Discussion Paper, Series A, No.2018-322

Evaluating the Unconventional Monetary Policy in Stock Markets: A Semi-parametric Approach

Toyoichiro Shirota

March, 2018

Faculty of Economics and Business
Hokkaido University
Kita 9 Nishi 7, Kita-Ku, Sapporo 060-0809, JAPAN

Evaluating the Unconventional Monetary Policy in Stock Markets: A Semi-parametric Approach

Toyoichiro Shirota[†]

March, 2018

Abstract

This study analyzes the effect of a central bank's intervention in stock markets, while allowing for nonlinearities and state dependencies, using a semi-parametric approach. A causal inference on such intervention is difficult because of the self-selective behavior of central banks. To address these problems, we apply the propensity score method in a time series context, exploiting stock price information of a single day. We find that first, there are demand pressure effects in stock markets if an intervention is large enough. Second, the effects are state-dependent and stronger during market downturns. Finally, a central bank's interventions have a considerable impact on stock prices only when we take permanent demand pressure effects into consideration.

JEL classification: E52, E58, C14
Keywords: unconventional monetary policy; stock market intervention; demand pressure effect; semi-parametric approach; propensity score

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. To my knowledge, this study is one of the first attempts to examine the "causal" effects of daily stock market intervention, which is used as a monetary policy tool in normal times.[1]

[†]Hokkaido University, toyoichiro.shirota "at" econ.hokudai.ac.jp; Kita 9 Nishi 7, Kita-ku, Sapporo, Hokkaido, 060-0809, Japan. The author thanks the participants of the 4th IAAE Annual Conference, the 11th Joint Economics Symposium of the East Asian Universities, and the Asia-Pacific Conference on Economics and Finance for comments and suggestions. The author is also grateful to Ippei Fujiwara for helpful discussions and encouragement. This study was supported by JSPS KAKENHI Grant Number JP16H06587.

[1]Matsuki, Sugimoto and Satoma (2015) is one of the few studies. It reports that the stock purchasing program has a statistically significant impact on the stock price index, using a standard linear VAR model. Ide and Minami (2013) and Harada (2017) study the relationship between indivisual stock prices and market interventions.

To examine the intervention effects on aggregate stock prices, this study employs a semi-parametric approach, which does not require a particular specification of daily stock markets. Thus, it can flexibly deal with state dependencies (the effect is stronger in market downturns than in market upturns) and nonlinearities (e.g., a concave function of intervention amounts) of the effects.

The non-parametric identification of the causal effects 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 an 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.

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 intervention function of the BoJ's trading desk, we use the remaining policy variations to "re-randomize" days with intervention and days without it. We 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, Jorda and Kuersteiner (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.

This study 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. We exploit this opportunity as a natural experiment and attempt to identify the demand pressure effect in aggregate stock markets.[2][3]

[2]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, Isagawa and Fujiwara (2006). Garleanu, Pedersen and Poteshman (2009) estimate the demand pressure effects in derivatives markets.

[3]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 Hutchi-

An important feature of our setting is that the BoJ's operations were conducted consecutively in normal times over a relatively long period of more than 1,700 business days. Our setting is, therefore, not the one where the government temporarily intervenes in stock markets to counteract speculative attacks, as is common in the literature (e.g., Bhanot and Kadapakkam (2006)) or the one where the government sporadically intervenes in foreign-exchange rate markets. It is particularly better suited to measure the demand pressure effect in stock markets by isolating the effects of disruptions during the crisis and to consider the effectiveness of stock purchases as a regular monetary policy tool.

Another feature of this study is the identification of policy effects in high frequency, using daily and intra-daily data. The relation between conventional monetary policy and stock markets has been studied in high frequencies (e.g. Rigobon and Sack (2003) and Bernanke and Kuttner (2005)). Furthermore, recent studies such as Auerbach and Gorodnichenko (2016) and Nakamura and Steinsson (2013) examine the macroeconomic effects of fiscal and monetary policy in the high-frequency domain. Although the analysis of high-frequency data has a limitation in measuring the effects on major aggregate variables such as Gross Domestic Product (GDP), released once a quarter, it allows us to perform a clearer causal identification and to assess reactions of forward-looking financial variables. This work is related to studies on policy effects using daily or intra-daily data, with an emphasis on the identification of causal relationships.

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 effect is state-dependent and stronger in market downturns. Finally, the BoJ's interventions have a negligible impact on daily stock price changes but a considerable impact on stock prices when we take permanent demand pressure effects into consideration.

