) \mid D_t = 1\right]}_{\text{Average intervention effects}} \\ &+ \underbrace{E\left[\Delta EP_{t,l}(0) \mid D_t = 1\right] - E\left[\Delta EP_{t,l}(0) \mid D_t = 0\right]}_{\text{Self-selection bias}} \end{aligned} \tag{4}$$

If interventions and no-interventions are randomly assigned as in a randomized experiment, the self-selection bias will be zero. However, because interventions take place when markets are likely to deteriorate, the allocation of interventions and no-interventions is not independent of the developments in potential stock prices. Thus, the self-selection bias is not zero and the differential between group averages in (4) will deviate from the true intervention effects.

To eliminate this self-selection bias, I introduce the conditional independence assumption (CIA). The CIA means that the intervention decision is independent of the potential changes in stock prices once it is conditioned by predetermined covariates $z_t$:

$$\Delta EP_{t,l}(d) \perp D_t \mid z_t \text{ for all } l > 0,\ d \in \{0,1\}. \tag{5}$$

[16] It is possible to describe the observed changes in stock prices in terms of potential ones: $\Delta EP_{t,l} = \Delta EP_{t,l}(1)D_t + \Delta EP_{t,l}(0)\left(1 - D_t\right)$.

[17] Holland (1986) called it a "fundamental problem of causal inference."

If the CIA holds, the average intervention effect in (3) could be estimated as the causal effect of the intervention, even if non-experimental data are used. To calculate the conditional expectations of potential stock price changes, I follow Angrist and Kuersteiner (2011) and use the propensity score $P(D_t = d \mid z_t)$, which is the probability of interventions conditioned on the predetermined covariates $z_t$.[18] In estimation, the propensity score is modeled as a parametric probit model $P(D_t = 1 \mid z_t) = p(z_t, \psi)$ where $\psi$ refers to the parameters.[19] Then, I can write the conditional expectations in the following manner[20]:

$$E\left[\Delta EP_{t,l} \mid D_t = 1, z_t\right] = E\left[\Delta EP_{t,l}(1) \mid z_t\right] p(z_t, \psi), \tag{6}$$

$$E\left[\Delta EP_{t,l} \mid D_t = 0, z_t\right] = E\left[\Delta EP_{t,l}(0) \mid z_t\right] \left[1 - p(z_t, \psi)\right]. \tag{7}$$

Integrating both (6) and (7) over $z_t$, I can express the average intervention effect as follows:

$$\theta_l = E\left[\Delta EP_{t,l}(1) - \Delta EP_{t,l}(0)\right] = E\left\{\Delta EP_{t,l}\left[\frac{D_t}{p(z_t,\psi)} - \frac{1-D_t}{1-p(z_t,\psi)}\right]\right\}. \tag{8}$$

Here, (8) is the inverse probability weighted (IPW) estimator, which divides interventions and no-interventions by their respective propensity scores. As implied by (8), unlike parametric methods described at the beginning of Section 3, the propensity score method does not require a specific function form of stock-price determination.[21] Intuitively, the IPW estimator assigns higher weight to the more unexpected actions of the central bank and lower weight to the more expected ones. This uneven weighting allows me to estimate implicit intervention shocks that are considered to be surprises. If the policy reaction function can accurately predict interventions, (8) will successfully correct the bias induced by the self-selective behavior of the BoJ's trading desk, allowing us to estimate a causal effect of the intervention.

In the implementation, I estimate the sample version of the average intervention effects as follows:

$$\hat{\theta}_l = \frac{1}{N}\sum_t \left\{ \underbrace{\Delta EP_{t,l}\left[\frac{D_t}{\hat{p}_t} - \frac{1-D_t}{1-\hat{p}_t}\right]}_{\text{IPW term}} - \underbrace{\left(D_t - \hat{p}_t\right)\left[\frac{m_{1,l}(\chi_t,\xi_{1,l})}{\hat{p}_t} + \frac{m_{0,l}(\chi_t,\xi_{0,l})}{1-\hat{p}_t}\right]}_{\text{Augmentation term}} \right\}, \tag{9}$$

where $\hat{p}_t$ is the projected probability of intervention from the policy reaction function, $N$ is the number of observations, and $m_d(\chi_t, \xi_{d,l})$ the conditional mean from the regression of $\Delta EP_{t,l}$ on the predetermined covariates $\chi_t$ with parameters $\xi_{d,l}$ for $d = \{0, 1\}$. $\chi_t$ consist of $z_t$ and lags of $D_t$ and $\Delta EP_t$. The second term in curly brackets is an augmentation term to obtain the smallest asymptotic variance (e.g., Imbens, 2004; Wooldridge, 2010, and Lunceford and Davidian, 2004). (9) is called an augmented inverse propensity weighted (AIPW) estimator.[22]

The estimator in (9) helps to alleviate the problem specific to an application in a time-series context. Time series data tend to be serially correlated. In my case, a stock market intervention in the past may affect present and future stock prices. The AIPW estimator can address serial correlations by adding an augment term that is the conditional mean of $\Delta EP_{t,l}$ on past stock purchasing and other variables.

