CENTRAL BANK POLICY ANNOUNCEMENTS AND CHANGES IN TRADING BEHAVIOR: EVIDENCE FROM BOND FUTURES HIGH FREQUENCY PRICE DATA*

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Abstract

We present a theoretical model to explain how financial traders incorporate public and private information into security prices. One of the remarkable features of the model is its ability to identify simultaneously when surprising public information arrived and how large an impact it had on the market. By applying the model to the tick-by-tick data on Japanese bond futures prices, we show that the Bank of Japan's introduction of quantitative and qualitative monetary easing was one of the most surprising episodes during the period from 2005 to 2016. We also study the sensitivity of Japanese bond futures markets to new information. The analysis shows that the sensitivity to the Bank's announcements has strengthened since the introduction of the negative interest rate policy, whereas the sensitivity to economic indicators and surveys has weakened substantially.

Keywords: Central bank; Government bond futures; Herding behavior; Information; Market microstructure; Policy announcements

JEL classification: C14, D40, D83, E58, G12, G14

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1. INTRODUCTION

Since the 1990s, the Bank of Japan (BOJ) has introduced innovative monetary policy measures to achieve economic and financial stability in Japan. Particularly since 2013, under the command of Governor Kuroda, the BOJ made four large policy changes to combat long-lasting deflation and to raise inflation rates to its target rate of two percent: quantitative and qualitative monetary easing (QQE I) on April 4, 2013; its expansion (QQE II) on October 31, 2014; the introduction of the negative interest rate (NIR) policy on January 29, 2016; and the launching of yield curve control (YCC) on September 21, 2016 (see Bank of Japan, 2013, 2014, 2016a, 2016b for the related statements). A common strategy taken in these policies is to lower and stabilize bond yields, particularly those on long-term bonds, around an appropriate level through various policy measures such as large-scale purchases of government bonds. These policies had a substantial impact on financial markets. In particular, the impact of the introduction of quantitative and qualitative monetary easing was so large that the circuit breakers were triggered twice in the bond futures market on April 5, 2013.

The central bank's controllability of bond yields depends on its ability to communicate with market participants. Good communication is an essential part of good monetary policy. Particularly in recent years, with interest rates very low, central banks in advanced countries give a substantial role to communication tools such as forward guidance (see, e.g., Blinder et al., 2008). A lack of communication is often a cause of surprise in financial markets. In standard macroeconomics, surprises are thought of as something central banks should avoid. Surprises damage the credibility of the central bank. Without credibility, markets do not respond to the announcements of the central bank as expected. Surprises, however, are sometimes unavoidable, particularly when the central bank introduces innovative policy measures. Even in that case, the central bank should take an appropriate communication strategy that enables market participants to understand the central bank's policy intention correctly and quickly.

In this paper, we present an analytical framework to investigate surprises in financial markets. We define "surprises" as unexpected components of public information provided to traders. To identify and quantify surprises, we exploit Kamada and Miura's (2014) bond market model. One of the notable features of their model is its double-layered structure of information, consisting of public and private information.[1] Private information differs from public information in that anyone can freely access public information, but not private information. To make profits, traders attempt to predict the impact of public information before it is released. For that purpose, they gather private information and take a position based on it. This makes asset prices rise and fall before new public information is released. In the model, the volatility of asset prices reflects (i) traders' expected impact of public information on asset prices and (ii) the usefulness of private information to predict the impact of public information. Once public information is released, asset prices adjust to it. Surprises occur if asset prices go beyond traders' expectations.

For empirical analyses, we use tick-by-tick data to identify and quantify surprises in financial markets. New information—policy announcements, economic data, various surveys, economic reports written by influential economists, and all kinds of rumors—is coming every second, and sometimes even every millisecond. Some information is irrelevant for trading purposes, but some has long-lasting effects on asset prices. Daily or more infrequent data are sometimes not so informative as to capture psychological subtlety in financial markets. For this reason, we use tick-by-tick data to see behavioral changes in each market. Government bond markets are particularly important for us to see how traders' response to the BOJ's policy announcements has changed recently. We have a particular interest in the following question: Is there any behavioral change observed in government bond futures markets after the introduction of new policy measures in Japan?

There are a number of research papers about the impacts of monetary policy on financial markets. A classical approach is based on observation of daily changes in interest rates and/or interest rate futures prices around policy announcements. For

[1] The double-layered structure of public and private information is in line with the spirit of Morris and Shin (2002), who examine the welfare effect of dissemination of public information.

instance, Kuttner (2001), Cochrane and Piazzesi (2002), and Rigobon and Sack (2004) use the daily data on the interest rate (futures) to investigate the impact of U.S. monetary policy. Honda and Kuroki (2006) examine policy impacts on Japanese financial markets from 1989 to 2001, based on euro–yen futures daily data. Many event studies using tick-by-tick data have recently appeared, including Fleming and Piazzesi (2005), Andersson (2010), Nakamura and Steinsson (2018), and so on.

In contrast to the existing literature, the virtues of our framework are twofold. First, we use price data to search for surprising events during the sample period. In most of the preceding studies, even those using high frequency data, the authors limit their interest to some specific events and monitor the subsequent price developments within a prefixed time interval, say 30 minutes, immediately after those events. By using this approach, however, many surprising events would escape our attention. In contrast, a new framework allows us to use price data to identify exactly when surprises occurred in the market. Second, our framework is applicable to any markets for which tick-by-tick data are available. In order to distinguish what is expected and what is surprising, we do not need any kind of forward-looking data, such as futures and options data, analysts' forecast surveys, and latent variables estimations. Instead, everything is extracted only from the historical record of actual price movements in a completely non-parametric way.

The remainder of this paper is organized as follows. Section 2 presents a theoretical model to capture surprises in financial markets and conducts simulations to demonstrate the characteristics of the model. Section 3 proposes an empirical strategy used to identify and quantify traders' surprises in the tick-by-tick data on Japanese government bond futures prices and discusses how market behavior has changed since the BOJ's introduction of new monetary policy measures. Section 4 concludes.

2. THE MODEL

2.1. Public and private information in financial markets

Nirei, Takaoka, and Watanabe (2013) created a model to describe herding behavior in stock markets.[2] Their model has two ingredients: (i) traders gather private information on future stock prices before making investment decisions; (ii) traders make inferences about other traders' private information based on their observations of stock prices. When traders see stock prices going up, they infer that someone has information which indicates that stock prices will rise in the future. This inference creates additional demand for stocks and pushes up stock prices further. When stock prices are falling, traders make the opposite inference and sell stocks, resulting in further declines in stock prices. Due to this herding behavior among traders, stock prices become volatile and fat-tail distributions are created.

The model of Nirei, Takaoka, and Watanabe (2013) has limitations, however: Especially, it deals only with private information, not with public information. All traders have equal access to public information, but only some traders are allowed to access private information. The empirical literature on market microstructure shows that public information has a strong impact on price formation, particularly in bond markets (see, e.g., Fleming and Remolona, 1997, 1999).[3] Public information includes not only statistics that have a direct impact on asset prices, such as inflation expectations, the potential rate of growth, overseas interest rates, etc., but also a wide range of other types of information that affect asset prices indirectly, such as labor statistics and economic surveys.

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[2] A variety of herding models have been proposed to express the behavior in financial markets (e.g., Banerjee, 1992).

[3] Stock prices are considered to be determined mainly by private information, such as unconfirmed information about the development of new products and changes in management strategy. In contrast, little evidence has been provided that public information has significant effects on stock markets. See Cutler, Poterba, and Summers (1989) for related studies.

Public information of particular importance is central bank policy announcements and associated speeches by bank executives. As witnessed in Japan, the BOJ's policy announcements since April 2013 have had a substantial impact on price formation in bond markets. To analyze the impact of central bank announcements, Kamada and Miura (2014) introduced a double-layered structure of information, consisting of both public and private information. We slightly modify their model to exploit rich information contained in the tick-by-tick data we use for empirical studies in Section 3.

2.2. The structure of traders' subjective probability

There are two financial states, H and L. We denote the corresponding asset prices by p_H and p_L ($< p_H$), respectively. State H is a high-price state or a low-interest-rate state; state L is a low-price state or a high-interest-rate state. Traders do not know which state they live in but have a subjective probability distribution about it. Below, p_H and p_L are assumed to be common to all traders.

Suppose that the τ-th public information is released. Traders believe that they are in state H with probability π_τ and state L with probability $1-\pi_\tau$. The fair price of the asset is given by

$$p_\tau = \pi_\tau p_H + (1-\pi_\tau) p_L \, . \tag{1}$$

Denote the likelihood ratio of state L over H by $\theta_\tau \equiv (1-\pi_\tau)/\pi_\tau$. Then, the fair price is alternatively written as

$$p_\tau = p_L + \frac{p_H - p_L}{1+\theta_\tau} \, . \tag{2}$$

In the special case of $\pi_\tau = 0.5$, or $\theta_\tau = 1$, traders are completely uncertain about financial states. π_τ and θ_τ are common parameters across traders.[4]

[4] Since p_H and p_L are common to all traders and one asset price, p_τ, is observed at a time, the traders share a unique value of θ_τ and π_τ.

There are two types of information, *public* and *private*. Public information may not convey correct information about financial states.[5] Thus, traders remain uncertain about financial states even after public information is released. Public information is correct with probability q_τ (> 0.5) and wrong with probability $1 - q_\tau$. The role of q_τ is discussed in detail below. Here, we point out that the size of q_τ is related to the *plausibility* of public information and its *relevance* to financial states. No matter how precise, public information has no value if it has nothing to do with asset prices; no matter how relevant to asset prices, it has no value if completely wrong.

Traders use the Bayes' rule to update the likelihood ratio from $\theta_{\tau-1}$ to θ_τ after public information is released. An updating is conditional on which state new public information indicates: $\theta_\tau = q_\tau/(1 - q_\tau) \times \theta_{\tau-1}$ when state L public information is released; $\theta_\tau = (1 - q_\tau)/q_\tau \times \theta_{\tau-1}$ when state H public information is released. In either case, all traders share a unique value of θ_τ and $\theta_{\tau-1}$, as mentioned above. It follows that q_τ is common to all of the traders.

By private information, we mean unpublicized information that traders gather to predict future public information. Denote trader i's private information to predict the τ-th public information before its release by $x_{i\tau}$. He knows that $x_{i\tau}$ is likely to be generated from distribution F_H in state H or F_L in state L. Denote the associated densities by f_H and f_L, respectively. The likelihood ratio, $\delta(x) \equiv f_L(x)/f_H(x)$, is assumed monotonically decreasing in x. This assumption allows traders to make the following conjecture: If x is high, it is likely that they are in state H.

Traders make expectations about public information, which may differ from actual public information released later. Below, $\hat{q}_{i\tau}$ (> 0.5) stands for trader i's

[5] The BOJ's statement regarding the introduction of QQE I is a good example. The policy is aimed at the target inflation rate of two percent in around two years. The statement confused the majority of traders. Following the Fisher equation, a high inflation rate implies a high nominal interest rate. Thus, they took the statement as a signal that the Bank allowed a rise in long-term interest rates. The Bank's intention was, however, to purchase assets on a large scale to squeeze the term premium rather than to raise inflation expectations, thereby lowering long-term interest rates (Kamada, 2014). Overall, the QQE I episode highlights the difficulty of central bank communication at the time of a policy shift.

expected probability that correct public information is released. $\hat{q}_{i\tau}$ is not necessarily equal to q_τ and may vary across traders. To simplify the argument below, we make following assumption: Traders are divided into two groups, those on the *long side* and those on the *short side*; and $\hat{q}_{i\tau}$ is common to all traders on each side. On the long side, for instance, the traders believe that if they are in state H, private information is generated from F_H with probability $\hat{q}_{a\tau}$ and from F_L with probability $1 - \hat{q}_{a\tau}$; if they are in state L, it is from F_H with probability $1 - \hat{q}_{a\tau}$ and from F_L with probability $\hat{q}_{a\tau}$. For traders on the short side, the corresponding probability is denoted by $\hat{q}_{b\tau}$.

2.3. Informed traders on the long side

Two types of traders are playing in markets, *informed* and *uninformed*. Informed traders gather private information, but uninformed traders do not. As already mentioned, informed traders are divided further into two groups: *long-side* and *short-side* traders.[6] Long-side traders choose between buying assets or doing nothing, while short-side traders choose between selling assets or doing nothing.[7]

Let us begin with long-side traders. Trader i updates his subjective probability, using the asset price observed in the market as well as private information, $x_{i\tau}$, he collected. Denote the total number of long-side informed traders by n_a, of which k traders are ready to buy the asset, while the remaining $n_a - k$ do nothing. If traders buy the asset, they do so at an ask price, $p_{a\tau}(k)$, offered by uninformed traders. We assume that $p_{a\tau}(k)$ is an increasing function of k. Long-side informed traders know this function. Therefore, when the asset price is offered, traders infer how many long-side informed traders are ready to buy the asset.

Given private information, traders use Bayes' rule to update the prior

[6] Nirei, Takaoka, and Watanabe (2013) consider only long-side informed traders, while we consider both long side and short side.

[7] In the following subsections, we consider an interval between arrivals of the $(\tau - 1)$-th and the τ-th public information. Given the common prior likelihood ratio, $\theta_{\tau-1}$, informed traders wait for the arrival of the τ-th public information.

likelihood ratio, $\theta_{\tau-1}$. Denote trader i's posterior probability of state H and L by $\hat{\pi}_{ai\tau}$ and $1-\hat{\pi}_{ai\tau}$, respectively. Denote the posterior likelihood ratio of state L over H by $\hat{\theta}_{ai\tau} \equiv (1-\hat{\pi}_{ai\tau})/\hat{\pi}_{ai\tau}$. Trader i uses information set $\{x_{i\tau}, p_{a\tau}(k)\}$ to calculate $\hat{\theta}_{ai\tau}$ as follows.

$$\hat{\theta}_{ai\tau}(x_{i\tau}, p_{a\tau}(k)) = \frac{\Pr(L|x_{i\tau}, p_{a\tau}(k))}{\Pr(H|x_{i\tau}, p_{a\tau}(k))} = \frac{\Pr(x_{i\tau}, p_{a\tau}(k)|L)}{\Pr(x_{i\tau}, p_{a\tau}(k)|H)}\theta_{\tau-1} \,. \tag{3}$$

Define a critical value, $\bar{x}_\tau(k)$, such that when $p_{a\tau}(k)$ is offered, a trader buys the asset if his private information $x_{i\tau}$ is greater than or equal to it, but otherwise does nothing.

