ESSAYS ON EMPIRICAL ANALYSIS OF FINANCIAL RISK AND FIXED INCOME MARKET

BY

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CONTENTS

Chapter 1

Introduction

This dissertation consists of four chapters, where the first chapter is introduction and each of the latter chapters investigates financial markets from the perspective of financial risks and fixed income market. In chapter 2, I discuss investor's attitudes toward risk, especially in international financial markets. In chapter 3, I explore financial risks of the fixed income market, which is crucially important for the risk management of the commercial banks. In chapter 4, I discuss the determinants of the term structure of interest rate by taking advantage of quantitative and qualitative easing (QQE) conducted by the Bank of Japan (BOJ).

Chapter 2: Reserves and Risk: Evidence from China

Chapter 2 is a collaborative work with Rasmus Fatum and Yohei Yamamoto. This chapter investigates the risk from the foreign reserve's point of view. The build-up of international reserves across several emerging economies, including and most noticeably the case of China, took off after the Asian Financial Crisis (AFC) and has further accelerated since the Global Financial Crisis (GFC). Emerging economies accumulate reserves to provide insurance in the event of a financial crisis under the experience of the financial crisis. However, the counterproductive cost from moral-hazard induced private-sector risk-taking. If reserves correlate with the ability of the government to provide insurance in times of financial stress, private sector agents may be willing to take on more risk knowing that as reserve holdings increase, so does the ability of providing insurance and private sector bailouts. Considering the existing literature, there are very few researches related to the international reserve and the risk taking.

We focus our efforts on China as China is particularly interesting in this regard for two reasons. First, China holds more international reserves than any other country and has done so since before the GFC. Second, to our knowledge, China is the only emerging economy for which survey data on market expectations of reserve announcements exists. Specifically, survey expectations of Chinese reserve announcements are available from 2008 and onwards. This is important as it enables us to consider the surprise component of reserve announcements rather than having to rely only on either actual announcements or on model-based measures of expectations to identify the surprise component of a given reserve announcement.

To address whether reserve accumulation in China is associated with increased risk taking, we first carry out monthly frequency time-series estimations to assess the influence of GDP-normalized reserves separately on two risk-taking indicators, Chinese sovereign credit default (CDS) spreads and Chinese stock market (index) prices. Next, we consider daily data event study regressions of the effects of reserve announcement surprises on our two risk-taking indicators. Third, we extend our analysis to incorporate tick-level prices from three Chinese stock indices to perform an intraday analysis of whether reserve announcement surprises influence risk-taking as indicated by stock prices. Overall, our results suggest that as reserve holdings increase, CDS prices decrease while stock prices increase. This is consistent with the suggestion that an increase in reserve holdings is associated with an increase in risk-taking.

Chapter 3: The Information Content of the Implied Volatility of Interest Rates: Evidence from USD, EUR, and JPY Swaption

Chapter 3 investigates interest rate risk, which is a primary concern for risk management in financial institutions. Currently, traders tend to use IV (implied volatility) from the option price of interest rate swap (swaption) for forecasting interest rate risk, while financial institutions tend to use GARCH prediction or historical volatility. From a practitioner's point of view, it is vital to know the accuracy of a volatility prediction related to the interest risk.

Many studies have discussed the information content of IV based on other assets, such as equity options and foreign exchange. Even though it is vital for practitioners, to my knowledge, there is no paper that studies the information content of IV based on swaption for major currencies.

In chapter 3, I analyze the information content of IV based on swaption for three major currencies: the US dollar (USD), the Euro (EUR), and the Japanese yen (JPY). The result shows that IV has greater power to predict future realized volatility than GARCH predictions or historical volatility for the USD and EUR, which is consistent with the equity or futures options markets. However, GARCH forecasts and historical volatility have stronger predictive power for the JPY because of the lack of liquidity.

Chapter 4: The Impact of Quantitative and Qualitative Easing on Term Structure: Evidence from Micro-level Data

Chapter 4 investigates the effect of QQE conducted by the BOJ on the JGB price using micro-level panel data. I consider that the event of the implementation of the QQE policy should be an ideal situation to test the market segmentation theory (the preferred habitat theory), in which markets are segmented, investors demand bonds of a specific maturity, and the interest rate is determined by the supply and demand of bonds of that particular maturity. In this chapter, I use the micro-level panel data of JGBs to empirically show that the exogenous demand shock significantly affects the JGB price.