### 3.3. Identification strategy

In the identification scheme, the conditioning variables $z_t$ are predetermined and not affected by the potential stock price changes $\Delta EP_t(d)$ in the same period. This is equivalent to the recursive identification in VAR literature, as described in the beginning of this section. For the implementation, I will use intra-day data.

First, I will explain the time-line of events in a day. At the Tokyo Stock Exchange, the morning session starts at 9:00 a.m and closes at 11:30 a.m. The afternoon session starts at 12:30 p.m. and closes at 15:00 p.m. The BoJ announces the amount of stock purchases for the day in *Money Market Operations*, which is released on its web site around 18:00 p.m. on every business day (19:00 p.m. at month-end). Although it can be inferred that an intervention in one day happens during business hours, the exact time of intervention is not announced.

On the basis of the situation in the daytime, I postulate that the BoJ's trading desk decides whether to intervene based on the information obtained during the morning session.[23] Accordingly, I will measure the impact of intervention on stock prices by examining cumulative changes from the beginning of the afternoon session. In the next section, I will examine the validity of this presumption using data.

## 4. Policy reaction function

The estimation methodology consists of two steps: calculation of the propensity score and estimation of the intervention effects. This section reports the first half of the above procedure. Specifically, I estimate the BoJ's policy reaction function $p(z_t, \psi)$ as a probit model to calculate the propensity score.

### 4.1. Estimation of the policy reaction function

To estimate the policy reaction function, I use a probit model. The dependent variable is $D_t$ and the covariates are $z_t$.

The specific covariates are $\Delta EP_{t-1}$, returns in stock prices in the morning session $\Delta EP_{morning,t}$, and returns in the closing price of the *Nikkei225* futures traded on the Chicago Mercantile Exchange (CME) from the closing price of the *Nikkei225* in the Tokyo market the previous day $\Delta EP_{CME,t-1}$. $\Delta EP_{CME,t-1}$ reflects the events that occurred at night in Tokyo local time. In addition, I use the returns in the exchange rate and crude oil prices of the previous day as other financial variables ($\Delta JPY_{t-1}$ and $\Delta Oil_{t-1}$), as well as news on major economic indicators, which are deviations of market expectations of major economic indicators from the actual results released in the morning.[24][25]

[18] The propensity score method belongs to a class of semi- and non-parametric approach. Because I parametrically estimate the propensity score, I call my case as semi-parametric. See also Angrist et al. (2013).

[19] Because the primary purpose of estimating the policy reaction function is to calculate the propensity score that takes values between zero and one, I use a saturated probit model. The data characteristics summarized in Table 1 provide supporting evidence for studying the binomial intervention decision, taking the amount of intervention per day as given.

[20] As suggested in Rosenbaum and Rubin (1983), potential changes in stock prices are orthogonal to interventions conditional on $p(z_t, \psi)$ if the CIA holds.

[21] Hoshino (2009) discusses the advantage of the propensity score method over the parametric approach in details.

[22] Lunceford and Davidian (2004) show that the asymptotic variance of $\hat{\theta}_l$ can be estimated by using the concept of M-estimator. The consistent variance estimator is given as follows: $\hat{\sigma}_l^2 \equiv \frac{1}{N^2}\sum_t \left\{ y_{t+l}\left[\frac{D_t}{\hat{p}_t} - \frac{1-D_t}{1-\hat{p}_t}\right] - \left(D_t - \hat{p}_t\right)\left[\frac{m_{1,l}(\chi_t,\xi_{1,l})}{\hat{p}_t} + \frac{m_{0,l}(\chi_t,\xi_{0,l})}{1-\hat{p}_t}\right] - \hat{\theta}_l \right\}^2$.

[23] It has been reported that the BoJ's intervention takes place when stock prices are falling during the morning session (e.g. "BOJ steps up ETF purchases as shares slump," *Wall Street Journal*, August 12, 2014. "https://www.wsj.com/articles/boj-steps-up-etf-purchases-as-shares-slump-1407830786")

[24] These major economic indicators include GDP growth ($\Delta Y$), CPI inflation ($\pi^{cpi}$), job opening rate ($Job$), industrial-production growth ($\Delta IP$), *Tankan* survey of business conditions for manufacturing and non-manufacturing firms ($S^m$ and $S^{nm}$). The market expectations are taken from the QUICK Monthly Survey. See the appendix for other data sources.

[25] I check that additional lags are statistically insignificant and do not help to improve the AUC statistics.