The decision rule for long-side informed traders

$$x_{i\tau}\begin{cases} \geq \bar{x}_\tau(k) & \Rightarrow \quad Buy\ the\ asset\,; \\ < \bar{x}_\tau(k) & \Rightarrow \quad Opt\ out\,. \end{cases}$$

When an ask price $p_{a\tau}(k)$ is offered by uninformed traders, an informed trader infers that there are $k-1$ traders ready to buy the asset except for him, and the remaining $n_a - k$ do nothing. Therefore, depending on financial states, the probability of $\{x_{i\tau}, p_{a\tau}(k)\}$ being generated is given as follows.

$$\Pr(x_{i\tau}, p_{a\tau}(k)|L) = \hat{q}_{a\tau}\binom{n_a-1}{k-1}F_L(\bar{x}_\tau(k))^{n_a-k}(1-F_L(\bar{x}_\tau(k)))^{k-1}f_L(x_{i\tau})$$
$$+(1-\hat{q}_{a\tau})\binom{n_a-1}{k-1}F_H(\bar{x}_\tau(k))^{n_a-k}(1-F_H(\bar{x}_\tau(k)))^{k-1}f_H(x_{i\tau})\,; \tag{4}$$

$$\Pr(x_{i\tau}, p_{a\tau}(k)|H) = (1-\hat{q}_{a\tau})\binom{n_a-1}{k-1}F_L(\bar{x}_\tau(k))^{n_a-k}(1-F_L(\bar{x}_\tau(k)))^{k-1}f_L(x_{i\tau})$$
$$+\hat{q}_{a\tau}\binom{n_a-1}{k-1}F_H(\bar{x}_\tau(k))^{n_a-k}(1-F_H(\bar{x}_\tau(k)))^{k-1}f_H(x_{i\tau})\,, \tag{5}$$

where $\binom{n_a-1}{k-1}$ is a binomial coefficient denoting the number of $(k-1)$-combinations of a set of (n_a-1) elements. Substituting these equations into equation (3) gives

$$\hat{\theta}_{ai\tau}(x_{i\tau}, p_{a\tau}(k)) = \frac{\hat{q}_{a\tau}A(\bar{x}_\tau(k))^{n_a-k}B(\bar{x}_\tau(k))^{k-1}\delta(x_{i\tau}) + 1 - \hat{q}_{a\tau}}{(1-\hat{q}_{a\tau})A(\bar{x}_\tau(k))^{n_a-k}B(\bar{x}_\tau(k))^{k-1}\delta(x_{i\tau}) + \hat{q}_{a\tau}}\theta_{\tau-1}\,, \tag{6}$$

where $A(x) \equiv F_L(x)/F_H(x)$ and $B(x) \equiv (1-F_L(x))/(1-F_H(x))$. Since $\delta(x)$ is decreasing in x, inequalities $A(x) > \delta(x) > B(x)$ hold. In addition, $A(x)$, $\delta(x)$, and $B(x)$ are all decreasing in x (Nirei, Takaoka, and Watanabe, 2013).

To close the model, we need to solve for the critical value, $\bar{x}_\tau(k)$. Assume that long-side informed traders are risk neutral. If asset prices are expected to rise, traders buy the asset now and sell it when prices actually rise. Trader i buys the asset if

$$\hat{\pi}_{ai\tau} p_H + (1 - \hat{\pi}_{ai\tau}) p_L \geq p_{a\tau} \tag{7}$$

$$\Leftrightarrow \quad \frac{p_H - p_{a\tau}}{p_{a\tau} - p_L} \geq \hat{\theta}_{ai\tau} \,. \tag{8}$$

If $x_{i\tau} = \bar{x}_\tau(k)$, asset trading generates no profits by definition. Therefore, equations (6) and (8) hold simultaneously with equality through $\hat{\theta}_{ai\tau}(\bar{x}_\tau(k), p_{a\tau}(k))$. That is,

$$\frac{p_H - p_{a\tau}(k)}{p_{a\tau}(k) - p_L} = \frac{\hat{q}_{a\tau} A(\bar{x}_\tau(k))^{n_a - k} B(\bar{x}_\tau(k))^{k-1} \delta(\bar{x}_\tau(k)) + 1 - \hat{q}_{a\tau}}{(1 - \hat{q}_{a\tau}) A(\bar{x}_\tau(k))^{n_a - k} B(\bar{x}_\tau(k))^{k-1} \delta(\bar{x}_\tau(k)) + \hat{q}_{a\tau}} \theta_{\tau-1} \,. \tag{9}$$

This yields $\bar{x}_\tau(k)$.

We can show that the decision rule for long-side traders is incentive compatible. Let $C_{ai\tau}(x_{i\tau}) \equiv A(\bar{x}_\tau(k))^{n_a - k} B(\bar{x}_\tau(k))^{k-1} \delta(x_{i\tau})$. Since $\delta(x_{i\tau})$ is decreasing in $x_{i\tau}$, $C_{ai\tau}(x_{i\tau})$ is also decreasing in $x_{i\tau}$. With $\hat{q}_{a\tau} > 0.5$, the right-hand side of equation (6) is increasing in $C_{ai\tau}$, and thus decreasing in $x_{i\tau}$. By definition, if trader i is ready to buy assets, $x_{i\tau} \geq \bar{x}_\tau(k)$ must hold. Thus, the right-hand side of equation (6) is smaller than that of equation (9), which satisfies inequality (8) and proves the incentive compatibility of the rule.

Now, we can show that the total demand for the asset is an increasing function of the asset price. As shown in *Lemma 1* in the appendix, when n_a is sufficiently large, $\bar{x}_\tau(k)$ is a decreasing function of k, as drawn in Figure 1(a). Suppose that trader 1 has private information $x_{1\tau}$ ($\geq \bar{x}_\tau(3)$) in the figure. He buys one unit of the asset if the asset price is higher than or equal to $p_{a\tau}(3)$, but nothing otherwise. Suppose that trader 2 has private information $x_{2\tau}$ ($\geq \bar{x}_\tau(2)$). Trader 2 buys one unit of the asset if the asset price is higher than or equal to $p_{a\tau}(2)$. If there are only two informed traders on the long side, the total demand for the asset is given as an upward sloping curve, as shown in Figure 1(b). This property contrasts with the usual downward-sloping demand function found in standard microeconomics text books and generates herding behavior among traders.

The equilibrium asset price and trading volume are determined as follows. Suppose that uninformed traders supply k units of the asset at price $p_{a\tau}(k)$. Each long-side informed trader compares his private information, $x_{i\tau}$, with critical value $\bar{x}_\tau(k)$. If the former is greater than or equal to the latter, he buys one unit of the asset. Otherwise, his demand is zero. The total demand is given by the sum of all long-side informed traders' demand, which is denoted by $D_{a\tau}(k)$. Equilibrium trading volume, which is denoted by k^*, must satisfy the equality $D_{a\tau}(k^*) = k^*$. When there are multiple k^*, the minimum k^* is chosen as a unique solution, as in Nirei, Takaoka, and Watanabe (2013). *Proposition 1* in the appendix shows the existence of such an equilibrium.

2.4. Informed traders on the short side

A similar argument holds for informed traders on the short side. Suppose that there are n_b short-side informed traders. Let $p_{b\tau}(h)$ be a bid price offered by uninformed traders when h short-side informed traders are ready to sell the asset. Assume that $p_{b\tau}(h)$ is decreasing in h. Define critical value $\underline{x}_\tau(h)$ such that each trader sells the asset if her private information is equal to or smaller than this critical value but does not otherwise.

The decision rule for short-side informed traders

$$x_{j\tau}\begin{cases} \leq \underline{x}_\tau(h) & \Rightarrow \quad \mathit{Sell\ the\ asset}\ ; \\ > \underline{x}_\tau(h) & \Rightarrow \quad \mathit{Opt\ out}\ . \end{cases}$$

When each short-side trader is offered a bid price, $p_{b\tau}(h)$, she infers that h traders as well as she are ready to sell the assets and the remaining $n_b - h$ do nothing. The likelihood ratio of state L over H is calculated as follows.

$$\hat{\theta}_{bj\tau}(x_{j\tau}, p_{b\tau}(h)) = \frac{\hat{q}_{b\tau} A(\underline{x}_\tau(h))^{h-1} B(\underline{x}_\tau(h))^{n_b-h} \delta(x_{j\tau}) + 1 - \hat{q}_{b\tau}}{(1-\hat{q}_{b\tau}) A(\underline{x}_\tau(h))^{h-1} B(\underline{x}_\tau(h))^{n_b-h} \delta(x_{j\tau}) + \hat{q}_{b\tau}} \theta_{\tau-1}. \tag{10}$$

Informed traders are assumed to be risk neutral. Thus, if the asset price is expected to go down, traders sell the asset and buy it back when the asset price actually falls. Trader j sells the asset, if

$$\hat{\pi}_{bj\tau}p_H + (1 - \hat{\pi}_{bj\tau})p_L \le p_{b\tau} \tag{11}$$

$$\Leftrightarrow \quad \frac{p_H - p_{b\tau}}{p_{b\tau} - p_L} \le \hat{\theta}_{bj\tau}\,. \tag{12}$$

By definition, traders' profits are zero if $x_{j\tau} = \underline{x}_\tau(h)$. Thus, equations (10) and (12) hold simultaneously with equality through $\hat{\theta}_{bj\tau}(\underline{x}_\tau(h), p_{b\tau}(h))$. That is,

$$\frac{p_H - p_{b\tau}(h)}{p_{b\tau}(h) - p_L} = \frac{\hat{q}_{b\tau}A(\underline{x}_\tau(h))^{h-1}B(\underline{x}_\tau(h))^{n_b-h}\delta(\underline{x}_\tau(h)) + 1 - \hat{q}_{b\tau}}{(1-\hat{q}_{b\tau})A(\underline{x}_\tau(h))^{h-1}B(\underline{x}_\tau(h))^{n_b-h}\delta(\underline{x}_\tau(h)) + \hat{q}_{b\tau}}\theta_{\tau-1}\,. \tag{13}$$

This solves for $\underline{x}_\tau(h)$.

Given that $C_{bj\tau}(x_{j\tau}) \equiv A(\underline{x}_\tau(h))^{h-1}B(\underline{x}_\tau(h))^{n_b-h}\delta(x_{j\tau})$ is decreasing in $x_{j\tau}$, the incentive compatibility of the decision rule for short-side traders is easy to show. We notice that $\underline{x}_\tau(h)$ is increasing in h, when n_b is sufficiently large (see *Lemma 1* in the appendix). This is in contrast to $\overline{x}_\tau(k)$, which is decreasing in k. An equilibrium price is defined as follows. Denote the total supply from short-side informed traders at price $p_{b\tau}(h)$ by $S_{b\tau}(h)$. Suppose that uninformed traders demand h units of the asset. Equilibrium volume h^* must satisfy the equality $S_{b\tau}(h^*) = h^*$. When there exist multiple h^*, the minimum h^* is chosen as a unique solution. *Proposition 1* in the appendix shows the existence of such an equilibrium.

2.5. Defining surprises

One of the novel features of the current model is that it enables us to identify and quantify surprises in financial markets. Let us start with the long side. The right-hand side of equation (6) is increasing in $C_{ai\tau}$, which is defined above and takes any value between zero and infinity. Therefore, we have $\hat{\theta}_{ai\tau}(x_{i\tau}, p_{a\tau}(k)) \ge \hat{\eta}_{a\tau}\theta_{\tau-1}$, where $\hat{\eta}_{a\tau} \equiv (1-\hat{q}_{a\tau})/\hat{q}_{a\tau}$. Combining this with inequality (8), we have $p_{a\tau} \le \overline{p}_{a\tau}$, where $\overline{p}_{a\tau}$ is the upper bound of ask prices, defined as

$$\overline{p}_{a\tau} \equiv p_L + \frac{p_H - p_L}{1 + \hat{\eta}_{a\tau}\theta_{\tau-1}}\,. \tag{14}$$

We say that surprises occur if the fair price is updated to satisfy the inequality $\overline{p}_{a\tau} < p_\tau$, when the τ-th public information is released. Given that $\overline{p}_{a\tau}$ corresponds to traders' upper bound of expectations, surprises are quantified by the extent to which p_τ exceeds $\overline{p}_{a\tau}$.

Recall that we defined private information as the information used to predict public information. Therefore, once public information is released, the private information loses its value. This implies that all traders have the same posterior probability distribution. This setting differs from that in Nirei, Takaoka, and Watanabe (2013), in which private information does not become obsolete but accumulates over time. Under their assumption, as time goes by, each trader's information structure becomes more and more complex. The assumption employed in this paper simplifies the model substantially.

A similar argument can be made on the short side. The right-hand side of equation (10) is increasing in $C_{bj\tau}$, which is defined above and takes any value between zero and infinity. Therefore, we have $\hat{\theta}_{bj\tau}(x_{j\tau}, p_{b\tau}(k)) \leq \hat{\eta}_{b\tau}\theta_{\tau-1}$, where $\hat{\eta}_{b\tau} \equiv \hat{q}_{b\tau}/(1-\hat{q}_{b\tau})$. Combining this with inequality (12), we have $\underline{p}_{b\tau} \leq p_{b\tau}$, where $\underline{p}_{b\tau}$ is the lower bound of bid prices, defined as

$$\underline{p}_{b\tau} \equiv p_L + \frac{p_H - p_L}{1 + \hat{\eta}_{b\tau}\theta_{\tau-1}}. \tag{15}$$

We say that surprises occur if the fair price is updated to satisfy the inequality $p_\tau < \underline{p}_{b\tau}$, when the τ-th public information is released. Surprises are quantified by the extent to which p_τ falls below $\underline{p}_{b\tau}$.[8]

The following definition of surprises is equivalent to that given above but simplifies the empirical treatments significantly in a later section. Let $\eta_\tau \equiv \theta_\tau/\theta_{\tau-1}$. We call η_τ the realized *marginal value of public information* in this paper. Similarly, $\hat{\eta}_{a\tau}$ and $\hat{\eta}_{b\tau}$ are called traders' expected *marginal value of public information on the long* and *short sides*, respectively, and are not necessarily equal to η_τ. These marginal values of information correspond one-to-one to the asset prices of p_τ, $\overline{p}_{a\tau}$, and $\underline{p}_{b\tau}$ through

[8] The definition of surprises is our major modification to the original model of Kamada and Miura (2014). They update the fair price p_τ to either $\overline{p}_{a\tau}$ or $\underline{p}_{b\tau}$ and exclude surprises.

equations (2), (14), and (15).[9] We can alternatively define surprises in terms of these marginal values. This alternative definition of surprises is summarized in Table 1 along with those defined by prices.

2.6. Uninformed traders' ask and bid price functions

So far, we have not explicitly described uninformed traders' ask and bid price functions. To conduct simulation analysis, however, we have to define them explicitly. We employ the following functional forms, which are standard in the literature:

$$p_{a\tau}(k) = p_{\tau-1} + \phi_{a\tau}\left(\frac{k}{n_a}\right)^{\gamma_a} \quad for \;\; 0 \le k \le n_a\,; \tag{16}$$

$$p_{b\tau}(h) = p_{\tau-1} - \phi_{b\tau}\left(\frac{h}{n_b}\right)^{\gamma_b} \quad for \;\; 0 \le h \le n_b\,, \tag{17}$$

where $p_{\tau-1}$ is the fair price; and $\phi_{a\tau}$ and $\phi_{b\tau}$ are defined as follows:

$$\phi_{a\tau} \equiv \lambda_a\left(\frac{1}{1+\hat{\eta}_{a\tau}\theta_{\tau-1}} - \frac{1}{1+\theta_{\tau-1}}\right)(p_H - p_L)\,; \tag{18}$$

$$\phi_{b\tau} \equiv \lambda_b\left(\frac{1}{1+\theta_{\tau-1}} - \frac{1}{1+\hat{\eta}_{b\tau}\theta_{\tau-1}}\right)(p_H - p_L)\,, \tag{19}$$

where γ_a and γ_b are price elasticity. We assume $\gamma_a = \gamma_b = 0.5$, following the preceding studies (e.g., Lillo, Farmer, and Mantegna, 2003).[10]

We set the parameters so that the motion range of ask and bid prices offered by uninformed traders coincides with the range of prices acceptable to informed

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[9] Conversely, we can define marginal values of information in terms of asset prices. Realized marginal values are equivalent to differences between p_τ and $p_{\tau-1}$. Expected marginal values also correspond to differences between $\overline{p}_{a\tau}$ and $p_{\tau-1}$ or between $p_{\tau-1}$ and $\underline{p}_{b\tau}$, which we refer to as ex ante price mobility. In the empirical analysis, we illustrate expected marginal values by ex ante price mobility, depending on graphical purposes.