For identification, I take advantage of the institutional change in BOJ's market operations, which is unique to the BOJ's policy. Before March 2017, the BOJ notified the market participants at 10:10 a.m. whether it would conduct an operation or not. However, after March 2017, the BOJ decided to publish detailed schedules of its planned asset purchases in advance and inform market participants of the dates of its bond-buying operations. Following this policy change, the open market operation schedule is predetermined and cannot be institutionally changed by the BOJ; therefore, I can interpret the purchases by the BOJ as an exogenous shock, which suggests that this is an ideal situation for empirically testing the market segmentation theory.

I show that the BOJ's purchase significantly affects the JGB price, which is consistent with previous research such as D'Amico and King (2013). However, the estimated effect is considerably small; e.g., the operation could affect the yield of the 10-year JGBs by less than 1%. As Vayanos and Vila (2021) describe, the extent of the market segmentation depends on the investors' attitude to risk. The FRB conducted its QE policy during the financial crisis, which amplified the effect, while the BOJ implemented its QQE policy in a stable period, which should be a natural situation where the impact of the QQE is considerably small.

Chapter 2

Reserves and Risk: Evidence from China

2. 1 Introduction

We attempt to contribute to the empirical literature on reserves by considering if Chinese reserve accumulation after the global financial crisis (GFC) is associated with counterproductive costs in the form of increased private sector risk taking. Using sovereign credit default swap spreads (CDS) and stock index prices as indicators of risk taking we provide evidence to suggest that as reserve holdings increase, so does the willingness to take on more risk.

China is particularly interesting when considering the effects of reserve accumulation for two reasons. First, China holds more reserves than any other country and has done so since before the GFC.[1] The reserve levels of China have been consistently excessive well before the GFC and beyond according to most models of optimal reserve levels as well as according to various rules of thumb guidelines, thereby making China particularly at risk for adverse and unintended consequences of reserve accumulation.[2] Second, to our knowledge, China is the only emerging economy for which survey data on market expectations of reserve announcements exists. Specifically, survey expectations of Chinese reserve announcements are available from 2008 and onwards. This is important as it enables us to identify the surprise component of reserve

[1] At the end of 2015, China overtook Japan as the country holding the largest amount of reserves in the world.

[2] For example, when Obstfeld et al. (2010) compare actual levels of reserves to predictions from models of optimal reserves augmented to account for changes in financial openness and financial development, they only find systematic and substantial deviations between actual and predicted reserves for the case of China (and only after 2002 when the pace of reserve accumulation in China increased markedly). Similarly, reserve levels in China deviate dramatically from what rule of thumb guidelines would suggest, e.g. since the GFC reserves have consistently been in excess of at least six times the value of three months of imports, and reserves have consistently been in excess of more than double the value of external short term debt. It is noteworthy, however, that Bianchi et al. (2018), in a study of reserve accumulation and roll-over risk, find that simulated optimal reserve levels can reach 40% of GDP, corresponding to roughly double the current Chinese reserves to GDP ratio, indicating that as per this metric Chinese reserve holdings are not necessarily excessive.

announcements and, in turn, effectively address reverse causality endogeneity bias when estimating the effects of reserve accumulation on risk taking.[3]

As indicators of risk taking we employ two model-free and market based measures: Sovereign CDS spreads and stock index prices.[4] The CDS spreads represent the cost of insuring against default on US dollar denominated Chinese sovereign debt.[5] A likely manifestation of an increase in the willingness to take on more risk is a reduction in demand for default insurance which, ceteris paribus, would lead to a decrease in the price of obtaining insurance. Therefore, a decrease in CDS spreads as reserves increase would be consistent with reserve accumulation leading to an increase in risk taking. Similarly, an increase in risk taking is likely to increase the demand for, and thus willingness to pay more for, inherently risky assets. Thus, an increase in stock prices as reserves increase would also be consistent with reserve accumulation leading to an increase in risk taking. Since CDS spreads provide a risk measure specifically pertaining to extreme events, i.e. default or restructuring of sovereign debt, whereas stock prices provide a broad measure of risk reflecting changes in market sentiment that are not necessarily related to extreme events, the two risk indicators, while complementary, capture different types of risk.

To address whether reserve accumulation in China is associated with increased

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[3] It is well-known that failure to disentangle the expected component of an announcement may lead to an underestimation of the impact of the announcement. See, for example, Fatum and Scholnick (2008).