**Table 3**
Policy Reaction Function of the Probit Model: $p(z_t, \psi)$.

| | Subsample: *QQE 1* | | Subsample: *QQE 2* | | Subsample: *QQE 3* | |
|---|---|---|---|---|---|---|
| | (a) | (b) | (a) | (b) | (a) | (b) |
| $\Delta EP_{t-1}$ | −44.950*** | −40.465*** | 2.481 | 2.850 | −32.187** | −32.068** |
| | (10.580) | (9.904) | (7.965) | (7.893) | (13.422) | (13.335) |
| $\Delta EP_{morning,t}$ | −272.636*** | −266.239*** | −176.057*** | −173.956*** | −248.599*** | −244.779*** |
| | (33.037) | (31.951) | (18.632) | (18.179) | (34.917) | (34.584) |
| $\Delta EP_{CME,t-1}$ | −193.764*** | −192.366*** | −128.184*** | −125.808*** | −147.835*** | −146.930*** |
| | (25.552) | (24.892) | (15.394) | (14.960) | (22.684) | (22.600) |
| $\Delta Oil_{t-1}$ | 2.563 | 2.046 | 1.808*** | 1.779*** | 0.294 | 0.240 |
| | (1.869) | (1.799) | (0.454) | (0.443) | (1.259) | (1.240) |
| $\Delta JPY_{t-1}$ | 28.143 | 32.402 | 18.201 | 18.037 | 62.891*** | 63.600*** |
| | (26.834) | (26.312) | (18.826) | (18.519) | (19.360) | (19.307) |
| $\Delta Y - E[\Delta Y]$ | −0.023 | | −1.690 | | −0.558 | |
| | (2.289) | | (1.324) | | (5.399) | |
| $\pi^{cpi} - E[\pi^{cpi}]$ | −11.913 | | 3.001 | | 5.081 | |
| | (10.258) | | (6.741) | | (9.574) | |
| $Job - E[Job]$ | −12.855 | | −8.440 | | −2.868 | |
| | (10.816) | | (7.473) | | (7.120) | |
| $\Delta IP - E[\Delta IP]$ | −0.677 | | −0.801 | | 0.584 | |
| | (0.627) | | (0.666) | | (1.216) | |
| $S^m - E[S^m]$ | −0.946 | | 7.516 | | −1.692 | |
| | (3.854) | | (11.882) | | (4.165) | |
| $S^{nm} - E[S^{nm}]$ | −2.746 | | −0.089 | | 0.540 | |
| | (2.736) | | (4.743) | | (2.655) | |
| $N$ | 387 | 387 | 424 | 424 | 331 | 331 |
| *Log likelihood* | −92.425 | −95.871 | −138.610 | −142.091 | −121.928 | −123.027 |

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. $\Delta EP_{morning,t}$ refer to the returns in stock prices (*TOPIX*) in the morning session. $\Delta EP_{CME,t-1}$ is the return in the closing price of the *Nikkei225* futures traded on the Chicago Mercantile Exchange from the closing price of the *Nikkei225* in the Tokyo market the previous day. $\Delta JPY$ and $\Delta Oil$ represent the returns in the dollar-yen exchange rate and in crude oil prices on the NYMEX. The other independent variables are deviations of major macroeconomic variables from market expectations in the QUICK Monthly Survey on the *Nikkei Shinbun*. $\Delta Y$, $\pi_{cpi}$, $Job$, $\Delta IP$, $S^m$, and $S^{nm}$ stand for GDP growth rate, CPI inflation, job opening rate, growth of industrial production, and the *Tankan* survey of business conditions for manufacturing and non-manufacturing firms. The constant terms are omitted.

According to the estimation results in Table 3, the returns in stock prices during the morning session are statistically significant at the 1% level.[26] Because the coefficient is negative, I can conclude that the BoJ's trading desk is likely to intervene in the markets when stock prices fall in the morning.[27] In addition, the changes in stock prices at night are significantly negative in all subsamples, suggesting that the news in U.S. business hours also affect the trading desk's decision. It is interesting that oil prices and foreign exchange rates are significant in *QQE2* and *QQE3*, respectively, reflecting that the policy reaction function may be time-varying. At the same time, the BoJ's trading desk does not systematically correspond to market surprises about major economic indicators. Such information is deemed to be already reflected in stock prices in the morning session. Hereafter, I use specification (b) as a baseline model.

The significantly negative coefficient of stock-price changes in the morning session implies that the BoJ makes an intervention decision on the basis of the information available in the morning session. To explore this point in greater detail, I calculate the predictive power of the baseline model.