[10] Market liquidity is determined not only by λ_a and λ_b but also by γ_a and γ_b. Gabaix et al. (2006) show that the cost of restoring inventories to their initial level depends on market liquidity and theoretically derive an ask price function that is similar to equation (16) when uninformed traders are risk averse. However, when considering market liquidity, it is sufficient to examine only the role of λ_a and λ_b and take γ_a and γ_b as constant.

traders. We see first that $p_{a\tau}(0) = p_{b\tau}(0) = p_{\tau-1}$. Uninformed traders can offer an ask price higher than the fair price but should not offer an ask price lower than the fair price. If an ask price is lower than the fair price, informed traders can gain from buying the asset at the ask price and immediately selling it at the fair price, even when they have received no new information. For a similar reason, uninformed traders can choose a bid price lower than the fair price but should not set a bid price higher than the fair price.

Second, with $\lambda_a = 1$, we see $p_{a\tau}(n_a) = \overline{p}_{a\tau}$, the right-hand side of which is the upper bound of an ask price that informed traders can accept.[11] Uninformed traders can choose any ask price higher than the upper bound. In that case, however, all traders stay out of the market waiting for a decline in ask prices. Similarly, with $\lambda_b = 1$, we see $p_{b\tau}(n_b) = \underline{p}_{b\tau}$, the right-hand side of which is the lower bound of a bid price that informed traders can accept.

2.7. Simulation analysis

Nirei, Takaoka, and Watanabe (2013) built up a model to describe the herding behavior observed in security markets and show that the model generates theoretically a fat-tail distribution of asset prices. The current model is an extension of their model and thus thought of as inheriting its main characteristics. Below, we conduct several simulations to show that this conjecture is correct. We are particularly interested in whether the distribution of asset prices generated by the current model is indeed characterized by fat tails. We are also interested in under what conditions the tails of the distribution become fatter.

First, we show that the fat-tail asset price distribution is generated by the

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[11] We assume $0 \leq \lambda_a, \lambda_b \leq 1$ so that $\overline{x}_\tau(k)$ and $\underline{x}_\tau(h)$ become interior solutions. This is not a necessary condition for the analysis here. We can alternatively assume $\lambda_a, \lambda_b \geq 1$ and define the ask price as the smaller of the following two values: the price indicated by equation (16) and the upper-bound defined by equation (14). Similarly, we can define the bid price as the larger of the following two values: the price indicated by equation (17) and the lower-bound defined by equation (15).

current model. Assume that F_H and F_L are normal distributions with mean μ_H and μ_L ($< \mu_H$), respectively, and common standard deviation σ. Below, the following parameter set is used as a benchmark: $p_H = 100$, $p_L = 86$; $\mu_H = 1$, $\mu_L = -1$; $\sigma = 200$; $n_{a\tau} = n_{b\tau} = 10{,}000$; $\theta_{\tau-1} = 1$ (or $p_{\tau-1} = 93$); $\hat{q}_{a\tau} = \hat{q}_{b\tau} = q = 0.8$ (or $\hat{\eta}_{a\tau} = 1/4$, $\hat{\eta}_{b\tau} = 4$); $\lambda_a = \lambda_b = \lambda = 0.8$. Below, private information is always generated from distribution F_H. The simulation is iterated 25,000 times for each of the long and short sides. The result is presented in Figure 2, where the horizontal axis indicates percent changes in prices from $p_{\tau-1}$, while the vertical axis is relative frequency. Compared with a normal distribution and even an exponential distribution, the simulated distribution clearly shows fat tails.[12]

Next, we explore comparative statics to see under what conditions the tails of the price distribution become fatter. We replace values in each of the parameters and simulate the distribution of asset prices. The results are shown in Figure 3. We see from Figures 3(a) to (d) that the distribution becomes more fat tailed, (i) when traders become more uncertain about the current financial state (i.e., $\theta_{\tau-1}$ is close to 1); (ii) when traders expect future public information to be more valuable (i.e., $\hat{q}_{a\tau}$ and $\hat{q}_{b\tau}$ are high); (iii) when traders receive more valuable private information to infer the marginal value of future public information (i.e., $\mu_H - \mu_L$ is large; σ is small).

Interesting results are obtained regarding λ_a and λ_b, the parameters of market liquidity. Uninformed traders, when selling the assets to informed traders, infer that it becomes costly to restore their initial inventory levels, as the assets become scarce in the market. This implies that as market liquidity increases, λ_a and λ_b decrease. However, as shown in Figure 3(e), a decrease in λ_a and λ_b does not necessarily weaken the volatility of the asset price. One interpretation is as follows. As market liquidity increases, uninformed traders offer informed traders more favorable prices, which attract more informed traders into the market. This boosts demand for the asset and makes the asset price more volatile. The effects of market liquidity on

[12] Note that the distribution in Figure 2 is skewed toward the right. This is because private information is generated from F_H.

asset price volatility depend on which of these two forces is stronger.

3. EMPIRICAL ANALYSIS

3.1. Data

Tick-by-tick price data are indispensable to our empirical analysis of traders' psychological movements in response to new information arriving at every moment, especially the BOJ's policy announcements. We focus here on the Japanese government bond futures market, because we expect policy announcements to have the most straightforward impact on this market compared to other markets in which such tick-by-tick data are available. Specifically, we utilize the "NEEDS" database provided by Nikkei Inc.[13] This database contains historical tick-by-tick transaction records of Japanese government bond futures listed on the Osaka Exchange from March 24, 2014, and on the Tokyo Stock Exchange prior to that date.

Our main dataset is constructed from the "NEEDS" database as follows. First, we consider only contract prices but not indicative prices. This is because contract prices are actually accepted by informed traders, whereas indicative prices are not always accepted.[14] We emphasize that contract prices are recorded in a distinguishable manner between ask prices (buyer-initiated prices) and bid prices (seller-initiated prices), which is critical to implementing the empirical strategy described below. In addition, we use the nearest-contract-month futures contract on ten-year bonds, since transaction of this contract is the most active compared to other miscellaneous contracts. We exclude mini ten-year bond futures. Given that information coming from overseas is far from negligible, we incorporate contracts during both the day session

[13] "NEEDS" is the data source for Table 2 and Figures 5 to 19.

[14] It is true that indicative prices reflect traders' psychology in another way. For instance, when surprising information arrives, traders often cancel existing limit orders and widen bid–ask spreads, which leads to decline in market liquidity. We mention this issue later.

and the night session.[15] Finally, our sample period starts from the beginning of 2005 and terminates at the end of 2016.

3.2. *The empirical strategy*

We are interested in when surprises occurred in the Japanese bond futures market during the period from 2005 to 2016 and how much. The key to applying our model to the actual data is to find the series of the fair price, p_τ. Based on this, we identify the upper bound of ask prices, $\overline{p}_{a\tau}$, and the lower bound of bid prices, $\underline{p}_{b\tau}$. Based on these, we can finally quantify surprises in the market. Below, we explain our non-parametric empirical methodology step by step (see Figure 4).

The fair price, p_τ, is estimated as follows. Let the initial value of the fair price be the first contract price during the sample period. The fair price is updated every time new public information arrives, but is untouched until then. A question is how to identify the time at which market participants receive the public information. To do so, we exploit the following simple facts. First, ask prices are always above bid prices, and bid prices are never above ask prices. Second, the fair price is always in between ask prices and bid prices. Hence, we can say that traders have received new public information when we observe (i) a bid price which is above the fair price or (ii) an ask price which is below the fair price. In this paper, the fair price is updated to this bid or ask price.

The upper bound of ask prices, $\overline{p}_{a\tau}$, is estimated as follows. Ask prices, $p_{a\tau}$'s,

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15 Trading hours have been changed several times during our sample period. The day session consists of the morning session and the afternoon session. Currently, the morning session is open from 8:45 to 11:02; the afternoon session is from 12:30 to 15:02. Prior to November 21, 2011, the corresponding hours were from 9:00 to 11:00 and from 12:30 to 15:00, respectively. The night (evening) session starts from 15:30 and closes at 5:30 on the next day currently. The closing time has been gradually extended: 18:00 prior to November 21, 2011; 23:30 prior to March 24, 2014; 3:00 on the next day prior to July 19, 2016. Daily time series displayed in the figures and tables is on a literally calendar basis unless noted otherwise; each day consists of the night session from midnight, the day session, and the subsequent night session until midnight.

fluctuate around an old fair price, $p_{\tau-1}$, until a new fair price, p_{τ}, arrives. As shown in the previous section's simulation analysis, the distribution of asset prices has fat tails when the market is driven by participants' herding behavior. Therefore, with $\lambda_a = 1$, asset prices are frequently likely to reach, or at least be very close to, the upper bound. Thus, $\overline{p}_{a\tau}$ can be approximated by the maximum value of $p_{a\tau}$'s. Similarly, assuming $\lambda_b = 1$, the lower bound of bid prices, $\underline{p}_{b\tau}$, is approximated by the minimum value of $p_{b\tau}$'s.[16] Figure 4 illustrates this methodology in the case of updating the fair price to the bid price above the current fair price.

A few caveats are in order here. First, to deal with noise in the data, we make some allowance for the detection of the arrival of public information. To be precise, we say that traders have received new public information either if a bid price rises three basis points above the fair price or if an ask price falls three basis points below the fair price. The size of the allowance can be chosen arbitrarily. Note, however, that if we set the allowance too big, important public information could be discarded unintentionally together with the noise. Thus, the size of the allowance should be chosen carefully.

Second, some conditions should be satisfied to justify the approximation of $\overline{p}_{a\tau}$ and $\underline{p}_{b\tau}$ by the maximum and minimum prices observed in between the release of $p_{\tau-1}$ and that of p_{τ}. Recall the simulation analysis in the previous section. With $\theta_{\tau-1}$, $\hat{q}_{a\tau}$, and $\hat{q}_{b\tau}$ given, the distribution of asset prices is more fat tailed, as $\mu_H - \mu_L$ is larger and/or as σ is smaller. Therefore, the approximation is good if traders receive private information sufficiently valuable to infer the marginal value of future public information. Otherwise, we underestimate traders' expected marginal value of future public information.

[16] Note that this argument assumes the presence of herding behaviors and the resulting fat-tail asset price distribution in Japanese government bond futures markets. Since fat-tailed asset price distributions are very common in the finance literature, we do not need to question this assumption. Furthermore, the validity of the assumption $\lambda_a = \lambda_b = 1$ throughout the sample period is supported by the minimum possible value of $p_{a\tau} - p_{b\tau}$. Given the tick size of Japanese governemt bond futures, it is one Japanese yen (JPY) cent. Smaller values of λ_a, λ_b might not keep $p_{a\tau} - p_{b\tau}$ larger than or equal to one JPY cent.

3.3. *A bird's-eye view of fair prices and surprises*

Figure 5 presents the estimated series of the fair price. As shown in the figures 5(a) and (b), p_τ follows an upward trend, and θ_τ a downward trend, respectively. Interestingly, the estimate of θ_τ began falling well before the financial crisis hit the global economy. From the business cycle point of view, this implies that the Japanese economy began to slow down and was in a recession phase before the crisis started.

Figure 6 shows the estimated series of marginal value of public information, realized and expected. The realized marginal value of public information, η_τ, is calculated from the estimate of θ_τ and $\theta_{\tau-1}$.[17] As shown in Figure 6(a), it fluctuated wildly when the Lehman Brothers bankrupted on September 15, 2008. In the same figure, we see that the range of fluctuation expanded twice thereafter, firstly around the Great East Japan Earthquake on March 11, 2011 and secondly after the BOJ's introduction of QQE I on April 4, 2013. Looking at the series closely, we also find relatively large fluctuations around the launching of the NIR policy and the YCC policy.

Figure 6(b) provides estimates of $\hat{\eta}_{a\tau}$ and $\hat{\eta}_{b\tau}$, which are obtained from $\overline{p}_{a\tau}$ and $\underline{p}_{b\tau}$ through equations (14) and (15). It appears that the range defined by $[\hat{\eta}_{a\tau}, \hat{\eta}_{b\tau}]$ widened together with the enlargement of the fluctuation of η_τ. Recall that $\hat{\eta}_{a\tau}$ and $\hat{\eta}_{b\tau}$ indicate traders' expected marginal value of public information. The simultaneity among their fluctuations implies that traders' expectations are not far from reality.

Figure 7 shows the time series of surprises in the Japanese bond futures market separately on long and short sides. Since our framework can identify when surprises were brought to traders and can quantify the size simultaneously, surprises

[17] To calculate $\hat{\eta}_{a\tau}$ and $\hat{\eta}_{b\tau}$, we set p_H = 1.1 × the highest sample ask price and p_L = 0.9 × the lowest sample bid price. In this paper, p_H and p_L are assumed constant. The assumption, however, is unrealistic from a long-run perspective. It is natural to think that these parameters will change if the potential rate of growth or mid to long-term inflation rates change over time. Thus, when using the current empirical strategy, we should be careful that the sample period is not too long.

are displayed in two distinct ways, amount and frequency. Amount is the total size of surprises within a day, while frequency is the number of times that traders are surprised within a day.

Let us begin with the amount of surprises (Figure 7(a)). As easily expected, spikes are observed around the Lehman Brothers bankruptcy, the Great East Japan Earthquake, and the BOJ's introduction of QQE I. Table 2 is the list of days of the twenty largest surprises, observed on long and short sides, since 2005. The list also shows the events that were the most likely to bring surprises to traders on those days. The biggest surprises that led to higher interest rates occurred on April 5, 2013, i.e., the day after the Bank's introduction of QQE I. The biggest surprises that led to lower interest rates occurred a week later, when the Bank had a meeting with market participants to exchange their views on the current and future market. It is also noteworthy that the then Federal Reserve Chairman Ben S. Bernanke's testimony concerning the tapering of asset purchases on May 22, 2013 (Bernanke, 2013) caused huge surprises on both long and short sides.

The recent trend of the frequency of surprises is also interesting (Figure 7(b)). If some extreme cases are excluded, the frequency of surprises appears to have increased, while the amount of surprises seems to have decreased recently. This implies that traders have experienced small surprises many times. This situation is likely to continue, since traders have only a small incentive to incur costs to improve their prediction further, when prediction errors are small. We will return to this issue later when analyzing the sensitivity of traders to various economic indicators.

Some comments are in order here, concerning the relationship between surprise and liquidity. In Figure 8, we show the time series of two basic indicators for liquidity: bid–ask spreads and market depth. Clearly, the amount of surprises is strongly related to the bid-ask spread: surprise is large, when liquidity is low. It is especially impressive that both indicators have two clusters, around the Lehman Brothers bankruptcy and immediately after QQE I. However, the frequency of surprise is not closely correlated with the bid-ask spread. In particular, liquidity was extremely low around the Lehman Brothers bankruptcy, while the frequency of surprises was not substantially high. This allows us the following interpretation: in the Lehman-Brothers case, relatively great liquidity shocks hit the market in a distinct way; in the case of QQE I, however, relatively small liquidity shocks occurred in a continuous way.