[4] Augustin et al. (2014) show that market participants primarily use CDS instruments for risk taking purposes, and Illing and Aaron (2005) note that a high degree of risk appetite may lead to rising stock prices. Since there is no universally accepted way to measure risk appetite, and different theoretical and empirical approaches to measuring risk appetite tend to provide markedly different outcomes, as discussed in Illing and Aaron (2005), it is preferable to use model-free and market based measures of risk taking.

[5] Obstfeld et al. (2009) point out the utility of foreign exchange reserves referring the document by the International Monetary Fund (2008, 37) such as "[I]n the face of sharp capital outflows, countries will need to respond quickly to ensure adequate liquidity and deal with emerging problems in weaker institutions. The exchange rate should be allowed to absorb some of the pressure, but stockpiles of reserves provide room for intervention to avoid disorderly market conditions."

risk taking we first carry out monthly frequency time-series estimations to assess the influence of GDP-normalized reserves separately on the two risk taking indicators, CDS and stock market index prices. Our full sample spans the July 2001 to October 2019 time-period. We pay particular attention to the post-GFC sub-sample. We first estimate our time-series models using OLS and, subsequently, we consider non-linearities by estimating threshold models with endogenously defined thresholds according to reserve levels as well as according to global market uncertainty. Next, we carry out daily data event study regressions of the effects of reserve announcement surprises on our two risk taking indicators. Third, we extend our analysis to incorporate tick-level prices from three Chinese stock indices to perform an intraday analysis of whether reserve announcement surprises influence risk taking as indicated by stock prices over 1-, 2-, and 5-minute windows. This is an important extension as it addresses endogeneity stemming from possible omitted variable concerns pertaining to the lower frequency estimations. Forth, we conduct the robustness check by using the different measure of risk taking and controlling additional variable. Finally, to complement, and provide context to, our China-focused investigation we also carry out monthly frequency time-series estimations of the influence of reserve accumulation on risk taking for five other Asian emerging economies (Indonesia, South Korea, Malaysia, Philippines, and Thailand).

Overall, our results suggest that as reserve holdings increase, CDS prices decrease while stock prices increase. This is consistent with the suggestion that an increase in reserve holdings is associated with an increase in risk taking. When we consider the effects of reserve accumulation separately across before and after GFC sub-samples, we show that our full sample results are driven by post-GFC effects. Our threshold estimations further confirm that reserves matter more for risk taking after the GFC. Daily data as well as intraday estimations provide additional evidence consistent with the suggestion that reserve accumulation is systematically and significantly associated with increased risk taking after the GFC. These are important findings that add credence to the suggestion that additional insurance in the form of costly reserve accumulation leads to private sector actions that, viewed in isolation, can make it more likely that the insurance will be used.

Although a very different study with respect to methodology, data, and sample period, our findings are broadly consistent with those of the study by Tong and Wei (2019) in which they use pre-GFC firm-level data on corporate leverage spanning 6610 non-financial companies across 23 emerging economies to show that higher levels of reserves is systematically and significantly related to higher corporate leverage.[6] By contrast, our findings are different from those of Fatum and Yetman (2020) and their country-specific daily data event study analysis of whether official announcements of reserves influence risk taking. Fatum and Yetman (2020) consider a sample of 10 economies, emerging as well as advanced, over the 1999 to 2017 period and find no systematic evidence that reserve accumulation influences risk taking as per their focal risk measure of implied volatility of currency options. However, our findings are not at odds with their stock price and CDS spread risk indicator based results to the extent that for these two measures Fatum and Yetman (2020) do not reject that reserve accumulation matters for risk taking. Our CDS-based results can be seen as in line with Ismailescu and Phillips (2015) and their finding that high levels of reserves are associated with less trading of sovereign CDS

[6] Tong and Wei (2019) use firm-level data on corporate leverage spanning 6610 non-financial companies across 23 emerging economies to show that higher levels of reserves is systematically and significantly related to higher corporate leverage. In line with Tong and Wei (2019), Sengupta (2010) uses firm-level data spanning 1500 firms across six Latin American emerging economies to show that higher levels of reserves are associated with higher levels of USD denominated corporate debt.

in the sense that less CDS trading could reflect that less efforts are being taken to insure against risk.

The rest of this chapter is organized as follows. Section 2. 2 provides some background on reserve accumulation. Section 2. 3 provides some background on reserve accumulation. Sections 2. 4 and 2. 5 present and discuss the empirical framework and the results, respectively. Section 2.6 check the robustness of the estimation. Section 2. 7 provides extensions and robustness checks. Section 2. 6 concludes.