Table 4 summarizes the predictive power of the reaction functions in a single statistic, an AUC[28]. Specifically, the AUC takes the value of 1 when a probit function can predict interventions with perfect accuracy and 0.5 when a probit function can only predict interventions with accuracy comparable to a random predictor.[29] The AUCs of the baseline model in the second row of Table 4 exceed 0.9 in all subsamples, suggesting that probit functions predict interventions almost correctly with a probability of 90%–95%.[30] Once the stock price information in the morning session is omitted from the baseline model, the predictive power deteriorates considerably. The third row of Table 4 reports that the AUCs of specification without the stock price information in the morning session fall to 79%–83% in respective subsamples. It is

**Table 4**
Predictive Power of the Policy Reaction Function: AUC Statistics.

| | *QQE 1* | *QQE 2* | *QQE 3* |
|---|---|---|---|
| Baseline model | 0.951 | 0.929 | 0.901 |
| | (0.012) | (0.012) | (0.017) |
| Baseline model without $\Delta EP_{morning,t}$ | 0.827 | 0.798 | 0.791 |
| | (0.024) | (0.021) | (0.027) |

Note: Standard errors are in parentheses. The baseline model of the policy reaction function is specification (b) in Table 3.

[26] In Table 3, I only present the results using the *TOPIX* as a stock price index but the results using the *Nikkei 225* are similar. The results using the *TOPIX* are slightly better than those using the *Nikkei225* in terms of the fit to the data (log likelihood). Theoretically, it is not surprising because the BoJ have increased the relative share of TOPIX-linked ETFs especially in the *QQE2* and *QQE3* periods.

[27] Although these are omitted due to space limitations, changes in stock prices in the afternoon session are not significantly negative at the 10% level.

[28] The AUC stands for the area under the receiver operating characteristic (ROC) curve, which was first developed in communications engineering and has been applied in various fields including biometrics and machine learning. In the appendix, I present details of the ROC curve and the estimated ones behind the AUC statistics in Table 4.

[29] According to Hosmer and Lemeshow (2000), a probit function has acceptable predictive power when the AUC takes a value from 0.7 to 0.8, excellent predictive power when the AUC takes a value from 0.8 to 0.9, and outstanding predictive power when the AUC takes a value higher than 0.9.

[30] The propensity score method requires both observations on the days with interventions and on the days without interventions for each estimated propensity score. This prerequisite is called as a common support for the distributions of treatments and controls (Heckman et al., 1998). Despite the very high AUCs, I find considerable overlaps between the distributions of treatments (days with interventions) and controls (days without interventions), suggesting that the property of the first-stage estimation is satisfactory enough for the second-stage estimation of intervention effects.

**Table 5**
$p$-values of Conditional Independence Tests.

| | Macroeconomic covariates | | | | Lagged outcome variables | | |
|---|---|---|---|---|---|---|---|
| | $\Delta EP_{CME,t-1}$ | $\Delta EP_{morning,t}$ | $\Delta Oil_{t-1}$ | $\Delta JPY_{t-1}$ | $\Delta EP_{t-1}$ | $\Delta EP_{t-2}$ | $\Delta EP_{t-3}$ |
| *QQE 1* | 0.138 | 0.295 | 0.277 | 0.666 | 0.212 | 0.401 | 0.070* |
| *QQE 2* | 0.458 | 0.813 | 0.730 | 0.480 | 0.653 | 0.264 | 0.349 |
| *QQE 3* | 0.397 | 0.680 | 0.341 | 0.304 | 0.667 | 0.564 | 0.862 |

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. $p$-values for tests that policy interventions are independent of the variables listed, conditional on the propensity score.

reasonable to infer that the BoJ uses the information available during the morning session to make its decision.

### 4.2. Conditional independence test

It is important to diagnose whether the CIA holds when the propensity score based on the estimated probit model is in use. For this purpose, Angrist and Kuersteiner (2011) propose a semi-parametric conditional independence test. The null of the test is the conditional moment restriction: $E\left[D_t - p_t(z_t, \psi) \mid z_t\right] = 0$, which is implied by the CIA in (5).

Table 5 reports $p$-values of the test and shows that interventions are independent of the major predetermined covariates listed when conditioned on the estimated propensity score. This result indicates that the first-stage model suffices an important assumption for estimating the average effects of intervention.

## 5. Main results

This section reports the average intervention effects $\hat{\theta}_l$ and their state dependency. Further, I present the counterfactual simulations to see how much of an impact stock-market interventions have on stock prices.

### 5.1. Average intervention effects on stock prices

Table 6 reports the average effects of the BoJ's stock market interventions.[31,32] The upper panel (panel (a)) of Table 6 shows a clear contrast with sample averages by group in Table 2. Stock market interventions do not have statistically significant causal effects on stock prices in the *QQE 1* period. Further, in the *QQE 2* and *QQE 3* periods, interventions have statistically significant "positive" effects on stock prices on the day of intervention, although the effects do not last until the next day. Once self-selection bias is controlled, the significantly negative correlation between interventions and stock prices in Table 2 disappears.[33]

It should be noted that the results of this study are consistent with the efficient market hypothesis, which states that only unexpected policies have effects. The approach used in this study is not a simple comparison of the stock prices when the BOJ purchased with those when the BOJ did not purchase. Specifically, I estimate the propensity of whether the intervention (or non-intervention) is unexpected or not in the first step, and then, use it to estimate the policy effects in the second step. Therefore, the results presented in Table 6 are the effects of the unexpected intervention.