Section 2 provides an overview of the stock purchasing program. Section 3 presents the conceptual framework for the causal inference and our identification strategy. Section 4 reports estimation results and counterfactual simulations. Section 5 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.

son (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.

2.1 Overview of the stock purchasing program

In October 2010, the BoJ decided to start purchasing stock-based exchange-traded funds (ETFs),[4] 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.[5] 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. 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.[6]

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.[7] At that time, the target amount was 0.45 trillion yen. After the program was introduced, the BoJ raised the target four times.[8] On April 4, 2013, the Bank decided to adopt the QQE and announced that it would purchase ETFs 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

Figure 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. Figure 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)).

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

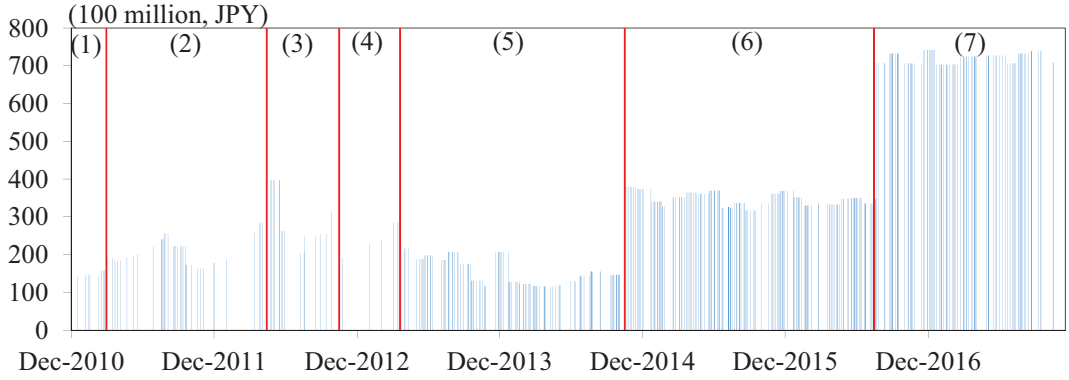
[5] As of 2017, all the *Nikkei225*-, *TOPIX*-, and *JPX400*-indexed ETFs listed on the Tokyo Stock Exchange are physical ETFs and not synthetic ones.

[6] 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.

[7] 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.

[8] 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.

Figure 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	436	1708	25.5	361.6	209.2
Dec. 15, 2010 - Nov. 30, 2017					
(I) *pre-QQE* period	71	566	12.5	230.2	68.5
Dec. 15, 2010 - Apr. 4, 2013					
Subsample (1): *pre-QQE 1*	10	59	16.9	149.9	8.0
Dec. 15, 2010 - Mar. 14, 2011					
Subsample (2): *pre-QQE 2*	38	278	13.7	213.0	36.7
Mar. 15, 2011 - Apr. 27, 2012					
Subsample (3): *pre-QQE 3*	16	126	12.7	306.3	76.5
May 1, 2012 - Oct. 30, 2012					
Subsample (4): *pre-QQE 4*	7	103	6.8	264.0	47.3
Oct. 31, 2012 - Apr. 4, 2013					
(II) *QQE* period	365	1142	32.0	387.2	217.7
Apr. 5, 2013 - Nov. 30, 2017					
Subsample (5): *QQE 1*	113	387	29.2	155.9	34.2
Apr. 5, 2013 - Oct. 31, 2014					
Subsample (6): *QQE 2*	154	426	36.2	348.5	17.3
Nov. 1, 2014 - Jul. 29, 2016					
Subsample (7): *QQE 3*	98	329	29.8	712.5	55.1
Aug. 1, 2016 - Nov. 30, 2017					

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

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, we 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.[9]

3 Causal Inference of Stock Market Interventions

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

$$\begin{aligned} \Delta EP_t &= \alpha \cdot I_t + \nu_{1,t}, \\ I_t &= -\beta \cdot \Delta EP_t + \nu_{2,t}, \end{aligned}$$

where ΔEP_t, and I_t are daily percentage changes in stock prices and intervention amounts, respectively. $\nu_{i\in\{1,2\},t}$ are *i.i.d.* stochastic shocks with standard deviations σ_{ν_i}. In this subsection, we 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 (α, β, σ_{ν_1}, and σ_{ν_2}) are fewer than the available moments of data (variances and a covariance of ΔEP_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 ΔEP_{t-1} and by restricting the coefficient of ΔEP_t to zero in the intervention function.[10] This assumption shares the spirit of the recursive identification in vector autoregression (VAR) models (e.g. Christiano, Eichenbaum and Evans (1996)).

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

[9]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.