2. 2 Reserve Accumulation

2.2.1 Literature

The build-up of international reserves across several emerging economies, including and most noticeably in the case of China, took off after the Asian financial crisis (AFC) and has further accelerated since the GFC. Generally, an essential rationale underlying accumulation of reserves is the precautionary savings motive, i.e. the desire to hold liquid insurance, in the form of foreign currency, against adverse financial market shocks and sudden capital outflows.[7] Other key drivers are export-driven growth in conjunction with varying degrees of managed exchange rate systems pushing up the level of reserves if foreign exchange intervention operations aimed at mitigating pressure for the domestic currency to appreciate are undertaken, as well as less developed domestic financial systems where, for example, capital controls interfere with private investments.[8]

While the precautionary savings motive may explain part of the observed accumulation of reserves, several Asian emerging economies hold reserves in excess of

[7] See Jeanne and Sandri (2020) for a recent contribution on optimal reserves and precautionary savings.
[8] See ECB (2006) for a useful overview of traditional drivers of reserve accumulation. Cheung and Qian (2009) suggest keeping up with the Joneses as an alternative driver of reserve accumulation.

levels typically dictated by models of optimal reserve holdings as well as by rule of thumb guidelines.[9] This may seem surprising, considering that holding reserves is costly.[10] However, the willingness to incur the cost of holding high levels of reserves can be rationalized by the expectation that holding substantial reserves may reduce the severity of a financial crisis, expedite subsequent recovery, and make a financial crisis itself less likely.[11,12]

Traditionally, the cost of holding reserves is measured as the spread between the return on reserves held versus the opportunity cost of reserves held, i.e. the foregone return on investment in physical or human capital or, simply, the cost of external borrowing.[13] However, the cost of holding reserves goes beyond opportunity costs from foregone returns, or incurred borrowing costs, and includes indirect costs such as sterilization costs, interest rate costs and difficulties in implementing monetary policy.[14] For example, Yun (2020) studies a crowding-out effect in the form of reduced commercial

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[9] For example, Jeanne (2007) uses a model of optimal reserve levels with an insurance motive to show that the build-up of reserves in Asian emerging economies after the AFC can only be explained if the expected output cost associated with a sudden stop capital account crisis is unrealistically large. Similarly, Jeanne and Rancière (2011) show that the build-up of reserves in Asian emerging economies can only be explained within the confines of their model when expected output cost of a sudden stop crisis is combined with a high degree of risk aversion. As for rule of thumb guidelines for reserve accumulation, these typically pertain to reserves relative to imports or reserves relative to external short-term debt ratios. While the former suggests that the level of reserves should amount to the value of three months of imports, and the latter, known as the Guidotti-Greenspan rule, suggests that the level of reserves should cover (at least) the external short-term debt of a country, reserve levels in Asian emerging economies are often in excess also of these rule of thumb guidelines.

[10] See Aizenman and Jinjarak (2020) for a recent study of optimal management of reserves aimed at mitigating the cost of holding reserves. People's Bank of China (PBC) (2019) addresses reserves management practices aimed at reducing the cost of holding reserves in the context of China.

[11] See, for example, Feldstein (1999).

[12] Interestingly, there is no consensus on whether a high level of reserves helped facilitate faster post-GFC recovery. For example, Blanchard et al. (2009) do not report that more reserves lowered output declines whereas Dominguez et al. (2012) find that higher levels of reserves prior to the GFC are associated with higher post-GFC output growth.

[13] See Baker and Walentin (2001) and Rodrik (2006). Rodrik (2006) refers to the opportunity cost of holding reserves as the social cost of self-insurance. Yeyati (2008) suggests that the social cost of self-insurance via reserves is overstated if reserves reduce default risk.

[14] See ECB (2006) for a detailed discussion of indirect costs associated with holding reserves.

bank credit expansion as a result of reserve accumulation.

Importantly, and the focus of our study, reserve accumulation may also be associated with an additional and perhaps particularly concerning counterproductive cost from moral-hazard induced private sector risk taking. If reserves correlate with the ability of the government to provide insurance in times of financial stress, private sector agents may be willing to take on more risk knowing that as reserve holdings increase, so does the ability of providing insurance and private sector bailouts. In doing so, private sector risk taking can increase the probability of overinvestment and asset bubbles which, in turn, can make a financial crisis more likely. In other words, while emerging economies accumulate reserves to provide insurance in the event of a financial crisis, this may have the unintended counterproductive effect of increasing the likelihood of a financial crisis. If this is the case, rather than the insurance premium paying for itself, as suggested by Rodrik (2006), the insurance premium includes an increase in the probability of a financial crisis and thus that the insurance will be put to use.