**Table 6**
Average Intervention Effects on *Stock Prices*.

| | *day 1* | *day 2* | *day 3* | *day 4* | *day 5* |
|---|---|---|---|---|---|
| *(a) propensity score estimation: baseline probit model* | | | | | |
| *QQE 1* | 0.110 | −0.364* | −0.205 | −0.201 | −0.258 |
| | (0.067) | (0.185) | (0.190) | (0.203) | (0.263) |
| *QQE 2* | 0.224*** | −0.348 | −0.123 | −0.067 | 0.362 |
| | (0.072) | (0.332) | (0.321) | (0.450) | (0.460) |
| *QQE 3* | 0.246*** | −0.014 | 0.242 | 0.197 | −0.051 |
| | (0.075) | (0.158) | (0.256) | (0.231) | (0.227) |
| *(b) propensity score estimation: IV probit model* | | | | | |
| *QQE 1* | 0.110 | −0.363* | −0.205 | −0.201 | −0.258 |
| | (0.067) | (0.185) | (0.190) | (0.203) | (0.263) |
| *QQE 2* | 0.226*** | −0.367 | −0.141 | −0.101 | 0.338 |
| | (0.072) | (0.337) | (0.316) | (0.438) | (0.451) |
| *QQE 3* | 0.251*** | −0.018 | 0.244 | 0.196 | −0.059 |
| | (0.078) | (0.158) | (0.258) | (0.232) | (0.225) |

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. The conditional mean controls: the lag of intervention, the growth rate of stock prices, the growth rate of exchange rate, and the growth rate of crude oil prices. Lags are up to three. The instrumental variables of an IV probit model are the growth rate of stock prices in the CME market the previous day, and the lagged growth rates of crude oil prices, exchange rates, and stock prices.

The lower panel (panel (b)) of Table 6 shows that the main results in panel (a) is robust to the timing assumption. In the panel (a) of Table 6, I presume that the BoJ's trading desk decides whether to intervene or not based on the stock prices in the morning session. To examine the robustness of results to this timing assumption, I reestimate the model using alternative specification. Specifically, I estimate the first-stage probit model using instrumental variables that are observed before the morning session starts. Then, I calculate the propensity score and estimate the second-stage average effects of the stock market intervention. The similar results in the panel (a) and (b) suggest that the simultaneity problem in the first-stage probit model is negligible.

Attentive readers might consider that the significant effect on Day 1 includes not only the demand pressure effect but also the announcement effect. However, it is not the case because the BoJ announces the intervention after the stock market is closed.

Why do interventions in stock markets have significant impacts on stock prices only in the latter subsamples: *QQE 2* and *QQE 3*? According to Fig. 1, the average purchases per day increased from 155.9 million yen to 348.5 million yen when the BoJ enhanced monetary easing and moved from *QQE 1* to *QQE 2*. In the *QQE 3*, the daily purchases was almost doubled again and increased to 712.5 million yen. A consideration of these policy developments leads to an interpretation: a significant effect can be raised for the first time by a large enough intervention.

Table 7 supports this interpretation. It reports the difference in the number of trading spikes between intervention days and no-intervention days after controlling for the self-selection bias. In this calculation, I define the trading spike as an increase of trading volume that exceeds 1/2 S.D. In addition, the difference is larger in the subsamples with a greater intervention per day. It reaches 0.973 in the *QQE 3* but it is only 0.399 in the *QQE 1*. Market participants may find it hard to recognize small interventions in real time.

At the same time, it should be noted that the intervention effect is a concave function of intervention amounts, i.e., while the amount of interventions is doubled from *QQE 2* to *QQE 3*, the impact of interventions in Table 6 is only 1.1 times or less. This result shows that the intervention effect is not a simple linear relationship even if interventions are large enough to be recognized.

[31] The AIPW estimator could be biased in the case of significantly high/low propensity scores because propensity scores are denominators in the average intervention effect in (9). Imbens (2004) recommends setting a cutoff between $\hat{p} \in [0.1, 0.9]$ and $\hat{p} \in [0.02, 0.98]$, depending on the sample size. Following this proposal, I set a cutoff at $\hat{p} \in [0.025, 0.975]$. I check its robustness to alternative cutoff points in the online appendix.

[32] I confirm that daily stock purchase is not correlated with the other open-market purchases of commercial papers, corporate bonds, government bonds, and treasury bills.

[33] Attentive readers may be concerned that the BoJ might inform authorized participants (APs) or market makers of individual ETFs in advance to minimize market disruptions caused by the market intervention. However, since the BoJ employs a trust bank as an agent and delegates the purchasing practice, the Bank does not have an opportunity to directly contact APs or market makers of individual ETFs.