3.4. Market reactions to the announcements of the four policy changes

In this paper, we are interested in how monetary policy announcements change, or do not change, the behavior of market participants. Here we focus on the announcements of the four policy changes made recently by the BOJ: the QQE I on April 4, 2013; the QQE II on October 31, 2014; the NIR on January 29, 2016; and the YCC on September 21, 2016. The analysis below indicates the following fact: Having experienced the BOJ Governor Kuroda's "bazooka shot", the QQE I, traders have become rather quick to learn the BOJ's intentions embedded in its policy announcements.

Figure 9 shows the intra-day behavior of the fair price, p_τ, on the four policy announcement days. The dots indicate the timing of fair price updates. The fair price began to swing up and down wildly immediately after the BOJ's announcement of QQE I.[18] In contrast, after the announcements of NIR and YCC, the adjustment of the fair price was completed fairly quickly and concentrated around the announcement time. By seeing the intra-day developments more carefully, we also note that the fair price was updated more or less around 16:00 on all of the four policy announcement days. These behaviors of fair prices reflect the importance of the Governor's press conference, which is usually held from 15:30 to 16:30 on the policy announcement days, for the creation of public information.

The case of the announcement of QQE II is counterintuitive at first glance. Although QQE II were supposed to be very surprising to market participants, fair price updates were infrequent throughout the day. One of the possible reasons is as follows. Before the BOJ's policy announcement, much uncertainty had already pervaded the market, due to the anticipated announcement by the Government Pension Investment

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[18] It is also notable that the fair price was updated many times in the morning session on the day of QQE I.

Fund (GPIF) concerning its asset allocation policy. The amplified uncertainty might have prevented traders from updating fair prices.

Figure 10 shows the marginal value of public information that appeared every five minutes and its decomposition into expected and unexpected (or surprising) parts. Following the announcement of QQE I, the appearance of public information was dispersed over 380 minutes; in contrast, it was concentrated around the time of policy announcement in the case of NIR and YCC. Similarly, the occurrence of surprises was dispersed over six hours, following the announcement of QQE I; in contrast, it was concentrated during the two hours after the policy announcement in the case of NIR and YCC.[19] Almost no surprises were observed in the case of QQE II due to the aforementioned infrequent fair price updates.

Figure 11 shows the market responses over longer horizons. Figure 11(a) shows how often the fair price was updated on the day of policy announcement and over the next five days. In the case of QQE I, the fair price was updated substantially during the next five days after the policy announcement. In fact, the large swings in the fair price on the announcement day, shown in Figure 9(a), were followed by much larger swings on the following days.[20] By contrast, more than half of the update was completed on the day of policy announcement in the case of NIR and YCC. A similar result is obtained for surprises. As shown in Figures 11(b) and (c), most surprises occurred during the next five days after the policy announcement in the case of QQE I; in contrast, they were observed on the very day of policy announcements in the case of NIR and YCC. Despite nearly zero surprises, in the case of QQE II, behavioral characteristics of fair price updates and surprises are still close to the case of QQE I.

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[19] On the day of NIR announcement, big surprises were recorded before the announcement. This was due to the report by the Nikkei newswire, which broadcast its monetary policy outlook before the BOJ's announcement with a headline "the BOJ has discussed setting a negative interest rate."

[20] The large swings in the fair price after QQE I were consistent with traders' confusion noted in footnote 5.

3.5. Market behavior just before the announcements of the four policy changes

Here, we examine the market behavior just before the announcements of the four policy changes. In Figure 12, the complementary cumulative distribution of ask prices just before the announcement is compared to the corresponding distribution observed four business days ahead of the announcement (i.e., on the previous day of the "blackout" before the monetary policy meeting). As in Figure 12(a), the two distributions coincide mostly with each other in the case of QQE I. As indicated in Figures 12(b) to (d), however, the distribution on the announcement day is diverted upward from the corresponding distribution observed four business days ahead of the announcement in the case of QQE II, NIR, and YCC. An upward diverted complementary cumulative distribution implies that a price has higher chance of taking on extreme values, or that a price is distributed with fatter tails. Hence, Figure 12 is the evidence that the market has changed since QQE I and strengthened its herding behavior on a policy announcement day.

In Figure 13, the bars indicate the sum of $\hat{\eta}_{a\tau}$ and $\hat{\eta}_{b\tau}$ observed just before the announcements. The size of $\hat{\eta}_{a\tau}$ and $\hat{\eta}_{b\tau}$ shows how large profit opportunities traders expect. Traders' expectations on the announcement day of NIR were smaller than those on the other three policy announcement days. The introduction of this new policy was so hard for the majority of traders to expect beforehand. In comparison, on the announcement day of QQE I, it was no question that new policy measures would be introduced, whatever they were. As for QQE II and YCC, it is noteworthy that much uncertainty had already prevailed on their announcement days, that is, on the announcement day of QQE II due to the anticipated announcement by the GPIF and of YCC due to the prior notice of publishing *Comprehensive Assessment* by the BOJ.

There was another source of uncertainty on the three days of QQE I, QQE II, and YCC. In Figure 13, we show the time gap between the opening of the afternoon session and the release of the policy announcement.[21] Clearly, traders' expectations are

[21] The time of policy announcements release after monetary policy meetings is not predetermined by the BOJ, in contrast with the Federal Open Market Committee or the

correlated with the time gap positively. We pursue this issue further below, using Figures 14 to 16.

As shown in Figure 14(a), positive correlation has been observed between the ex ante price mobility of long-side traders and the delays of policy announcements since Governor Kuroda took his position on March 2013. Here, ex ante price mobility is measured by $\overline{p}_{a\tau} - p_{\tau-1}$ on the long side and $p_{\tau-1} - \underline{p}_{b\tau}$ on the short side, just before policy announcements (see footnote 9). If policy announcements are delayed, market participants expect a substantial policy change to be made. This increases traders' expected marginal value of public information and thus ex ante price mobility. In contrast, as shown in Figures 14(b) and (c), no such correlation had been observed during the Shirakawa and Fukui regimes.[22] It is also noteworthy that, as shown in Figure 15(a), no (or even negative) correlation is observed on the short side. That is, traders' expectations were so biased toward monetary easing that the risk of monetary tightening was out of consideration during the sample period. As shown in Figures 15(b) and (c), there is no correlation on the short side during the Shirakawa and Fukui regimes.

As a related issue, it is interesting to see the effects of live broadcasting of press conferences on market surprises. On April 8, 2014, the BOJ began on-spot broadcasting of the Governor's press conference after the monetary policy meeting. As shown in Figure 16, on average, surprises measured during and after the press conference have halved on the long side and have almost been extinguished on the short side. This proves that quick and direct communication is an effective way to save market participants from misunderstanding the Bank's policy announcement.

European Central Bank.

[22] Former Governors Shirakawa and Fukui held their positions from April 2008 to March 2013 and from March 2003 to March 2008, respectively. Our sample period, starting from 2005, does not fully cover the Fukui regime.

3.6. Market reactions to the release of economic indicators

Not only the central bank's policy announcements but also economic indicators are considered to be important public information available in financial markets. Here, we examine whether market participants' reaction to economic indicators has changed since they experienced QQE I. In particular, we focus on traders' response to the monthly release of the Indices of Industrial Production (IIP), the Consumer Price Index (CPI), and the Economy Watchers Survey (EWS).[23]

Figure 17 shows the size of fair price updates in reaction to the release of the three economic indicators, traders' expectations just before the release, and surprises at the release. The values are averaged over samples prior to the introduction of QQE I (i.e., April 4, 2013) and later, respectively. As is clearly seen in Figure 17(a), the reactions to the release of IIP have been downsized by half on average since QQE I. The size of reactions to the release of CPI has more than halved. Interestingly, the reactions to the release of the EWS has decreased on the long side but not on the short side, meaning that traders take the Survey as a useful source to look out for a downturn of the asset price or for the upturn of the interest rate. On the other hand, as shown in Figure 17(b), traders' ex ante marginal value of public information have not decreased as much as the ex post value. As a result, market surprises have recently become smaller, as shown in Figure 17(c). As an exceptional case, high interest rate surprises caused by the release of the EWS have increased slightly.

Several explanations are possible for the downsizing of fair price updates after QQE I. The first explanation is that the interest rate has little room to move near the zero lower bound. If this were the case, the upward reaction of fair prices would be reduced more than the downward reaction. However, no such relationship is observed in Figure 17(a). Thus, this explanation is not plausible. The second explanation is that the movements of the economic indicators have declined. However, this explanation is also implausible when we look at the time series of these indicators. The third and the most plausible explanation is that the tendency has recently been strengthened that

[23] Concerning IIP, we focus on the release of its preliminary results.

market participants learn the meaning of each indicator not from their experiences but from the interpretation by the BOJ. Figure 17(d) shows the size of fair price updates following policy announcements relative to the size of updates following economic indicators. Clearly, fair prices are more responsive, both downward and upward, to the BOJ's policy announcements than to the release of economic indicators.

The explanation above can be supported by the time taken for the fair price to update. Figures 18(a) and (b) indicate how many minutes it takes before the fair price first reacts to the release of economic indicators. The speed at which traders react to economic indicators, the IIP and the CPI, has become slower since 2011. By contrast, the speed at which traders respond to the BOJ's announcements has not slowed. Figures 18(c) and (d) show how many minutes it takes for the fair price to react to the release of the statements by the BOJ. Although market participants became temporarily less sensitive to the Bank's release of the results of monetary policy meetings after QQE I, their sensitivity has strengthened again since QQE II. A similar tendency is observed for traders' reaction to the BOJ's announcement of a monthly schedule of government bond purchases.[24] Although they became less sensitive to the release of the asset purchase schedule after QQE II, this sensitivity has returned to its normal level since the NIR policy.

In this context, it is also interesting to see the effects on market behavior of reducing monetary policy meetings. Since 2016, the frequency of the BOJ's monetary policy meetings has been reduced from fourteen to eight times a year. And the Bank ceased to publish the *Monthly Report of Recent Economic and Financial Developments*, which was released after the monetary policy meeting. Instead, the issuing of the *Outlook for Economic Activity and Prices*, the BOJ's economic outlook, has increased from two to four times a year. In addition, the *Outlook* has richer information than the *Monthly Report*.[25] A question is whether the BOJ's information transmission has

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[24] After QQE II, the Bank decided to announce the schedule of the outright purchases of Japanese government bonds for the following month, in principle on the last business day of every month.

[25] While the *Monthly Report* explains recent economic and financial developments upon

weakened or not.

Figure 19(a) shows the reaction of the fair price after the release of the BOJ's economic reports (the *Outlooks* and the *Monthly Reports*). The reaction to the *Outlook* is greater than that to the *Monthly Report* on average. Interestingly, the total reaction to the two *Outlooks* and the twelve *Monthly Reports* issued in 2015 is almost the same as the total reaction to the four *Outlooks* issued in 2016. The new publication scheme allows the BOJ to send the same amount of information to the market. It is also shown in Figure 19(b) that the total expected information value of the two *Outlooks* and the twelve *Monthly Reports* is the same as the total expected information value of the four *Outlooks*. The amount of information sent by the BOJ, whether realized or expected, has not been reduced by the reduction of the number of monetary policy meetings and economic reports.

4. CONCLUSION

In this paper, we present a theoretical model to explain how traders incorporate public and private information into asset prices by extending Nirei, Takaoka, and Watanabe (2013) and Kamada and Miura (2014). We also propose an empirical framework that enables us to fit the model to tick-by-tick data and to identify and quantify surprises in financial markets, particularly those in the Japanese government bond futures market.

Many shocks caused large surprises in the Japanese bond futures market during the period from 2005 to 2016, for instance, the Lehman Brothers bankruptcy in 2008, the Great East Japan Earthquake in 2011, the BOJ's introduction of QQE I in 2013, and the tapering speech by the then Federal Reserve Chairman Ben S. Bernanke in 2013.

Our empirical analysis also shows that drastic changes occurred in the sensitivity of bond futures prices to the BOJ's announcements of new policy measures.

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which the Bank bases its monetary policy decisions, the *Outlook*, in addition to that, outlines the Bank's views on the future conduct of monetary policy.

We examined closely the intra-day developments of market participants' beliefs. It was shown that their reactions to the introduction of NIR policy on January 29, 2016 and YCC on September 21, 2016 were much quicker than those to the introduction of QQE I on April 4, 2013 and QQE II on October 31, 2014.

Market participants are now so sensitive to the BOJ's policy actions that the delay of statement release after monetary policy meetings has a substantial impact on the price formation in bond futures markets. In this context, the live press conference broadcast after monetary policy meetings, which was introduced on April 8, 2014, was effective in reducing surprises in bond futures markets. Similarly, the early announcement of scheduled dates for government bond purchases, which was introduced in 2017, is also useful to minimize market surprises.

In contrast, traders' sensitivity to other economic indicators has weakened. The impact of IIP, CPI, and EWS on bond futures prices is now smaller than it was before the introduction of QQE I. Interestingly, the value of information provided by the BOJ's economic analysis has not decreased, even though the Bank has reduced the frequency of monetary policy meetings from fourteen to eight times a year and that of economic reports from monthly to quarterly.

There remains interesting issues to work on. It is theoretically interesting to extend the present model by incorporating interaction between the long side and short side markets, which are now separately treated. It is also interesting empirically to apply our framework to various financial markets other than Japanese government bond futures markets. The same policy announcements by the BOJ might have a different impact on the stock market, the foreign exchange market, and so on. We hope to address these interesting issues elsewhere in the near future.

Appendix. Proof of the Existence of Market Equilibrium

Lemma 1. $\bar{x}_\tau(k)$ is monotonically decreasing in k when n_a is sufficiently large. $\underline{x}_\tau(h)$ is monotonically increasing in h when n_b is sufficiently large.

Transforming equation (9) yields

$$V_{a\tau}(k) = A\left(\bar{x}_\tau(k)\right)^{n_a-k} B\left(\bar{x}_\tau(k)\right)^{k-1} \delta(\bar{x}_\tau(k)), \tag{A1}$$

where

$$V_{a\tau}(k) \equiv \frac{(1-\hat{q}_{a\tau}) - \hat{q}_{a\tau}\dfrac{1}{\theta_{\tau-1}}\dfrac{p_H - p_{a\tau}(k)}{p_{a\tau}(k) - p_L}}{(1-\hat{q}_{a\tau})\dfrac{1}{\theta_{\tau-1}}\dfrac{p_H - p_{a\tau}(k)}{p_{a\tau}(k) - p_L} - \hat{q}_{a\tau}}. \tag{A2}$$

Taking the log differences of both sides of equation (A1) yields

$$\ln\frac{A(\bar{x}_\tau(k))}{B(\bar{x}_\tau(k))} + \ln\frac{V_{a\tau}(k+1)}{V_{a\tau}(k)}$$

$$= (n_a - k - 1)\ln\frac{A\left(\bar{x}_\tau(k+1)\right)}{A\left(\bar{x}_\tau(k)\right)} + k\ln\frac{B\left(\bar{x}_\tau(k+1)\right)}{B\left(\bar{x}_\tau(k)\right)} + \ln\frac{\delta(\bar{x}_\tau(k+1))}{\delta(\bar{x}_\tau(k))}. \tag{A3}$$

The first term on the left-hand side is positive since $A(x) > B(x)$. It is clear from equation (16) that as n_a increases, the difference between $(k+1)/n_a$ and k/n_a converges to zero, and so does the difference between $p_{a\tau}(k+1)$ and $p_{a\tau}(k)$. Thus, the difference between $V_{a\tau}(k+1)$ and $V_{a\tau}(k)$ converges to zero, and so does the second term on the left-hand side. This implies that the left-hand side of equation (A3) is positive when n_a is sufficiently large. Since $A(x)$, $B(x)$, and $\delta(x)$ are all decreasing in x, the right-hand side is positive only if $\bar{x}_\tau(k) > \bar{x}_\tau(k+1)$. This shows that $\bar{x}_\tau(k)$ is decreasing in k. Similarly, we can show that $\underline{x}_\tau(h)$ is increasing in h when n_b is sufficiently large.