2.2.2 The Foreign Reserve of China

Before the GFC, the foreign reserves of China continued to increase, reflective of the consistent increase of Chinese exports (Neely, 2017). However, after the GFC, exports started to decline gradually, thereby negatively impacting the foreign reserves. Since 2014, the foreign reserves started to decline. This is partially because the People's Bank of China has sold USD and purchased CNY to maintain the value of CNY.

In addition, Neely (2017) highlights that there has been relative demand for foreign assets (decreased demand for CNY). If Chinese residents purchase USD from an exchange bank, the bank has to buy USD from the People's Bank of China, which decreases the foreign reserves of China. In particular, McCauley and Shu (2016) emphasize that Chinese firms have reduced their USD-denominated debt, which also contributes to the relatively higher demand for foreign assets.

The Chinese policy regarding its foreign reserves also changed around 2015. Before this, the Chinese government did not disclose its foreign reserve portfolio, but China has begun to report this to the IMF from October 2015. In 2019, China disclosed for the first time the return of investment and the currency structure of its foreign reserves.

2.2.3 The Foreign Reserve and Default

The foreign reserve level is related to the solvency of countries since foreign reserves should work as buffers for repaying external debt, such as USD-denominated debt. The State Administration of Foreign Exchange (SAFE) releases China's external debt data with the ratio of short-term external debt to foreign exchange reserves, and it comments on the external debt risk using the concept based on the status of the foreign reserves. For example, the SAFE has commented "[a]s at the end of 2019, the liability ratio was 14.3 percent, the debt ratio was 77.8 percent, the debt servicing ratio was 6.7 percent, and the ratio of short-term external debt to foreign exchange reserves was 38.8 percent. China's major external debt metrics were all within the internationally recognized thresholds, indicating that the external debt risk is controllable on the whole."

One of the strands in the literature using the foreign result is to focus on the foreign reserve as the role of preventing the default risk, and the empirical evidence exist for supporting this idea. For example, Ben-Bassat and Gottlieb (1992) firstly introduce sovereign risk into the consideration for precautionary reserve demand. Haque et al. (1996) discuss the foreign reserve can explain the variation of indicator of the creditworthiness of developing countries. Gumus (2016) discusses whether the relationship between international reserves and sovereign spreads depends on exchange rate policy, and shows that international reserves reduce sovereign spreads for all levels of exchange rate flexibility.

2. 3 Data

Our data on Chinese reserves consists of date- and time-stamped PBC announcements and spans the July 2001 to October 2019 time-period. The reserve announcements occur at a monthly frequency. Following rapid growth rates from the onset of our sample period Chinese reserve holdings peaked at almost USD 4,000 billion in June 2014. Subsequently, reserve holdings gradually declined before stabilizing at around USD 3,000 billion. Figure 1 shows the evolution of Chinese reserves and Table 1 provides descriptive statistics.[15]

Our data on survey expectations of Chinese reserve announcements is obtained from Money Market Services (MMS) and Bloomberg News Service. Quarterly survey data is available from January 2008 and monthly after September 2015. Following Andersen et al. (2003) and others we construct for each reserve announcement the standardized announcement surprise as the unexpected component of the announcement divided by the sample standard deviation.[16]

[15] For the purpose of our empirical analysis we follow Fatum and Yetman (2020) and others in normalizing reserves by domestic GDP.

[16] Let A_t denote the value of a given reserve announcement on day t. Let E_t refer to the median value of the preceding survey expectations, and let $\hat{\sigma}$ denote the sample standard deviation of all reserve announcement surprise components across the entire sample period. The standardized reserve announcement surprise on day t is then defined as $\frac{A_t - E_t}{\hat{\sigma}}$.

The potential concern in this survey data is whether this survey reflects the true expectation of investors. First, we confirm that this survey is strongly correlated to the actual variation of the foreign reserves. Figure 2 (a) shows the time series of the actual and forecast data of the reserves. This figure indicates that the forecast can track the movement of the actual value of the foreign reserves. Second, Bloomberg assembles its forecasts from professional economists in large financial institutions, which mitigates the risk that respondents provided answers randomly. Figure 2 (b) shows the time series of reserve announcement surprises.[17]

Our stock market risk taking indicator is the Morgan Stanley Capital International (MSCI) China index and our sovereign CDS risk taking indicator is the five-year Chinese USD-denominated sovereign CDS spread obtained from Markit Inc. The two risk-indicator series are depicted at the top of Figure 3 and descriptive statistics provided in Table 1.