[10]The timing assumption is not the only restriction used for identification. For example, Kearns and Rigobon (2005) uses a regime switching opportunity in the intervention policy of the foreign exchange markets for identification. Rigobon and Sack (2003) uses the heteroskedasticity of stock market returns to identify the conventional monetary policy effects.

markets, the intervention effects may be state-dependent and nonlinear. For example, the intervention effects may be asymmetric and stronger in market downturns as implied by Bhanot and Kadapakkam (2006) 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 parametric models to the examination of the daily stock market intervention. The semi-parametric 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, we 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 percentage changes 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.[11]

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 percentage changes of the Tokyo Stock Price Index (*TOPIX*).

Table 2 does not necessarily suggest that the stock purchasing program is counterproductive. 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

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

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. We need a causal inference to separate the true causal effects from self-selection biases.

3.2 Conceptual framework of our 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 semi-parametrically. Now, we define $\Delta EP_{t,l}$ as the percentage change in ΔEP_t between t and $t+l$.

Our 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 $D_t = d$.[12] 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 we can observe realized stock prices only in one state and cannot observe them in the parallel world.[13] Therefore, we will estimate the intervention effects on an average instead of the effects on individual observations.

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

Now, we can show why the differential of sample averages by group in Table 2 could be biased. The left-hand side of (2) is the differential of sample averages by group. The first term on the right-hand side of (2) 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.

$$\begin{aligned} E\left[\Delta EP_{t,l} \mid D_t = 1\right] &- E\left[\Delta EP_{t,l} \mid D_t = 0\right] \\ &= \underbrace{E\left[\Delta EP_{t,l}(1) \mid D_t = 1\right] - E\left[\Delta EP_{t,l}(0) \mid D_t = 1\right]}_{\text{Average intervention effects}} \\ &+ \underbrace{E\left[\Delta EP_{t,l}(0) \mid D_t = 1\right] - E\left[\Delta EP_{t,l}(0) \mid D_t = 0\right]}_{\text{Self-selection bias}} \end{aligned} \tag{2}$$

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 (2) will deviate from the true intervention effects.

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

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

To eliminate this self-selection bias, we 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:

$$\Delta EP_{t,l}(d) \perp D_t \mid z_t \ \ for\ all\ l > 0,\ d \in \{0, 1\}. \tag{3}$$

If the CIA holds, the average intervention effect in (1) 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, we 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. In estimation, the propensity score is modeled as a parametric probit model $P(D_t = 1 \mid z_t) = p(z_t, \psi)$ where ψ refers to the parameters.[14] Then, we can write the conditional expectations in the following manner[15]:

$$E\left[\Delta EP_{t,l} \mid D_t = 1, z_t\right] = E\left[\Delta EP_{t,l}(1) \mid z_t\right] p(z_t, \psi), \tag{4}$$

$$E\left[\Delta EP_{t,l} \mid D_t = 0, z_t\right] = E\left[\Delta EP_{t,l}(0) \mid z_t\right] \left[1 - p(z_t, \psi)\right]. \tag{5}$$

Integrating both (4) and (5) over z_t, we can express the average intervention effect as follows:

$$\theta_l = E\left[\Delta EP_{t,l}(1) - \Delta EP_{t,l}(0)\right] = E\left\{\Delta EP_{t,l}\left[\frac{D_t}{p(z_t, \psi)} - \frac{1 - D_t}{1 - p(z_t, \psi)}\right]\right\}. \tag{6}$$

Here, (6) is the inverse probability weighted (IPW) estimator(e.g. Imbens (2004)) , which divides interventions and no-interventions by their respective propensity scores. 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 us to estimate implicit intervention shocks that are considered to be surprises. If the policy intervention function can accurately predict interventions, (6) 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 our implementation, we estimate the sample version of the average intervention effects as follows:

$$\hat{\theta}_l = \frac{1}{N}\sum_t \left\{ \underbrace{\Delta EP_{t,l}\left[\frac{D_t}{\hat{p}_t} - \frac{1 - D_t}{1 - \hat{p}_t}\right]}_{IPW\ term} - \underbrace{(D_t - \hat{p}_t)\left[\frac{m_{1,l}(\chi_t, \xi_{1,l})}{\hat{p}_t} + \frac{m_{0,l}(\chi_t, \xi_{0,l})}{1 - \hat{p}_t}\right]}_{Augmentation\ term} \right\}, \tag{7}$$

where $\hat{p}_t$ is the projected probability of intervention from the policy intervention function, N is the number of observations, and $m_d(\chi_t, \xi_{d,l})$ the conditional mean from the regression

[14]Because the primary purpose of estimating the policy intervention function is to calculate the propensity score that takes values between zero and one, we 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.