Proposition 1. There exists a k^* that satisfies $D_{a\tau}(k^*) = k^*$ when n_a is sufficiently large. Moreover, there exists an h^* that satisfies $S_{b\tau}(h^*) = h^*$ when n_b is sufficiently large.

We know from *Lemma 1* that $\bar{x}_\tau(k)$ is monotonically decreasing in k. Thus, $D_{a\tau}$ is a monotonic mapping. Therefore, following Nirei, Takaoka, and Watanabe (2013), we can show the existence of equilibrium k^* using Tarski's fixed-point theorem for a discrete monotonic mapping. The existence of equilibrium h^* can be proved in a similar manner.

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Table 1. Definition of Surprises

(a) Identification

	Surprise	*No surprise*
Price base	$p_\tau < \underline{p}_{b\tau}$ or $\overline{p}_{a\tau} < p_\tau$	$\underline{p}_{b\tau} \leq p_\tau \leq \overline{p}_{a\tau}$
Information value base	$\eta_\tau < \hat{\eta}_{a\tau}$ or $\hat{\eta}_{b\tau} < \eta_\tau$	$\hat{\eta}_{a\tau} \leq \eta_\tau \leq \hat{\eta}_{b\tau}$

(b) Quantification

Price base	$\left(\ln p_\tau - \ln \overline{p}_{a\tau}\right)^+$ or $\left(\ln p_\tau - \ln \underline{p}_{b\tau}\right)^-$
Information value base	$(\ln \eta_\tau - \ln \hat{\eta}_{a\tau})^-$ or $(\ln \eta_\tau - \ln \hat{\eta}_{b\tau})^+$

Table 2. The Twenty Largest Surprises

(a) Low interest rate surprises

Ranking	Date	Event	Surprise
1	2013/4/11	The BOJ had a meeting with market participants to exchange their views on the current and future market (4/11)	0.01326
2	2008/9/16	Bankruptcy of Lehman Brothers (9/15)	0.01310
3	2013/4/5	Introduction of QQE I by the BOJ (4/4)	0.01073
4	2008/9/10	Calendar rollover with large negative spreads (9/10)	0.00945
5	2013/5/23	Tapering speech by Federal Reserve Chairman Bernanke (5/22)	0.00781
6	2008/10/29	Mounting expectation of interest rate cuts at the forthcoming BOJ policy meeting (10/29)	0.00778
7	2013/4/12	Governer Kuroda made a speech in Tokyo for the first time after the introduction of QQE I (4/12)	0.00639
8	2007/11/2	Governer Fukui was summoned to the House of Representatives, Financial Monetary Committee (11/2)	0.00567
9	2013/5/15	The BOJ offered 2.8 trillion yen under the funds-supplying operation (5/15)	0.00543
10	2007/12/12	The FOMC announced interest rate cut by 25bps (12/11)	0.00543
11	2007/11/27	Decline in U.S. interest rates due mainly to the subprime mortgage problem (11/26)	0.00453
12	2011/3/14	The Great East Japan Earthquake (3/11)	0.00394
13	2013/6/25	Strong demand for JGBs in the auction for enhanced-liquidity. The bid-to-cover ratio was 5.95 (6/25)	0.00394
14	2006/9/22	——	0.00394
15	2013/6/13	Member of the BOJ Policy Board Shirai made a speech in Asahikawa (6/13)	0.00379
16	2013/5/22	The BOJ maintained the current policy (5/22)	0.00374
17	2007/8/29	——	0.00369
18	2008/5/16	——	0.00363
19	2013/5/17	The BOJ offered outright purchase of 1.3 trillion yen JGBs (5/17)	0.00358
20	2009/3/19	The FOMC announced the starting of treasury purchases (3/18)	0.00352

c.f.

60	2016/1/29	Introduction of NIR by the BOJ (1/29)	0.00200
71	2016/9/21	Introduction of YCC by the BOJ (9/21)	0.00178

Note: After surprises are quantified as $\left(\ln p_{\tau} - \ln \overline{p}_{a\tau}\right)^{+}$, each day is ranked by the amount of surprises within the day.

(b) High interest rate surprises

Ranking	Date	Event	Surprise
1	2013/4/5	Introduction of QQE I by the BOJ（4/4）	-0.01537
2	2006/6/9	Calendar rollover（6/9）	-0.01203
3	2013/5/15	It was reported that the Cabinet Ministers implied that a rise in interest rates was not an issue（5/14）	-0.01178
4	2013/5/23	Tapering speech by Federal Reserve Chairman Bernanke（5/22）	-0.00989
5	2010/12/9	Calendar rollover（12/9）	-0.00874
6	2006/3/9	Termination of QE by the BOJ（3/9）	-0.00862
7	2007/3/9	Calendar rollover（3/9）	-0.00779
8	2008/6/11	Calendar rollover（6/11）	-0.00771
9	2008/5/23	——	-0.00764
10	2013/4/8	A circuit breaker was triggered in the JGB futures market（4/8）	-0.00739
11	2008/10/9	The BOJ did not coordinate with accomodative interest rate cuts by six central banks in the U.S. and Europe（10/8）	-0.00562
12	2005/3/10	Calendar rollover（3/10）	-0.00544
13	2013/5/24	Tapering speech by Federal Reserve Chairman Bernanke（5/22）	-0.00513
14	2013/4/12	Governer Kuroda made a speech in Tokyo for the first time after the introduction of QQE I（4/12）	-0.00500
15	2013/4/11	The BOJ had a meeting with market participants to exchange their views on the current and future market（4/11）	-0.00492
16	2008/6/13	The BOJ's monetary policy meeting（6/13）	-0.00475
17	2013/12/11	Calendar rollover（12/11）	-0.00443
18	2008/11/14	The Ministry of Finance held a meeting of JGB Market Special Participants（11/14）	-0.00384
19	2010/12/15	The BOJ released the results of December 2010 Tankan survey（12/15）	-0.00367
20	2007/6/13	——	-0.00366

Note: After surprises are quantified as $\left(\ln p_\tau - \ln \underline{p}_{b\tau}\right)^-$, each day is ranked by the amount of surprises within the day.

Figure 1. Demand Function of Long-Side Informed Traders

(a) Investment decision-making based on private information

(b) Shape of the demand function

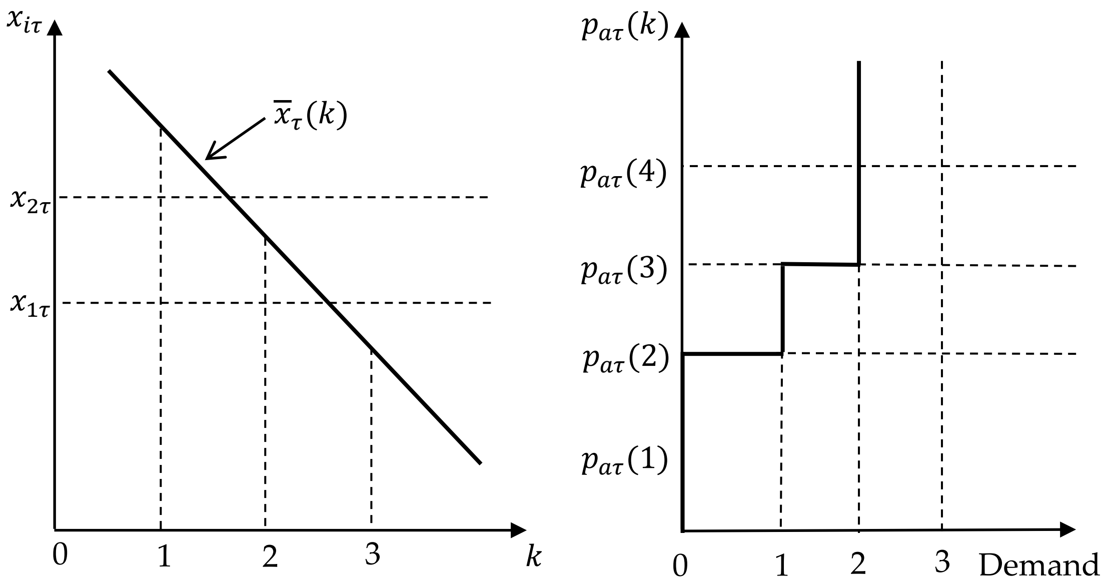
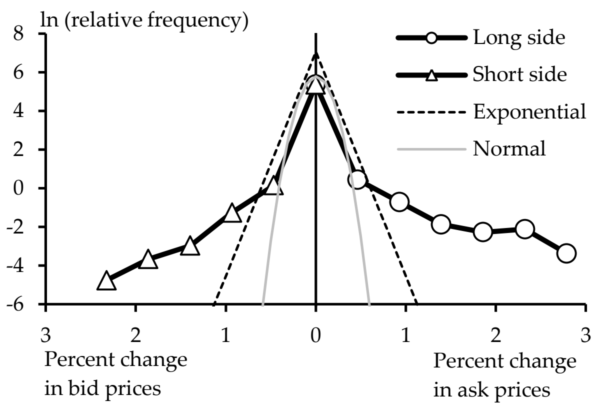


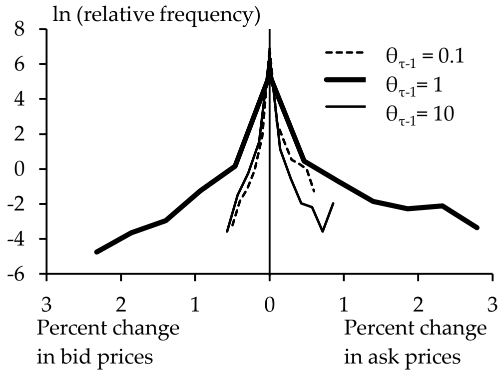
Figure 2. Fat-Tail Distribution of Asset Prices



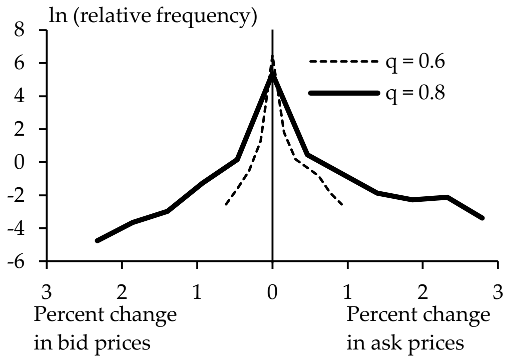
Note: Private information is generated from F_H. The simulation is iterated 25,000 times each for long and short sides.

Figure 3. Comparative Statics of the Asset Price Distribution

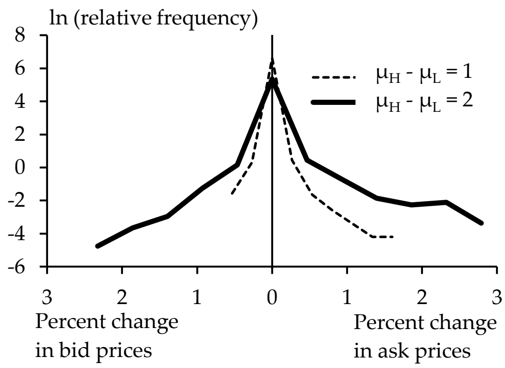
(a) Effects of likelihood ratios



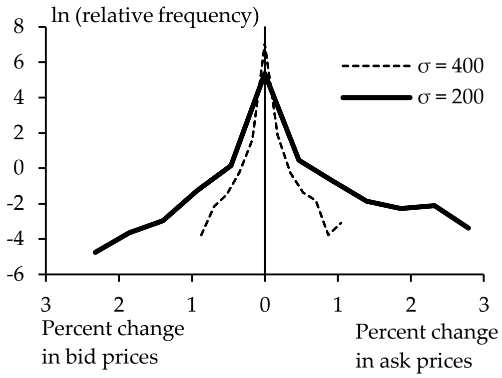
(b) Effects of traders' expected marginal value of public information



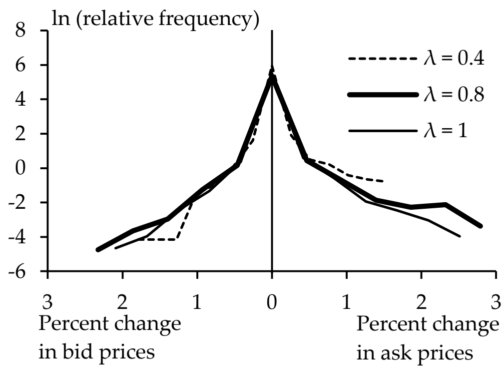
(c) Effects of accuracy of private information (mean difference)



(d) Effects of accuracy of private information (standard deviation)



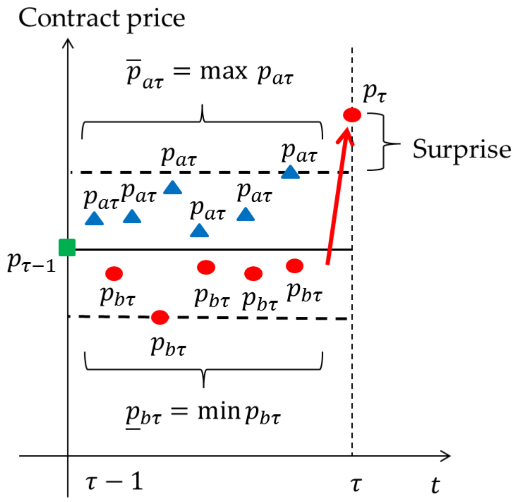
(e) Effects of market liquidity



Note: Private information is generated from F_H. The simulation is iterated 25,000 times each for long and short sides.