We employ as control variables the CNY/USD exchange rate and the MSCI US stock index. The control variables are displayed at the bottom of Figure 3 and descriptive statistics provided in Table 1. Additionally, as an indicator of global market uncertainty we make use of the VIX series.[18,19]

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[17] Note that Figure 2 depicts pre-scaled (i.e. $A_t - E_t$) surprises. Note also that announcements are typically made outside of market hours (59 out of 68) and that the expectation errors are smaller after 2014, the latter suggesting that Chinese reserve announcements are increasingly predictable.

[18] The Chicago Board Options Exchange (CBOE) Volatility Index (VIX) is an oft-used indicator of global risk. The VIX is a forward-looking, model-free measure of the near-term (30-day) implied volatility of S&P 500 index options.

[19] Risk indicators as well as VIX and control variables are obtained as daily data series. For the purpose of our monthly frequency estimations (baseline and threshold), monthly series data points are generated from the daily data as the difference between previous end of month and current end of month observations.

For the purpose of our intraday assessment of whether reserve accumulation influences risk taking we employ tick-level traded prices for three major Chinese stock market indices, the CSI 300 Index, the Shanghai SE Composite Index, and the Shenzhen SE Composite Index. The tick-level data series are provided by Tick Data Inc.

To provide a comparison point for our results on China, we extend our analysis to consider other Asian emerging market economies. Specifically, we consider reserve accumulation and risk taking in Indonesia, Malaysia, Philippines, South Korea, and Thailand.[20] Our data on normalized reserves for these countries also span the July 2001 to October 2019 time-period except for Indonesia where the reserve series start April 2004. Risk indicator series for the five comparison countries are also constructed from country-specific MSCI stock price indices and country-specific five-year sovereign CDS spreads obtained from Markit Inc.[21]

2. 4 Econometric Methodology

To assess whether reserve accumulation influences risk taking we first estimate (separately) the following monthly frequency baseline models:

$$\Delta S_t = \beta_0 + \beta_1 \Delta RES_t + \beta_2 \Delta CNYUSD_t + \beta_3 \Delta USS_t + e_t, \tag{1}$$

$$\Delta CDS_t = \beta_0 + \beta_1 \Delta RES_t + \beta_2 \Delta CNYUSD_t + \beta_3 \Delta USS_t + e_t, \tag{2}$$

where ΔS_t and ΔCDS_t denote, respectively, the change in the Chinese stock market

[20] The reserve accumulation of these five economies is also considered in Jeanne (2007).

[21] Descriptive statistics on intraday data and comparison country series are available upon request.

index and the CDS spread, i.e. these are our two risk indicators, ΔRES_t is the change in percent of normalized Chinese reserve holdings, i.e. this is our focal explanatory variable, $\Delta CNYUSD_t$ and ΔUSS_t are, respectively, the change in the CNY/USD exchange rate and the US stock market index, i.e. these are our control variables, and e_t is the zero-mean error term.

We include control variables to reduce omitted variable endogeneity bias in our estimates and choose as our controls US stock prices and the CNY/USD exchange rate for both models.[22] US stock prices are included to capture the changes in risk-taking behavior in the global market. Since China has adopted managed floating currency system, the exchange rate in China is highly related to foreign reserves, we also include the changes in the exchange rate. For example, Phylaktis and Ravazzolo (2005) and Longstaff et al. (2011), respectively, showed the relevance of exchange rates and US stock prices when modeling non-US stock prices and sovereign CDS spreads, respectively. The models are estimated using ordinary least squares (OLS) with White (1980) heteroskedasticity-robust standard errors.

To allow for the possibility that reserve accumulation influences risk taking differently depending on whether reserve levels are relatively high or relatively low, we extend our analysis to incorporate the non-temporal testing model originally developed by Hansen (2000) and estimate the following

[22] See, moreover, since reserve accumulation is in part a reflection of pursuing an active exchange rate management policy, including the exchange rate in our estimations ensures that the effects of reserve accumulation are not exaggerated from the reserve variable inadvertently serving as an exchange rate proxy variable.