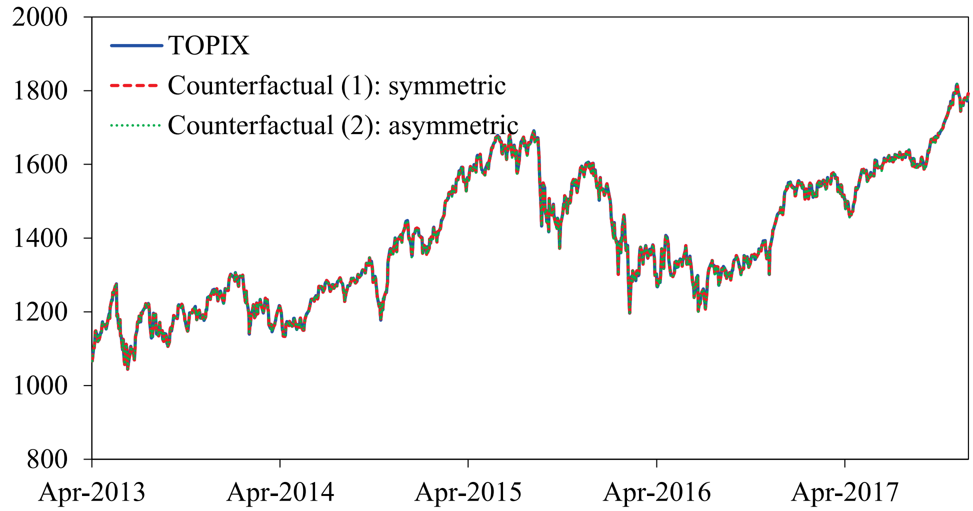


**Fig. 2.** Counterfactual Simulation of Policy Effects on Stock Prices (1).

**Table 7**
Differences in the Number of Trading Spikes: intervention days versus no-intervention days.

| | *QQE 1* | *QQE 2* | *QQE 3* |
|---|---|---|---|
| $E\left[N^{spike}(1)-N^{spike}(0)\mid z_t\right]$ | 0.399** | 0.720*** | 0.973*** |
| | (0.198) | (0.244) | (0.344) |
| Average number of spikes per day | 4.637 | 4.501 | 3.477 |

Note: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. $N^{spike}(d)$ is the number of spikes in case of $D_t=d$. A spike is the 1/2 S.D. percentage change of the *TOPIX* in a five minute window during the afternoon session.

**Table 8**
Average Intervention Effects on *Stock Prices* in a Market Downturn.

| | | *day 1* | *day 2* | *day 3* | *day 4* | *day 5* |
|---|---|---|---|---|---|---|
| *QQE 1* | *market downturn* | 0.103 | −0.423 | −0.304 | −0.417 | −0.412 |
| | *market upturn* | 0.116 | −0.306 | −0.109 | 0.009 | −0.108 |
| *QQE 2* | *market downturn* | 0.382*** | −0.424 | −0.135 | 0.551 | 0.885 |
| | *market upturn* | 0.089 | −0.318 | −0.147 | −0.673 | −0.140 |
| *QQE 3* | *market downturn* | 0.327*** | 0.189 | 0.468 | 0.480 | −0.065 |
| | *market upturn* | 0.181* | −0.199 | 0.061 | −0.044 | −0.033 |

Note: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Market downturn is defined as a day when the growth rate of stock prices is below the historical average. The conditional controls are same as those in Table 6.

### 5.2. State dependency of intervention effects

The next issue to consider is the state dependency of the demand pressure effect. I partition the data into "bullish" and "bearish" markets, on the basis of whether the growth rate of stock prices exceeds the average growth rate.

Table 8 reports the estimated average effects of intervention for each case; it shows that the effect of interventions is state-dependent.[34] In *QQE 1*, the effects are statistically insignificant as in the main case. In *QQE 2* and *QQE 3*, the BoJ's market interventions significantly and positively impact stock prices on day 1 when stock markets experience a downturn. On the contrary, during a market upturn, the effects are insignificant in all subsamples and lower than the effects during the market downturn, suggesting that stock purchases in a market downturn can more effectively support stock prices. The BoJ's stock purchasing program contributes to stabilizing stock markets. The semi-parametric approach flexibly accommodates state-dependent effects and shows that stock market interventions can have a different impact according to different market situations.

### 5.3. Counterfactual simulation

To evaluate the effects of the stock purchasing program, I conduct a counterfactual simulation of stock prices assuming that interventions did not take place during the *QQE* period. Because the estimated key coefficients in Tables 6 and 8 are the slopes of the demand curve, I can use them for the simulation. Hereafter, I conduct simulations using parameters that are estimated at 1% significance.