Figure 4. Fitting the Model to Tick-by-Tick Data

(a) Surprises identified



(b) No surprises identified

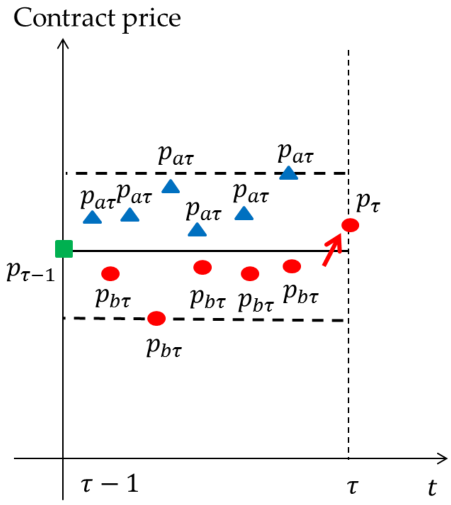
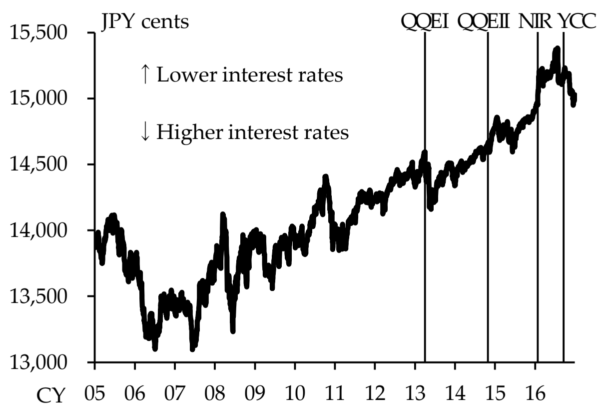
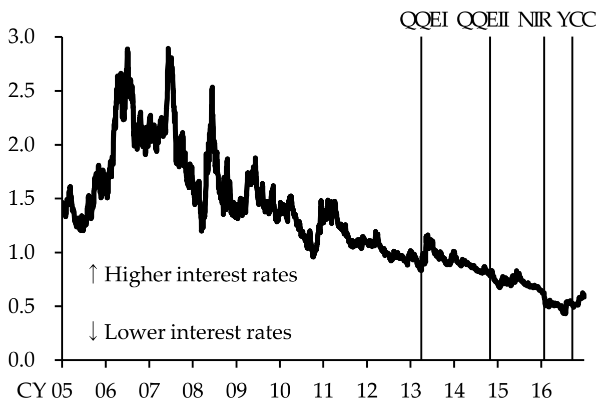


Figure 5. Fair Prices and Traders' Beliefs

(a) Estimated fair prices



(b) Traders' beliefs on financial states



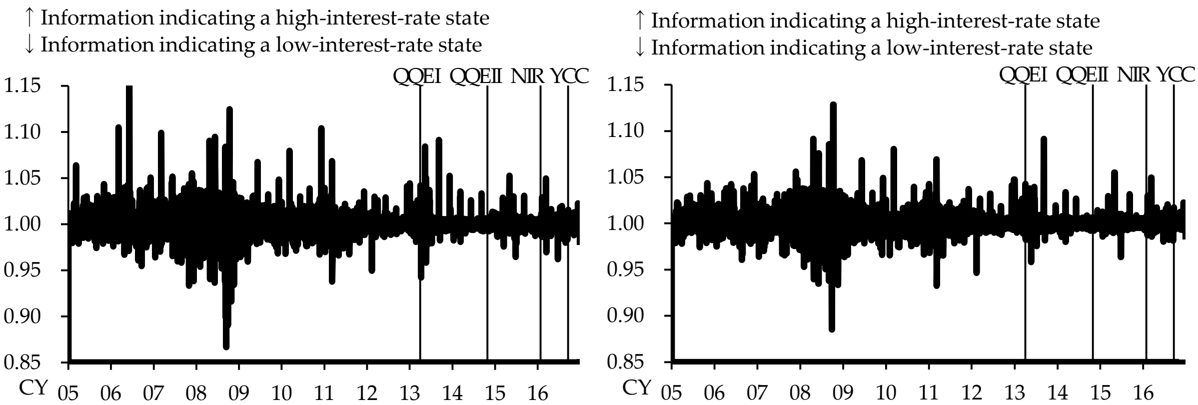
Notes: 1. Four vertical lines in each chart correspond to QQE I on April 4, 2013, QQE II on October 31, 2014, NIR on January 29, 2016, and YCC on September 21, 2016, respectively. This also applies to the following figures.

2. Figures are averaged on each day.

Figure 6. Realized and Expected Marginal Value of Public Information

(a) Realized marginal value of public information

(b) Expected marginal value of public information



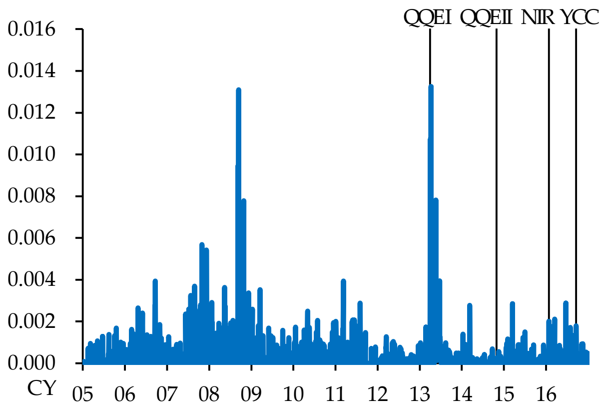
Notes: 1. The realized marginal value of public information is depicted as the range between the maximum and the minimum value of η_τ within each day.

2. The expected marginal value of public information is depicted as the range between the maximum value of $\hat{\eta}_{b\tau}$ and the minimum value of $\hat{\eta}_{a\tau}$ within each day.

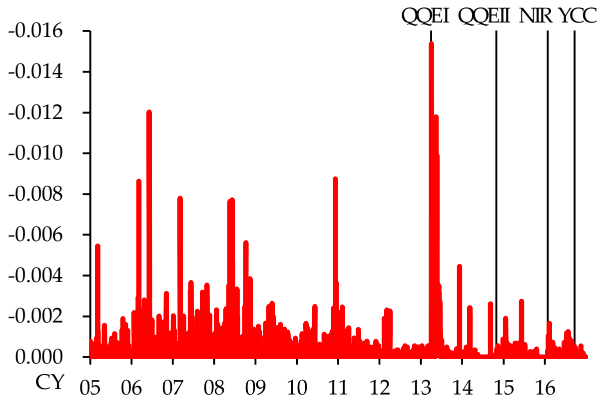
Figure 7. Surprises

(a) Amount of surprises

(a-1) Low interest rate surprises

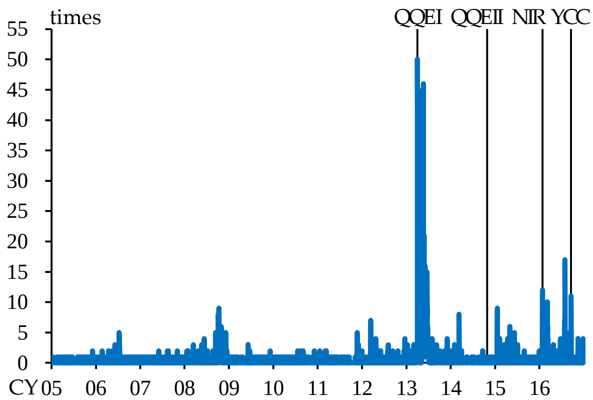


(a-2) High interest rate surprises

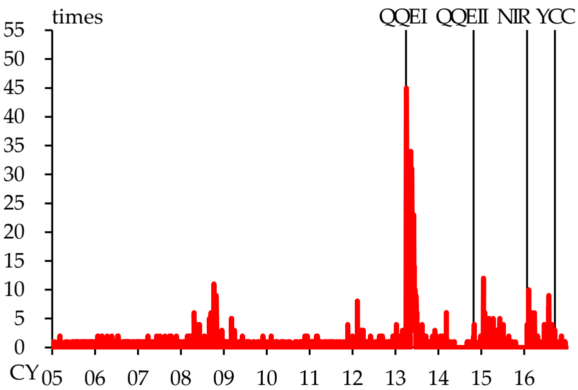


(b) Frequency of surprises

(b-1) Low interest rate surprises



(b-2) High interest rate surprises

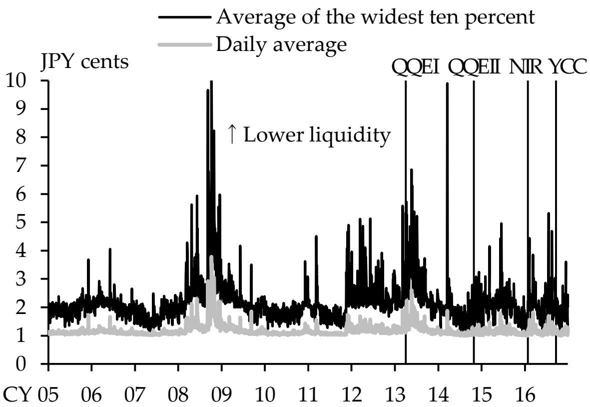


Notes: 1. Amount of surprises is the total size of surprises within a day. Frequency of surprises is the number of times that traders are surprised within a day.

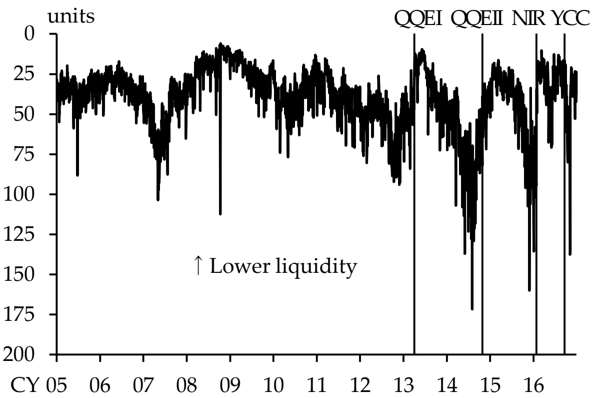
2. For amount, low and high interest rate surprises are quantified as $\left(\ln p_\tau - \ln \overline{p}_{a\tau}\right)^+$ and $\left(\ln p_\tau - \ln \underline{p}_{b\tau}\right)^-$, respectively.

Figure 8. Liquidity Indicators

(a) Bid–ask spreads



(b) Market depth



Notes: 1. Two series of bid–ask spreads are given by the average of whole bid–ask spread data and the widest ten percent of that data with a one-minute frequency on each day.

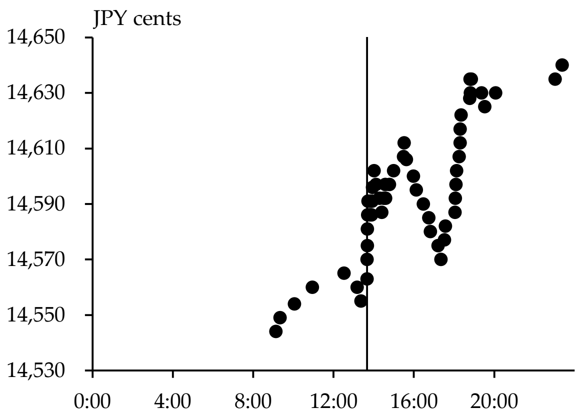
2. Market depth is given by the average of the volume of limit order at the best ask price with a one-minute frequency on each day.

3. Non-business days are excluded.

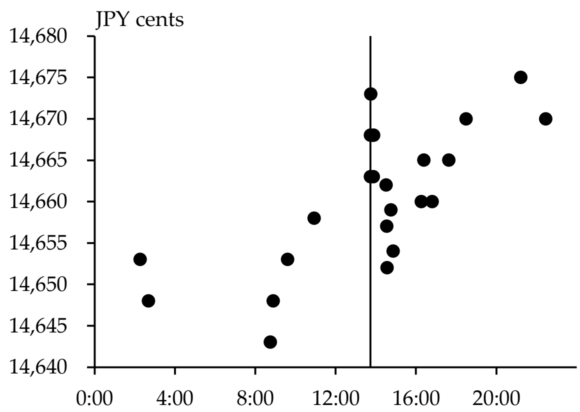
4. The way to construct liquidity indicators is in line with Bank of Japan (2017).

Figure 9. Intra-Day Developments of Fair Prices

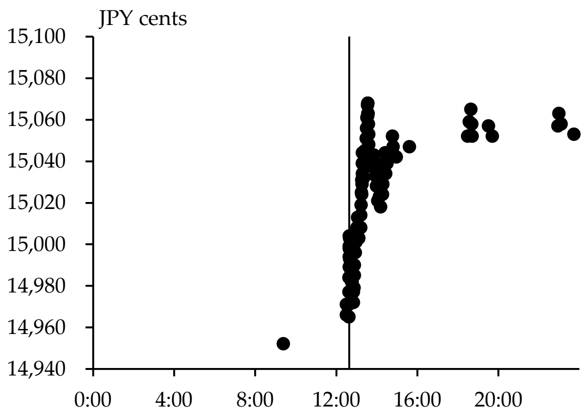
(a) QQE I (April 4, 2013)



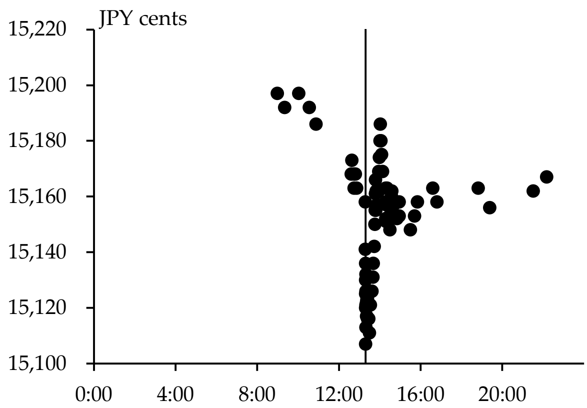
(b) QQE II (October 31, 2014)



(c) NIR (January 29, 2016)



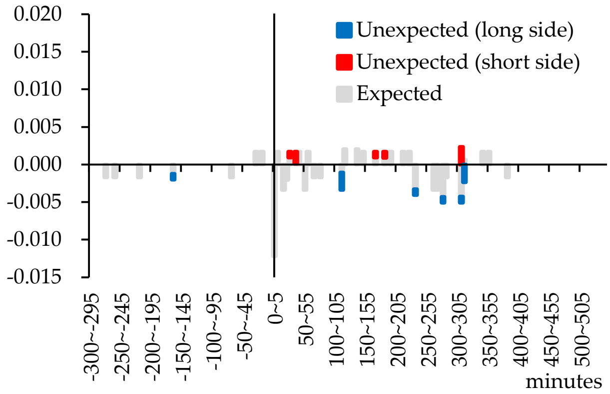
(d) YCC (September 21, 2016)



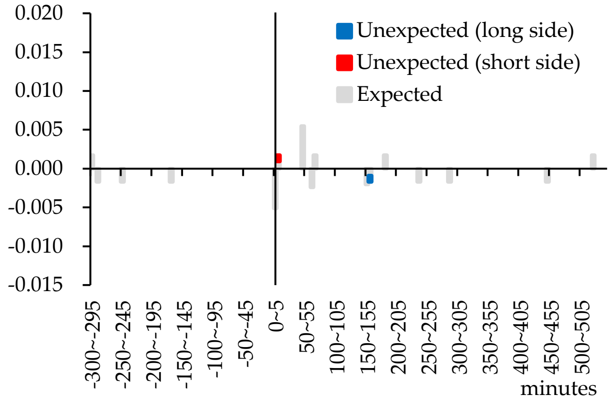
Note: Vertical lines correspond to announcement times.