[15]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.

of $\Delta EP_{t,l}$ on the predetermined covariates χ_t with parameters $\xi_{d,l}$ for $d = \{0, 1\}$. χ_t consist of z_t and lags of D_t and ΔEP_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)). (7) is called an augmented inverse propensity weighted (AIPW) estimator.[16]

The estimator in (7) helps to alleviate the problem specific to an application in a time-series context. Time series data tend to be serially correlated. In our 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 our 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, we 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 15:30 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, we postulate that the BoJ's trading desk decides whether to intervene based on the information obtained during the morning session.[17] Accordingly, we will measure the impact of intervention on stock prices by examining cumulative changes from the beginning of the afternoon session. In the next section, we will examine the validity of this presumption using data.

4 Empirical Assessments

In this section, we first estimate a policy intervention function $p(z_t, \psi)$ and calculate the second stage average intervention effects $\hat{\theta}_l$ semi-parametrically, on the basis of the propensity scores. The policy intervention function and average intervention effects are calculated for subsamples *QQE 1*, *QQE 2*, and *QQE 3*. In addition, we estimate the intervention effects parametrically without relying on the timing assumption. Finally, we

[16]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:
$\hat{\sigma}_l^2 \equiv \frac{1}{N^2} \sum_t \left\{ y_{t+l} \left[\frac{D_t}{\hat{p}_t} - \frac{1-D_t}{1-\hat{p}_t} \right] - (D_t - \hat{p}_t) \left[\frac{m_{1,l}(\chi_t, \xi_{1,l})}{\hat{p}_t} + \frac{m_{0,l}(\chi_t, \xi_{0,l})}{1-\hat{p}_t} \right] - \hat{\theta}_l \right\}^2$.

[17]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. "http://www.wsj.com/articles/boj-steps-up-etf-purchases-as-shares-slump-1407830786")

present the counterfactual simulations to see how much of an impact stock-market interventions have on stock prices.

4.1 Policy intervention function

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

The specific covariates are ΔEP_{t-1}, percentage changes in stock prices in the morning session $\Delta EP_{morning,t}$, and percentage changes 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, we use the percentage changes in the exchange rate and crude oil prices of the previous day as other financial variables (ΔJPY_{t-1} and ΔOil_{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.[18]

According to the estimation results in Table 3, the changes in stock prices during the morning session are statistically significant at the 1% level.[19] Because the coefficient is negative, we can conclude that the BoJ's trading desk is likely to intervene in the markets when stock prices fall in the morning.[20] 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. Market surprises about major economic indicators are not significant because such information is deemed to be already reflected in stock prices in the morning session. Hereafter, we 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, we calculate the predictive power of the baseline model.

Table 4 summarizes the predictive power of the intervention functions in a single statistic, an AUC[21]. 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

[18]These major economic indicators include GDP growth (ΔY), CPI inflation (π^{cpi}), job opening rate (Job), industrial-production growth (ΔIP), *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 online appendix for other data sources.

[19]In Table 3, we 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 log likelihood.

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

[21]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, we present details of the ROC curve and the estimated ones behind the AUC statistics in Table 4.

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

	Subsample: *QQE 1*		Subsample: *QQE 2*		Subsample: *QQE 3*	
	(a)	(b)	(a)	(b)	(a)	(b)
ΔEP_{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)
ΔOil_{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)
ΔJPY_{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 percentage changes in stock prices (*TOPIX*) in the morning session. $\Delta EP_{CME,t-1}$ is the percentage change 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. ΔJPY and ΔOil represents the percentage change 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*. ΔY, π_{cpi}, Job, ΔIP, S^m, and S^n 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.

Table 4: Predictive Power of the Policy Intervention 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 intervention function is specification (b) in Table 3.

predict interventions with accuracy comparable to a random predictor.[22] The AUCs of our 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%.[23] 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 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 (3).

Table 5: p-values of Conditional Independence Tests

	Macroeconomic covariates				*Lagged outcome variables*		
	$\Delta EP_{CME,t-1}$	$\Delta EP_{morning,t}$	ΔOil_{t-1}	ΔJPY_{t-1}	ΔEP_{t-1}	ΔEP_{t-2}	ΔEP_{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.

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.

[22] 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.

[23] 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, Ichimura, Smith and Todd (1998)). Despite the very high AUCs, we 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.

4.3 Average intervention effects on stock prices

Table 6 reports the average effects of the BoJ's stock market interventions.[24][25] To see the ramifications of our timing assumption, the Table presents the results on the basis of not only the baseline probit model (the upper panel (a)) but also an instrumental vairable (IV) probit model (the lower panel (b)), which presumes that intervention decisions and the morning stock prices can be endogenously determined.