Specifically, I consider that the realized stock price on a day of intervention is overvalued to the percentage degree of the slope of the demand curve. Consequently, I can recover the hypothetical stock price by deducing the slope-of-demand-curve percent from the realized stock price. It should be noted that the cumulative impulse response functions in Tables 6 and 8 suggest that the intervention has no significant effects on stock prices after day 2. Accordingly, the intervention effects in this simulation are only temporary and do not last longer than one day.

Fig. 2 compares the actual stock prices in the solid line and the counterfactual forecasts without interventions in the dashed and broken lines; dashed lines correspond to the symmetric case in Table 6 and broken lines correspond to the asymmetric case in Table 8. It clearly suggests that the intervention effects of BoJ's stock purchasing program are weak and do not have a visible impact on stock prices. This result is different from that in Harada and Okimoto (2021), which suggests that the BoJ's stock purchasing program considerably affects the stock prices. The difference between the counterfactual simulation in Harada and Okimoto (2021) and that in my study comes from the time horizon of the estimated impulse responses. The former only estimates the instantaneous impact on stock prices at the day of intervention and implicitly assumes that the impact of interventions remains after day 2 and onward in simulation. In contrast, my study estimates the cumulative impulse responses from day 1 to day 5 and finds that impact of interventions is only significant at day 1 and does not significantly last after day 2. Based on this evidence, in the simulation of Fig. 2, I assume that the intervention does not have a cumulative effect.

Fig. 3 confirms my interpretation. This figure uses the estimated effect of day 1 in Tables 6 and 8 and simulates the stock prices assuming the effects cumulatively remain as in Harada and Okimoto (2021). The results are very similar to those of Harada and Okimoto (2021). The assumption of whether the effect remains cumulatively or not matters for the simulation results. In addition, the simulation in this figure also

[34] This state-dependency also holds when I use an IV probit model for the first-stage estimation.

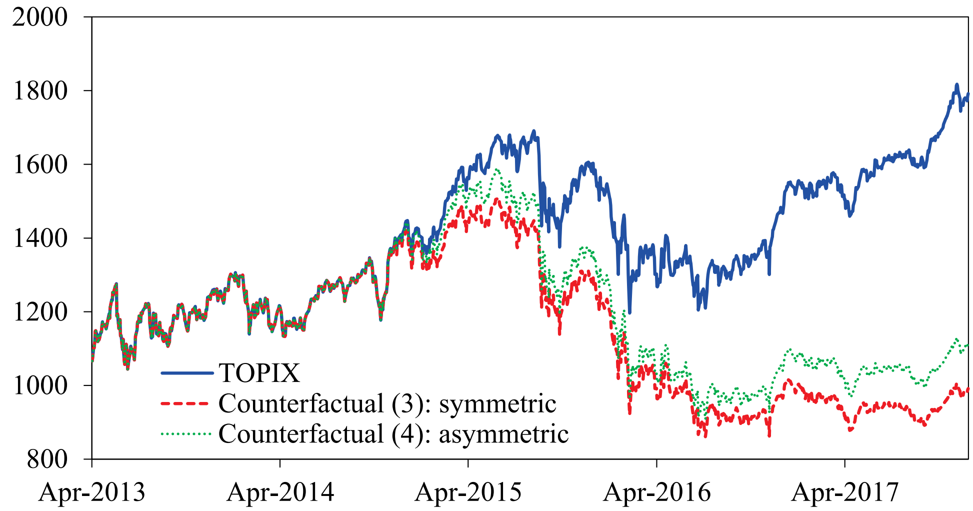


**Fig. 3.** Counterfactual Simulation of Policy Effects on Stock Prices (2). Note: In this simulation, I presume that the instantaneous effect at day 1 remains cumulatively.

illustrates that it is sufficient to purchase the ETF only when the stock market is in downturn.[35].

## 6. Conclusion

This study analyzes the causal effect of a central bank's intervention in stock markets. The analysis aims to provide empirical evidence of the stock purchasing program as an unconventional monetary policy measure. This evidence is valuable to policy makers who struggle with the effective lower bound of nominal interest rates and contemplate the next policy options. This study not only offers practical guidance but also contributes to the literature. It examines the demand pressure effect in stock markets by exploiting the natural experimental situation of policy interventions.

The semi-parametric approach employed in this study is flexible and can easily accommodate nonlinearities and state dependencies of the intervention effects without specifying the daily stock markets. However, the causal inference on this intervention is difficult because of the self-selective behavior of the trending desk. To alleviate these estimation biases, I use a propensity score method with stock price information in a single day.

The empirical results are summarized as follows. First, there is a demand pressure effect in stock markets if an intervention is large enough. Second, the intervention is effective only when markets experience downturns. Thus, the effects are state-dependent.