$$\Delta S_t = \begin{cases} \beta_0^L + \beta_1^L \Delta RES_t + \beta_2^L \Delta CNYUSD_t + \beta_3^L \Delta USS_t + e_t & if\ RES_t < q, \\ \beta_0^H + \beta_1^H \Delta RES_t + \beta_2^H \Delta CNYUSD_t + \beta_3^H \Delta USS_t + e_t & if\ RES_t \geq q, \end{cases} \tag{3}$$

$$\Delta CDS_t = \begin{cases} \beta_0^L + \beta_1^L \Delta RES_t + \beta_2^L \Delta CNYUSD_t + \beta_3^L \Delta USS_t + e_t & if\ RES_t < q, \\ \beta_0^H + \beta_1^H \Delta RES_t + \beta_2^H \Delta CNYUSD_t + \beta_3^H \Delta USS_t + e_t & if\ RES_t \geq q, \end{cases} \tag{4}$$

where q is the reserve level threshold value to be estimated by the maximand of the likelihood ratio statistics over all permissible values. [23] Superscripts L and H denote low and high reserve levels, respectively.

The reason why we chose to use Hansen (2000) is twofold. First, this test allows us to estimate the heterogenous effect when the reserve either is high or low. This feature aligns perfectly with the motivation behind our analysis. Second, this test can detect the heterogenous effect with an unknown breakpoint. The non-temporal test of Hansen (2000) is similar to a standard temporal parameter change test for a single unknown breakpoint (e.g. Andrews 1993). However, instead of analyzing a temporally-ordered data set, the Hansen (2000) procedure dictates that we sort our data in a non-temporal fashion according to, in our context, levels of reserve holdings. Doing so allows us to endogenously identify in a non-temporal modeling framework the reserve level, if any, around which the influence of reserve accumulation on risk taking changes.[24]

We subsequently extend the threshold analysis by also considering if the influence of reserve accumulation on risk taking depends on the level of global market uncertainty. To do so we re-estimate the models described in Equations (3) and (4) with sorting

[23] The permissible threshold values exclude the first and last 1% of the ordered sample.

[24] For completeness, we also employ a non-temporal version of the Bai and Perron (1998) sequential test to consider a null hypothesis of one threshold against an alternative of two thresholds.

according to market uncertainty as measured by VIX levels.[25]

Next, we estimate daily frequency event study versions of the models described in Equations (1) and (2) with the surprise component of the reserve announcement, denoted $RESSURP_t$, in place of ΔRES_t, and all other variables describing the corresponding daily change on the day of the announcement. We include in these estimations only announcement day observations. Importantly, since the PBC does not announce reserve holdings for a given month until the beginning of the following month (typically on day 7 of the following month), and survey expectations pertaining to the announcement of a given month are formed and released prior to the day of the announcement, the announcement surprises are pre-determined relative to the risk taking measures. Therefore, the daily frequency estimations are effectively addressing reverse causality endogeneity bias in the reserve variable coefficient estimates.

Lastly, we incorporate the intraday tick-level stock price data into our analysis. We do so by estimating 1-minute, 2-minute, and 5-minute intraday event study versions of Equation (1) for each of the three Chinese stock market indices considered (the CSI 300 Index, the Shanghai SE Composite Index, and the Shenzhen SE Composite Index). As in our daily frequency event study estimations we use the surprise component of reserve announcements in place of ΔRES_t.[26] As noted earlier, most Chinese reserve announcements occur outside of market hours, leaving us with only 9 announcements for which intraday windows can be constructed as described. Nevertheless, by assessing the

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[25] See Fatum and Yamamoto (2016) for a recent application of the non-temporal threshold procedure along with additional details.

[26] For each of the three stock price indices employed, the event window is set to start at the open price of the minute of the announcement and end at the closing price of the minute corresponding to the given window length. For example, if the announcement is made at 10:05, the windows start at the open price of 10:05 and the 1-, 2-, and 5-minute windows end at the closing prices of 10:05, 10:06, and 10:09, respectively.

influence of announcement surprises pertaining to pre-determined reserve levels across window lengths sufficiently short that we can reasonably assume that no other relevant news or events occur, we are effectively addressing both omitted variable and reverse causality endogeneity concerns.

2. 5 Results

2. 5. 1 Baseline Result

Table 2 shows the results of our full sample baseline regressions. The top panel pertains to estimations of the model described in Equation (1), where the Chinese stock price index is the risk indicator, and the bottom panel pertains to estimations of the model described in Equation (2), where the Chinese sovereign CDS is the risk indicator. To provide a nuanced picture of the influence of reserve accumulation on the risk indicators, we estimate all models without control variables included, with only the exchange rate control variable included, and with both exchange rate and US stock price control variables included. As the top panel results show, the reserve variable coefficient estimate with respect to the stock price risk indicator is consistently positive and significant. The addition of the exchange rate control variable does little to change the magnitude and significance of the reserve variable coefficient estimate, and while controlling for US stock prices noticeably does, the reserve variable remains positive and significant at conventional levels, thereby implying that an increase in Chinese reserve holdings is systematically associated with an increase in domestic stock prices and thus consistent with more willingness to assume risk. Similarly, the bottom panel results show that the reserve variable coefficient estimate with respect to the CDS spread indicator is consistently negative and significant at the 5% level or higher in all three estimations.