Figure 10. Expected and Unexpected Marginal Value of Public Information

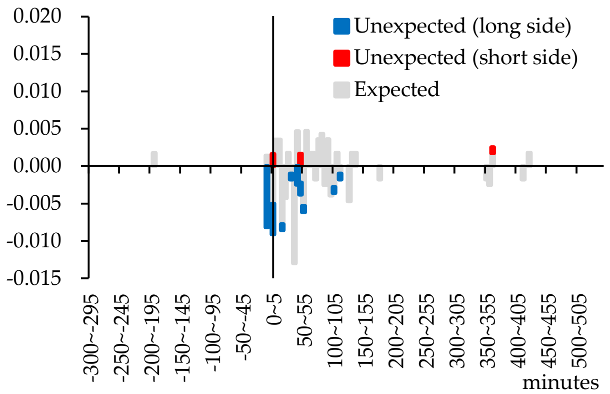
(a) QQE I (April 4, 2013)



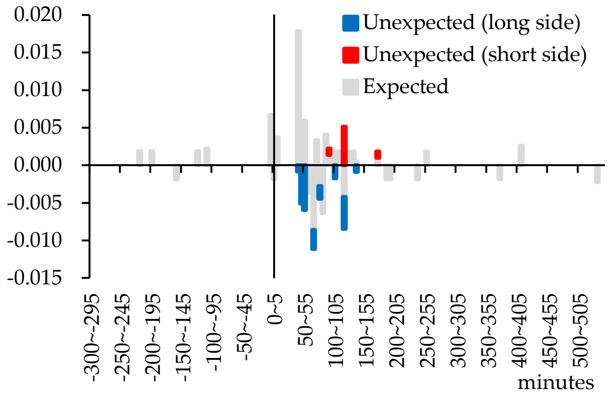
(b) QQE II (October 31, 2014)



(c) NIR (January 29, 2016)



(d) YCC (September 21, 2016)

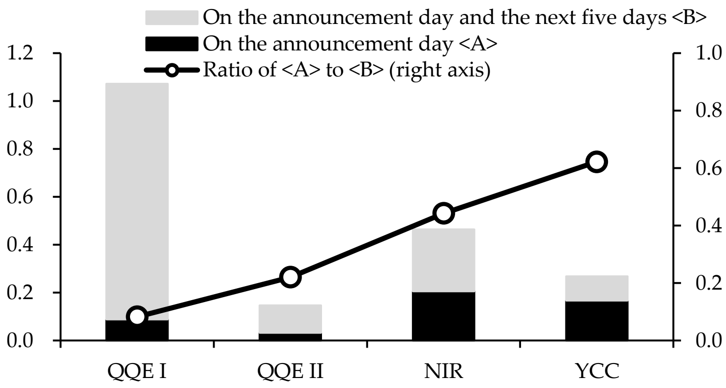


Notes: 1. Unexpected components are surprises quantified as $(\ln \eta_\tau - \ln \hat{\eta}_{a\tau})^-$ or $(\ln \eta_\tau - \ln \hat{\eta}_{b\tau})^+$. Expected components are derived by subtracting unexpected components from log realized marginal value of public information, $\ln \eta_\tau$.

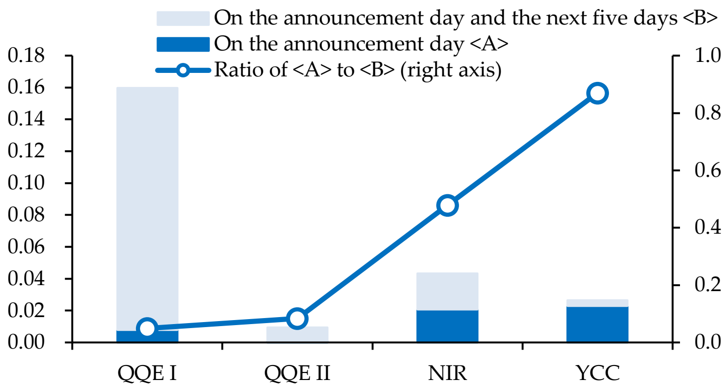
2. Vertical lines correspond to announcement times adjusted to zero. Figures are summed at the timing of fair price updates at intervals of five minutes.

Figure 11. Market Responses Observed over a Longer Horizon

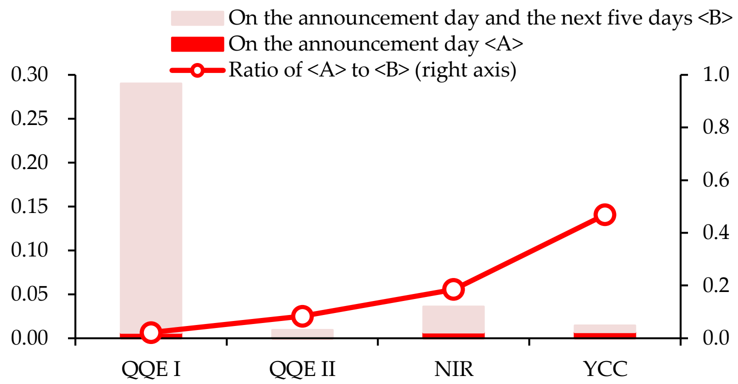
(a) Frequency of fair price updates



(b) Low interest rate surprises



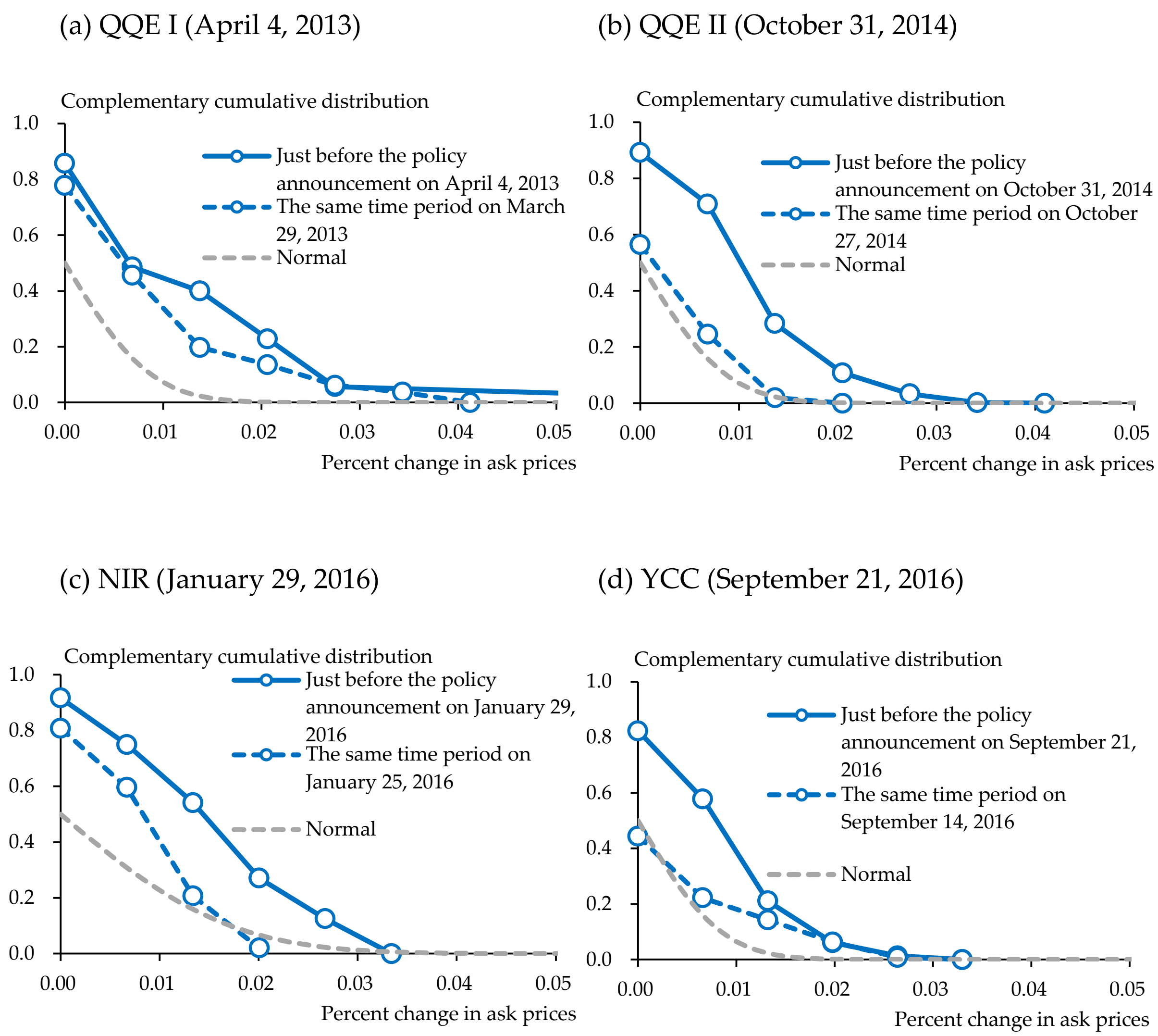
(c) High interest rate surprises



Notes: 1. Frequency of fair price updates is weighted by the absolute realized marginal value of public information, $|\ln \eta_\tau|$. Low and high interest rate surprises are quantified as $-(\ln \eta_\tau - \ln \hat{\eta}_{a\tau})^-$ and $(\ln \eta_\tau - \ln \hat{\eta}_{b\tau})^+$, respectively.

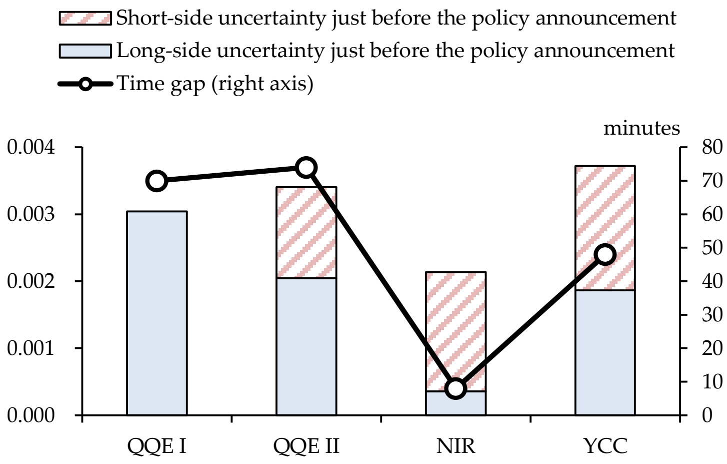
2. Figures on the announcement day are summed up at intervals between the policy announcement and the closing of the subsequent night session.

Figure 12. Herding Behavior Reinforced before Policy Announcements



Note: Normal distributions are depicted as a reference, where mean is zero and standard deviation is equal to the median of the distribution observed four business days ahead of policy announcements.

Figure 13. Uncertainty Enlarged by Policy Announcement Delays

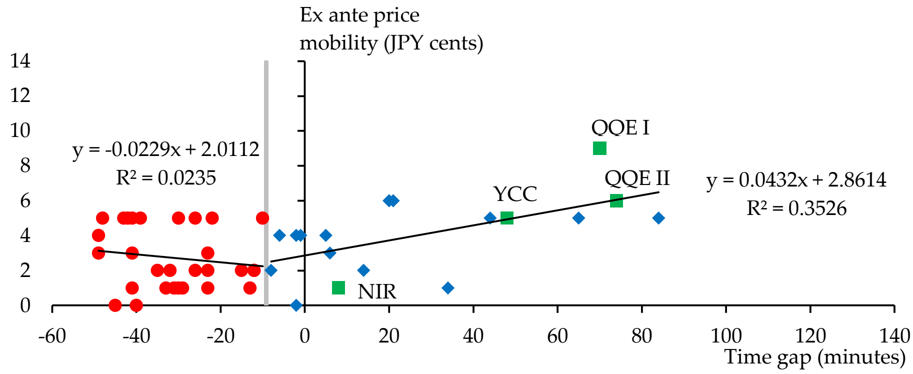


Notes: 1. Long-side and short-side uncertainty is given by the ex ante absolute expected marginal values of public information, i.e., $|\ln \hat{\eta}_{a\tau}|$ and $|\ln \hat{\eta}_{b\tau}|$, respectively.

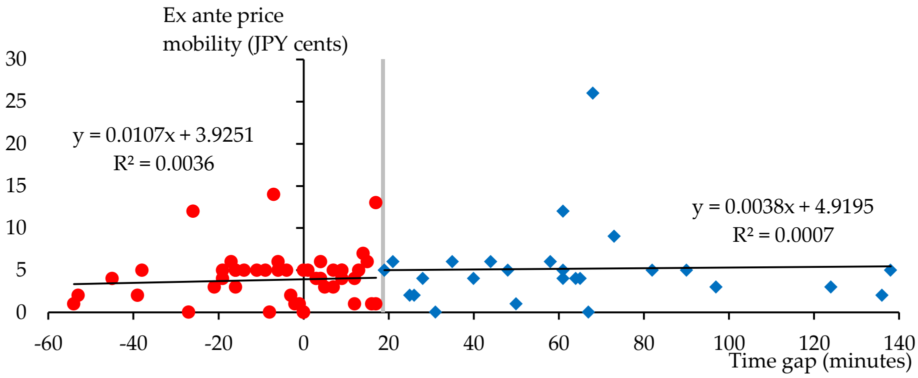
2. Time gap is the gap between the opening of the afternoon session (i.e., 12:30) and the release of the policy announcement.

Figure 14. Market Reaction to Policy Announcement Delays on the Long Side

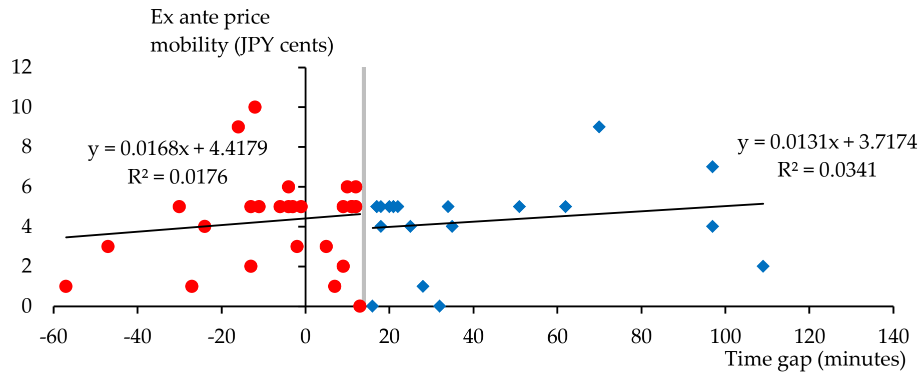
(a) Kuroda regime



(b) Shirakawa regime



(c) Fukui regime

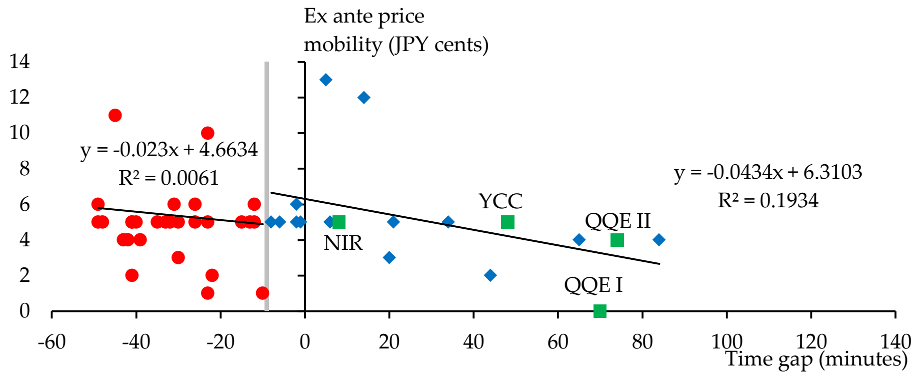


Notes: 1. Dots correspond to policy announcements released before 15:00. The announcement on October 31, 2008 is excluded because of extraordinarily high price mobility.

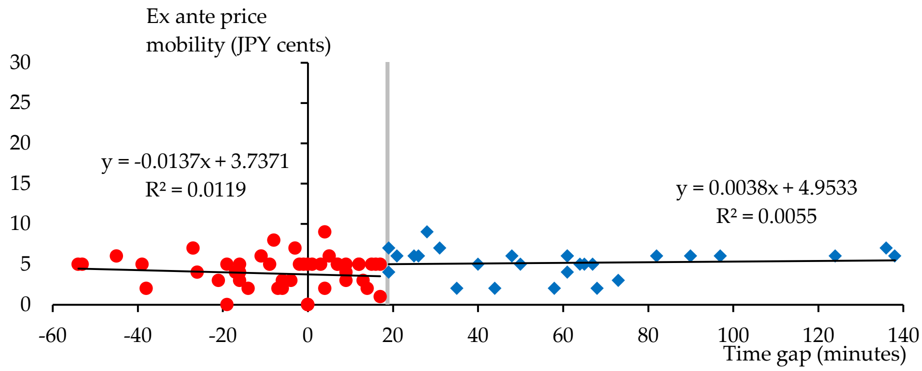
2. Vertical gray lines correspond to average time gap and divide samples under each regime. Red circles and blue (green) squares represent policy announcements released earlier (later) than the average, respectively.