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.

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.[26] The similar re-

[24]The (A)IPW estimator could be biased in the case of significantly high/low propensity scores because propensity scores are denominators in the average intervention effect in (7). 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, we set a cutoff at $\hat{p} \in [0.025, 0.975]$. We check its robustness to alternative cutoff points in the online appendix.

[25]We check the independence of daily stock purchases from the other open-market purchases of commercial papers, corporate bonds, government bonds, treasury bills, and J-REIT.

[26]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.

sults in the panel (a) and (b) suggest that the simultaneity problem in the first-stage probit model is negligible.

Why do interventions in stock markets have significant impacts on stock prices only in the latter subsamples: *QQE 2* and *QQE 3*? According to Figure 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 using the propensity score method. Trading spikes are more numerous in intervention days. 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. The mechanism behind the intervention impact on aggregate stock prices may be the information effect even in normal times.

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.

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.

4.4 State dependency of intervention effects

The next issue to consider is the state dependency of the demand pressure effect. We 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.[27] In *QQE 1*, the effects are statistically insignificant as in the main case. In *QQE 2* and *QQE 3*, the BoJ's market interventions

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

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.

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. Our semi-parametric approach flexibly accommodates state-dependent effects and shows that stock market interventions can have a different impact according to different market situations.

4.5 Identification without a timing assumption

For robustness analysis, we estimate the intervention effects with different approaches, as in Kearns and Rigobon (2005), which analyses the daily effects of foreign exchange market interventions without relying on a specific timing assumption. The parametric approach used by them is different from our semi-parametric approach in that it requires a linear and detailed specification of stock markets. Therefore, these two approaches can be considered complementary. The following is the system of equations for estimation.

$$\Delta EP_t = const_{ep} + \alpha I_t + \gamma_1 z_t + \nu_{1,t}, \tag{8}$$

$$I_t^* = const_i - \beta \Delta EP_t + \gamma_2 z_t + \nu_{2,t}, \tag{9}$$

$$I_t = \begin{cases} D\left(I_t^* > \bar{I}\right) \cdot \bar{I}^{qqe1} & t < \hat{t}_2, \\ D\left(I_t^* > \bar{I}\right) \cdot \bar{I}^{qqe2} & \hat{t}_2 \leq t < \hat{t}_3, \\ D\left(I_t^* > \bar{I}\right) \cdot \bar{I}^{qqe3} & \hat{t}_3 \leq t, \end{cases} \tag{10}$$

where I_t and I_t^* are the actual intervention and the latent variable that represents the likelihood of intervention, respectively. $\nu_{i\in\{1,2\},t}$ represent stock price shocks and policy shocks, respectively. z_t is the set of covariates, $D(\cdot)$ is the indicator function that takes zero or one, $const_{ep}$, $const_i$, $\alpha, \beta, \gamma_1, \gamma_2, \bar{I}, \bar{I}^{qqe1}, \bar{I}^{qqe2}$, and $\bar{I}^{qqe3}$ are parameters. $\hat{t}_2$ and $\hat{t}_3$ represent the beginning of *QQE 2* and *QQE 3*, respectively. We presume that shocks are *i.i.d.*, with mean zero and variances $\sigma^2_{\nu 1}$ and $\sigma^2_{\nu 2}$.

(8) is the function of stock prices. (9) determines the shadow intervention. If I_t^* hits the threshold value $\bar{I}$, the BoJ will intervene the market. (10) represents this decision function of BoJ's trading desk. The estimated effect in *QQE i* is $\alpha \cdot \bar{I}^{qqei}$ for $i = \{1, 2, 3\}$.

As shown in Section 3, two equation models of the stock prices and market intervention tend to be underidentified because the number of parameters is less than the number of available moment conditions. However, owning to policy changes, we can increase the number of available moments by calculating the moment conditions for each regime. In addition, if we restrict some parameters,[28] the model can be identified. This type of identification through policy changes is first developed by Kearns and Rigobon (2005). The parameters are estimated by using the simulated method of moments. See the online appendix for the detailed estimation procedure.

Table 9 reports that the parameters and intervention effects are significantly estimated. The intervention amounts in each regime $\overline{I}^{qqei}$ are consistent with the sample averages summarized in Table 1. The impact coefficient of a unit intervention α is 0.465. A positive β reflects the self-selective intervention pattern of the central bank.