The above findings have certain policy implications. First, if the BoJ aims to affect stock prices,[36] it is sufficient to purchase the ETF only when stock prices fall considerably because interventions are effective only when markets are downturns. Further, the findings may also contain an implication for how asset purchasing programs are designed. In general, asset purchasing programs tend to commit to purchasing a fixed amount of assets. The BOJ's ETF purchasing program is no exception. Once committing to purchase a fixed amount of assets within a fixed time frame, central banks tie their own hands. Consequently, to fulfill the commitment, they are forced to purchase assets even during periods of market upturns. Therefore, if the policy effects are state-dependent, central banks should be cautious about committing to purchasing a fixed amount of assets within a fixed time frame.[37]

## Appendix A. Data source

The data used in the empirical analysis are summarized in the following Table.

| | Description | Source |
|---|---|---|
| $\Delta EP_{morning,NKY}$ | The percent changes of $Nikkei225$ in the morning session | Bloomberg |
| $\Delta EP_{morning,TPX}$ | The percent changes of $TOPIX$ in the morning session | Bloomberg |
| $\Delta EP_{CME}$ | The percent difference between $Nikkei225$ and the yen-based $Nikkei225$ futures in the Chicago Mercantile Exchanges | Bloomberg |
| $\Delta JPY$ | The percent change in dollar-yen exchange rate | Bloomberg |
| $\Delta Oil$ | The percent changes of crude oil prices in NYMEX | Bloomberg |
| $\Delta Y$ | The growth rate of GDP | Cabinet Office |
| $\pi_{cpi}$ | CPI inflation | Ministry of Internal Affairs and Communications |
| $Job$ | Job Opening ratio | Ministry of Health, Labour, and Welfare |
| $\Delta IP$ | The growth rate of Industrial Production | Ministry of Economy, Trade, and Industry |
| $S^m$ | *Tankan* business survey (Manufacture firms) | Bank of Japan |
| $S^{nm}$ | *Tankan* business survey (Non-manufacture firms) | Bank of Japan |

[35] As mentioned above, I use the statistically significant parameters for simulation. Thus, Counterfactual (2) in Fig. 2 and Counterfactual (4) in Fig. 3 reflect the interventions executed only in the market downturn.

[36] For an accurate description, it should be noted that the BoJ's official purpose of stock purchasing program is not to affect the stock prices but to reduce the risk premium.

[37] Recently, the BoJ changed the stock purchasing program to purchase the ETFs during only market downturns.

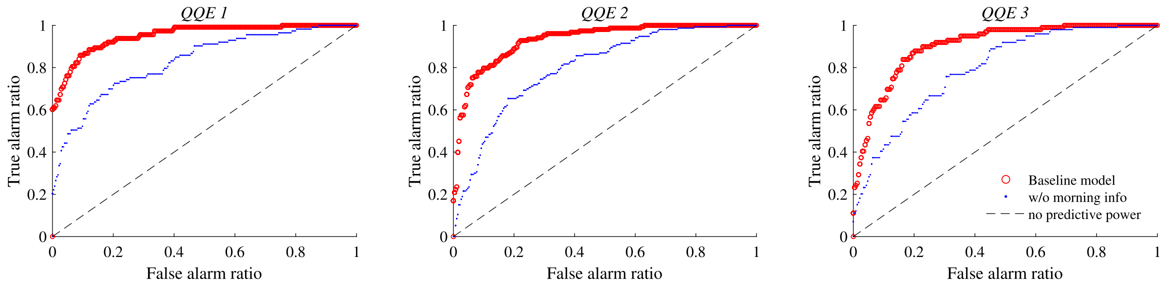


**Fig. 4.** Predictive Power of the Policy Reaction Function: ROC curves.

To calculate the number of trading spikes, we use the 1 min tick-by-tick data of stock prices (*TOPIX*), which is provided by the Tokyo Stock Exchange.

## Appendix B. AUC statistics and ROC curve

AUC statistic stands for the area under the receiver operating characteristic (ROC) curve, which can be used to illustrate the predictive power of probit functions. The vertical axis of the ROC graph represents the true alarm (true positive) ratio of how correctly the probit function predicts the intervention at a given cutoff value. The horizontal axis represents the false alarm (false positive) ratio of how incorrectly the probit function predicts the no-intervention at the same cutoff value. Each point on the ROC curve corresponds to a combination of these two ratios at various cutoff points. If a ROC curve sticks to the top side of the graph, a probit function classifies whether to intervene completely accurately. The AUC is 1 in this case. If a ROC curve is on the diagonal line of the graph, a probit function is equivalent to classifying whether to intervene completely at random. The AUC is 0.5 in this case. See Fawcett (2006) for details regarding the ROC curve.

Fig. 4 presents ROC curves, which corresponds to the AUCs in Table 4. In each subsample, the ROC curves of the baseline models are sufficiently far from the diagonal line, suggesting that the functions have satisfactory predictive power. However, Fig. 4 also shows that when I exclude the morning stock prices from the baseline model, the ROC curves considerably deviate from the ROC curves of the baseline models.

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