Figure 15. Market Reaction to Policy Announcement Delays on the Short Side

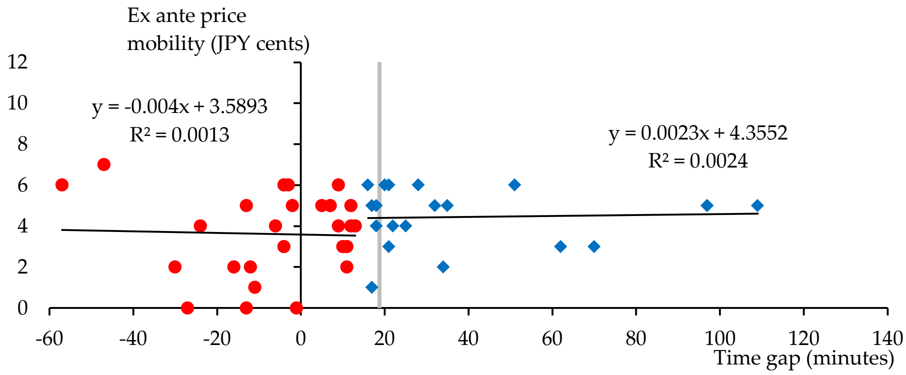
(a) Kuroda regime



(b) Shirakawa regime



(c) Fukui regime

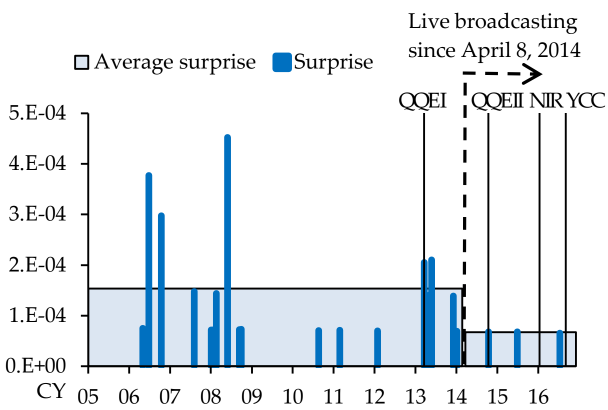


Notes: 1. Dots correspond to policy announcements released before 15:00. The announcement on October 31, 2008 is excluded because of extraordinarily high price mobility.

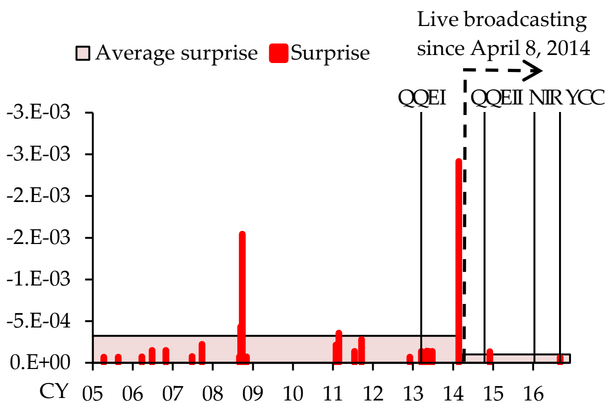
2. Vertical gray lines correspond to average time gap and divide samples under each regime. Red circles and blue (green) squares represent policy announcements released earlier (later) than the average, respectively.

Figure 16. Effects of Broadcasting the Governor's Press Conference

(a) Low interest rates surprises



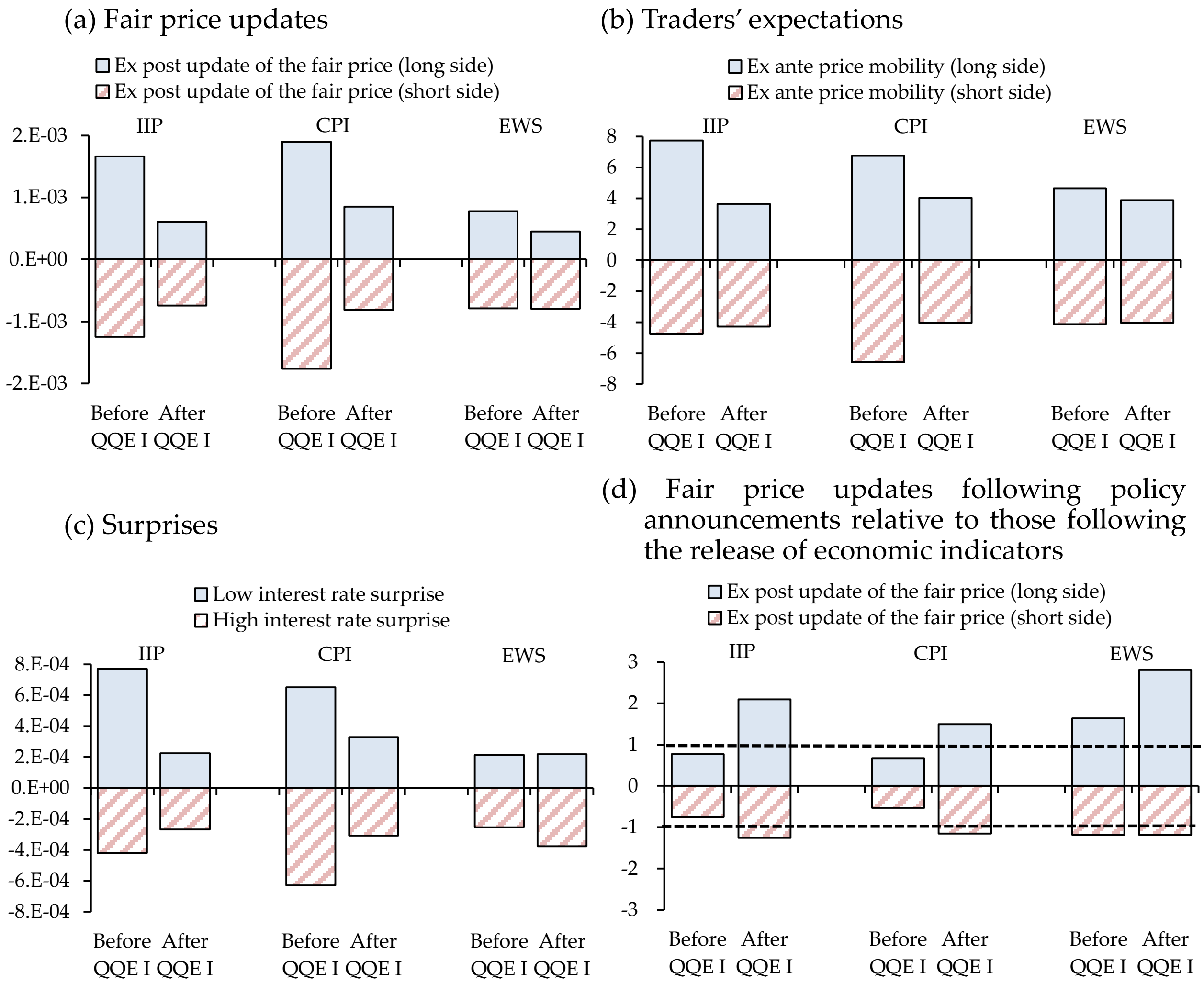
(b) High interest rates surprises



Notes: 1. Surprises are quantified in the same way as in Figure 7 and summed at the interval between 15:30 and 17:30 on the policy announcement days. While the press conference is usually held from 15:30 to 16:30, the interval between 16:30 to 17:30 is included to capture ex post responses of traders. If the press conference starts after 15:30, the interval for summing surprises is moved accordingly. If the press conference starts after the closing of the night session, the interval for summing surprises is an hour after the opening of the morning session on the next day.

2. Average is taken over samples with non-zero surprises prior to April 8, 2014 and later, respectively.

Figure 17. Fair Price Updates, Traders' Expectations, and Surprises at the Release of Economic Indicators: Comparisons before and after QQE I



Notes: 1. Ex post updates of the fair price are given by log differences between the fair price just before the release of economic indicators and the last fair price before the closing of the subsequent night session. Positive and negative fair price updates correspond to those on the long and short sides, respectively.

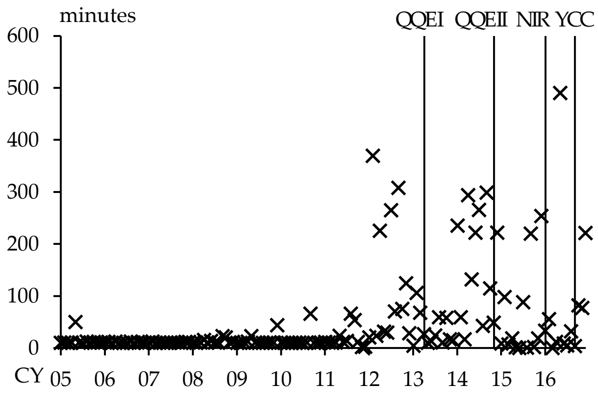
2. Ex ante price mobility is given by $\overline{p}_{a\tau} - p_{\tau-1}$ for the long side and $\underline{p}_{b\tau} - p_{\tau-1}$ for the short side just before the release of economic indicators.

3. Surprises are quantified in the same way as in Figure 7 and summed at the intervals between the release of economic indicators and the closing of the subsequent night session.

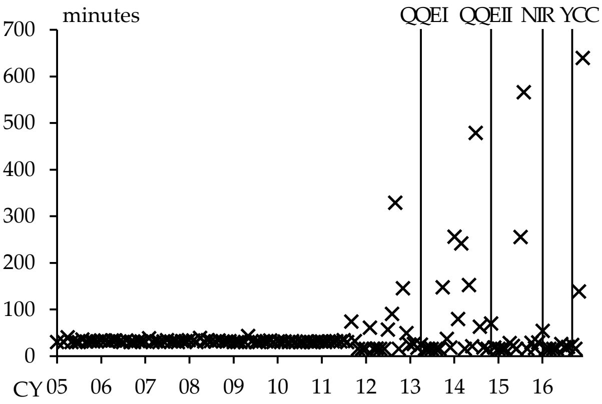
4. In the case where the indicators' release day coincides with the policy announcement day, fair price updates and surprises are replaced with zero.

Figure 18. Time to the First Responses to Economic News and Statements by the BOJ

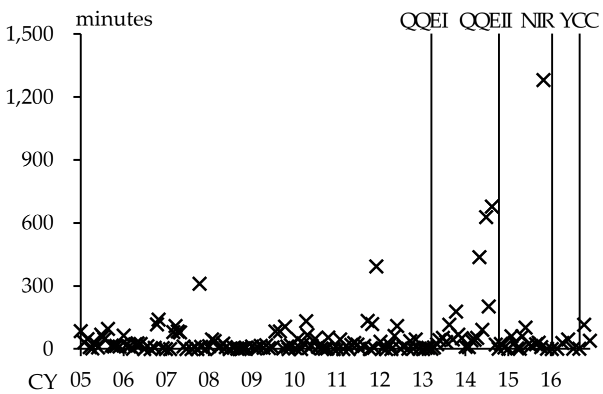
(a) IIP



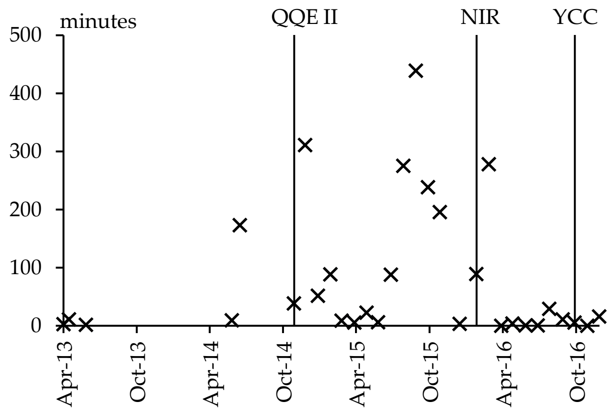
(b) CPI



(c) Policy announcements



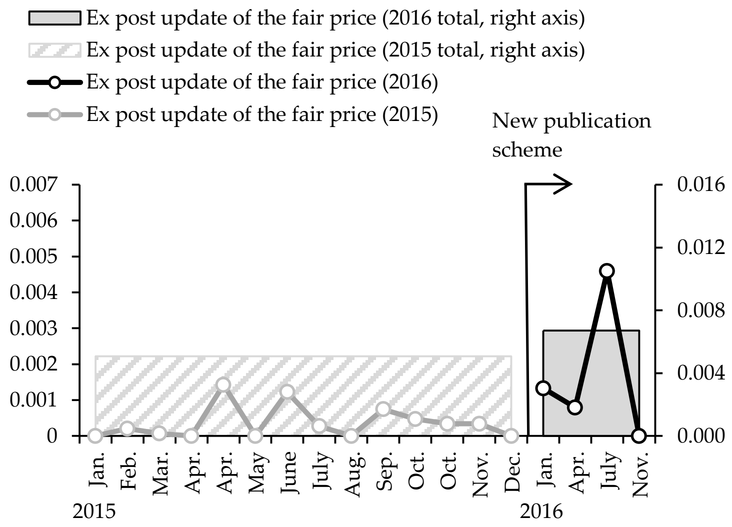
(d) Operation schedule



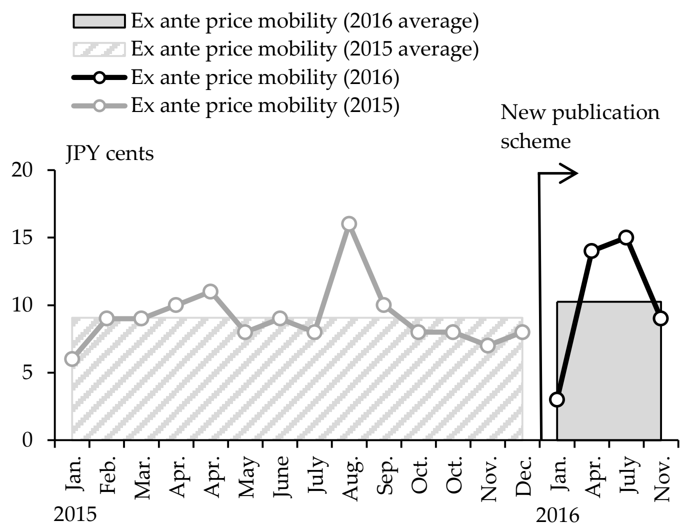
Note: The time gap is between the news release and the first update of the fair price after the release. If the release of a policy announcement comes after the closing of the night session, it is excluded from samples.

Figure 19. Total Information Value of the BOJ's Economic Analysis: Fair Price Updates and Traders' Expectations for the Release of Economic Reports

(a) Fair price updates



(b) Traders' expectations



Notes: 1. Ex post updates of the fair price are on the absolute value basis. Ex ante price mobility is the total mobility on both long and short sides. Otherwise, computations for the release of economic reports are the same as in Figure 16 for the release of economic indicators.

2. Of the two Aprils and Octobers of 2015 on each graph, the former and the latter correspond to the release of the *Monthly Report* and the *Outlook*, respectively.