The estimated effects, $\alpha \cdot \overline{I}^{qqei}$, are comparable to the day-1's average intervention effects in Table 6. The effects estimated by the parametric and semi-parametric approaches are quite close. The timing assumption adopted in the semi-parametric analysis seems to be acceptable.

Looking closely at the difference between the two estimates, we find that the effects estimated by the parametric approach are slightly smaller than those estimated by the semi-parametric approach in *QQE 2* but the former is slightly larger than the latter in *QQE 3*. These differences are considered to reflect that the parametric approach cannot capture nonlinearities of the effect because it presumes invariance α throughout the *QQE* period.

Table 9: Estimated Intervention Effects by Simulated Method Moments

	Estmated effects: $\alpha \cdot \overline{I}^{qqei}$			Selected coefficients				
	QQE 1	*QQE 2*	*QQE 3*	α	β	$\overline{I}^{qqe1}$	$\overline{I}^{qqe2}$	$\overline{I}^{qqe3}$
Coefficient	0.073	0.163	0.333	0.465	0.236	0.157	0.351	0.717
S.E.	(0.032)	(0.072)	(0.148)	(0.201)	(0.053)	(0.000)	-	-

4.6 Counterfactual simulation

To evaluate the effects of the stock purchasing program, we conduct a counterfactual simulation of stock prices assuming that interventions did not take place during the *QQE* period.

The simulation covers two cases. In one, we calculate hypothetical stock prices with only temporary demand pressure effects. In the other, we calculate hypothetical stock prices with temporary and permanent demand pressure effects. We assume that the permanent demand pressure effects, which arise from the increased demand, are immediately

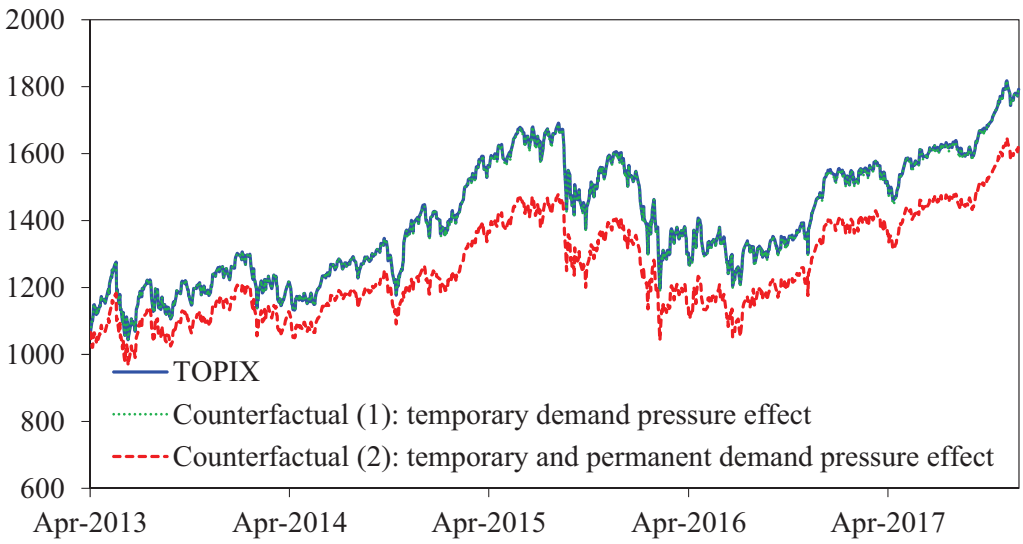
[28] We assume that the average amount of interventions in each regime is proportional to historical averages. Specifically, we estimate $\overline{I}^{qqe1}$ but calibrate $\overline{I}^{qqe2}$ and $\overline{I}^{qqe3}$ as follows: $\overline{I}^{qqe2} = \overline{I}^{qqe1} \times (\frac{1}{\hat{t}_3-\hat{t}_2}\sum_{t=\hat{t}_2}^{\hat{t}_3-1} I_t / \frac{1}{\hat{t}_2-\hat{t}_1}\sum_{t=\hat{t}_1}^{\hat{t}_2-1} I_t)$ and $\overline{I}^{qqe3} = \overline{I}^{qqe1} \times (\frac{1}{\hat{t}_e-\hat{t}_3+1}\sum_{t=\hat{t}_3}^{\hat{t}_e} I_t / \frac{1}{\hat{t}_2-\hat{t}_1}\sum_{t=\hat{t}_1}^{\hat{t}_2-1} I_t)$ where $\hat{t}_e$ is the end of observations.

reflected in stock prices when the policy schemes (*QQE 1*, *QQE 2*, and *QQE 3*) are announced.

The other assumptions are as follows. First, for each subsample, market participants believe that stock purchases will continue for (at the least) two years. Second, market participants believe that the central bank will hold the acquired stocks for an extended period. This assumption is necessary for a permanent demand pressure effect to arise. Finally, the size of the marginal demand-curve shift is fixed and taken from the Table 6.

Figure 2 compares the actual stock prices and the counterfactual forecasts without interventions. It clearly suggests that the temporary demand pressure effects of BoJ's stock purchasing program are weak and do not have a visible impact on stock prices. However, we take the permanent demand pressure effects into account, the stock market intervention show a sizable and economically significant impact on stock prices. The effect is approximately 7.5 percent at the timing of the introduction of *QQE 3*. Borrowing the impact coefficient of conventional monetary policy on stock prices from Bernanke and Kuttner (2005), the cumulative effect of stock purchasing program is almost equivalent to 1.9 percent cuts of policy rates.[29]

Figure 2: Counterfactual Simulation of Policy Effects on Stock Prices



5 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

[29]Bernanke and Kuttner (2005) find that an unanticipated 0.25% cut in policy rates is associated with a 1% increase in aggregate stock prices.

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, we 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. Finally, a central bank's interventions have a considerable impact on stock prices only when permanent price pressure effects are taken into consideration.

References

Amihud, Yakov and Haim Mendelson, "Asset pricing and the bid-ask spread," *Journal of Financial Economics*, December 1986, *17* (2), 223–249.

Angrist, Joshua D. and Guido M. Kuersteiner, "Causal Effects of Monetary Shocks: Semiparametric Conditional Independence Tests with a Multinomial Propensity Score," *The Review of Economics and Statistics*, August 2011, *93* (3), 725–747.

, Oscar Jorda, and Guido Kuersteiner, "Semiparametric Estimates of Monetary Policy Effects: String Theory Revisited," NBER Working Papers 19355, National Bureau of Economic Research, Inc August 2013.

Auerbach, Alan J and Yuriy Gorodnichenko, "Effects of Fiscal Shocks in a Globalized World," *IMF Economic Review*, May 2016, *64* (1), 177–215.

Bank of Japan, "Comprehensive Monetary Easing," October 2010.

Beneish, Messod D and Robert E Whaley, " An Anatomy of the S&P Game: The Effects of Changing the Rules," *Journal of Finance*, December 1996, *51* (5), 1909–30.

Bernanke, Ben S. and Kenneth N. Kuttner, "What Explains the Stock Market's Reaction to Federal Reserve Policy?," *The Journal of Finance*, 2005, *60* (3), 1221–1257.

Bhanot, Karan and Palani-Rajan Kadapakkam, "Anatomy of a government intervention in index stocks: Price pressure or information effects?," *The Journal of Business*, 2006, *79* (2), 963–986.

Christiano, Lawrence, Martin Eichenbaum, and Charles Evans, "The Effects of Monetary Policy Shocks: Evidence from the Flow of Funds," *The Review of Economics and Statistics*, 1996, *78* (1), 16–34.

Dominguez, Kathryn M. E., "The market microstructure of central bank intervention," *Journal of International Economics*, January 2003, *59* (1), 25–45.

Dominguez, Kathryn M.E., "When do central bank interventions influence intra-daily and longer-term exchange rate movements?," *Journal of International Money and Finance*, November 2006, *25* (7), 1051–1071.

D'Amico, Stefania and Thomas B. King, "Flow and stock effects of large-scale treasury purchases: Evidence on the importance of local supply," *Journal of Financial Economics*, 2013, *108* (2), 425–448.

Fatum, Rasmus and Michael M. Hutchison, "Is sterilised foreign exchange intervention effective after all? an event study approach," *Economic Journal*, April 2003, *113* (487), 390–411.

Fawcett, Tom, "Introduction to ROC analysis," *Pattern Recognition Letters*, June 2006, *27* (8), 861–874.

Fischer, Andreas M and Mathias Zurlinden, "Exchange Rate Effects of Central Bank Interventions: An Analysis of Transaction Prices," *Economic Journal*, October 1999, *109* (458), 662–676.

Garleanu, Nicolae, Lasse Heje Pedersen, and Allen M. Poteshman, "Demand-Based Option Pricing," *The Review of Financial Studies*, 2009, *22* (10), 4259–4299.

Harada, Kimie, "Nichigin no ETF kaiireseisaku to kobetsumeigara heikinkabuka no yugami (BoJ's ETF Purchasing Policy and distortions in average individual stock prices)," *Shoken Review*, 2017, *55* (1).

Harris, Lawrence and Eitan Gurel, "Price and volume effects associated with changes in the S&P 500 list: New evidence for the existence of price pressures," *The Journal of Finance*, 1986, *41* (4), 815–829.

Heckman, James, Hidehiko Ichimura, Jeffrey Smith, and Petra Todd, "Characterizing Selection Bias Using Experimental Data," *Econometrica*, September 1998, *66* (5), 1017–1098.

Holland, Paul W., "Statistics and Causal Inference," *Journal of the American Statistical Association*, December 1986, *81* (396), 945–960.

Hosmer, David W and Stanley Lemeshow, *Applied Logistic Regression, Second Edition*, Wiley Online Library, 2000.

Ide, Shingo and Shotaro Minami, "Nichigin no ETFkaiire ga shijowoyugameteiru ha hontouka? –genbutsukabusijou ni oyobosu eikyonokousatsu(Is it true that the BoJ's ETF Purchasing distorts the stock market? –A Study of its Effects on Current Stock Markets)," *Gekkan Shihon Shijo*, 2013, *335*.

Imbens, Guido W., "Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review," *The Review of Economics and Statistics*, February 2004, *86* (1), 4–29.

Jorda, Oscar and Alan M. Taylor, "The Time for Austerity: Estimating the Average Treatment Effect of Fiscal Policy," *Economic Journal*, 02 2016, *126* (590), 219–255.

Kandrac, John and Bernd Schlusche, "Flow effects of large-scale asset purchases," *Economics Letters*, 2013, *121* (2), 330–335.

Kearns, Jonathan and Roberto Rigobon, "Identifying the efficacy of central bank interventions: evidence from Australia and Japan," *Journal of International Economics*, May 2005, *66* (1), 31–48.

Lunceford, Jared K and Marie Davidian, "Stratification and weighting via the propensity score in estimation of causal treatment effects: a comparative study," *Statistics in medicine*, 2004, *23* (19), 2937–2960.

Lynch, Anthony W and Richard R Mendenhall, "New Evidence on Stock Price Effects Associated with Changes in the S&P 500 Index," *The Journal of Business*, July 1997, *70* (3), 351–83.

Matsuki, Takashi, Kimiko Sugimoto, and Katsuhiko Satoma, "Effects of the Bank of Japan ' s current quantitative and qualitative easing," *Economics Letters*, 2015, *133* (C), 112–116.

Meaning, Jack and Feng Zhu, "The impact of recent central bank asset purchase programmes," *BIS Quarterly Review*, December 2011.

Nakamura, Emi and Jon Steinsson, "High Frequency Identification of Monetary Non-Neutrality: The Information Effect," NBER Working Papers 19260, National Bureau of Economic Research, Inc July 2013.

Okada, Katsuhiko, Nobuyuki Isagawa, and Kenya Fujiwara, "Addition to the Nikkei 225 Index and Japanese market response: Temporary demand effect of index arbitrageurs," *Pacific-Basin Finance Journal*, 2006, *14* (4), 395–409.

Rigobon, Roberto and Brian Sack, "Measuring the reaction of monetary policy to the stock market," *Quarterly Journal of Economics*, May 2003, *118* (2), 639–669.

Rosenbaum, Paul R and Donald B Rubin, "The central role of the propensity score in observational studies for causal effects," *Biometrika*, 1983, *70* (1), 41–55.

Shleifer, Andrei and Robert W Vishny, " The Limits of Arbitrage," *Journal of Finance*, March 1997, *52* (1), 35–55.

Stoll, Hans R, "The Supply of Dealer Services in Securities Markets," *Journal of Finance*, September 1978, *33* (4), 1133–51.

Taylor, Mark P. and Lucio Sarno, "Official Intervention in the Foreign Exchange Market: Is It Effective and, If So, How Does It Work?," *Journal of Economic Literature*, September 2001, *39* (3), 839–868.

Williams, John, "Lessons from the financial crisis for unconventional monetary policy," Speech 125, Federal Reserve Bank of San Francisco 2013.

Wooldridge, Jeffrey M, *Econometric analysis of cross section and panel data*, MIT press, 2010.

Wurgler, Jeffrey and Ekaterina Zhuravskaya, "Does Arbitrage Flatten Demand Curves for Stocks?," *The Journal of Business*, October 2002, *75* (4), 583–608.

A 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.

Figure 3 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, Figure 3 also shows that when we exclude the morning stock prices from the baseline model, the ROC curves considerably deviate from the ROC curves of the baseline models.

Figure 3: Predictive Power of the Policy Intervention Function: ROC curves