This conforms to the suggestion that as reserve levels increase, investors become less inclined to obtain insurance against sovereign default or restructuring in reflection of more willingness to assume risk. Table 3 and 4 report the results of re-estimating Equations (1) and (2) separately across three sub-samples spanning, respectively, the pre-GFC period (August 2001 to July 2007), the GFC period (August 2007 to December 2008), and the post-GFC period (January 2009 to October 2019).[27] The results pertaining to both risk indicators are remarkably consistent. Both sets of estimations strongly indicate that reserve accumulation prior to the GFC did not systematically influence neither Chinese stock prices (first panel of Table 3) nor CDS spreads (first panel of Table 4). Similarly, even though some significant effects of reserve accumulation are reported across the reserves only and the reserves and exchange rates only specifications, once we control for US stock prices we again find no effects of reserves (second panel of Tables 3 and 4). However, when we consider the post-GFC sample, our full sample results for both risk indicators are repeated (third panel of Tables 3 and 4). Clearly, the sub-sample results suggest that the influence of reserves on risk is stronger after the GFC. This is an interesting finding that, since reserve levels at any point before and during the GFC are markedly lower than at any point after the GFC, might suggest that discernable risk taking effects of reserve accumulation do not manifest until reserve holdings have reached a given level.

Table 5 shows the results of re-estimating Equations. (1) and (2) for the period between August 2015 to October 2019, when the foreign reserves started to decline. As we describe in section 2.2.2, the foreign reserves started to decline, which provides us

[27] GFC dates are set in accordance with Melvin and Taylor (2009).

with different variations. Table 5 shows the reserves significantly affect the stock return at the 5% level, although it does not affect the stock return with the control of the foreign exchange change and US stock return. This table also shows that this significantly affects the CDS at the 5% or 10% level, which suggests that our prediction is also confirmed, even when the reserves have started to decline.

2. 5. 2 The Interpretation of Negative Relationship between Exchange Rate and Stock Return

Tables 1 and 2 report the negative relationship between the exchange rate and stock return. In the previous literature, there are two theories which can explain the relationship between the stock price and the exchange rate: (1) the flow-oriented model and (2) the portfolio balance theory (stock-oriented model). The flow-oriented model insists that the change of an exchange rate should influence importers and exporters and, therefore, the exchange rate can affect the stock price in an export-orientated country. Conversely, the portfolio balance theory insists that causality should run from the stock market to the exchange rate.

Although early research focused only on the relationship between stock prices and the exchange rate in the U.S. (see Bahmani-Oskooee and Sohrabian 1992), the Asian financial crisis has motivated economists to investigate the relationship between exchange rates and stock prices in Asian countries. Granger et al. (2000) initially investigate the appropriated Granger relations between stock prices and exchange rates using Asian data. This paper finds mixed results in terms of the lead and lag of foreign exchange and the stock market, but also confirms a negative relationship for many Asian countries, which is consistent with our result. After Granger et al. (2000), many papers began to explore this relationship using different methodologies and periods, but these papers all reach a consistent result in terms of the negative relationship (see Liang et al. (2013)).

2. 5. 3 The Threshold Estimation

To further consider whether this is the case we turn to threshold estimations. Tables 6A and 6B display the results of estimating Equation (3), i.e. the threshold model where Chinese stock prices serve as the risk indicator, with reserve levels and VIX levels, respectively, as the sorting variables. All threshold estimations are carried out separately across the full sample and across the post-GFC sample. Comparing significance of the reserve variable coefficient estimates across the full and the post-GFC sample, Table 6A confirms that reserves are particularly influential after the GFC. Noticeably, the table also shows that for the post-GFC sample reserves matter regardless of whether prevailing reserve levels are high or low. By contrast, this is not the case when considering the full sample results where the effects of reserve accumulation when prevailing reserve holdings are relatively low are found to be smaller in magnitude and mostly insignificant compared to when prevailing reserve holdings are relatively high. Again, since reserve levels at any point in time after the GFC are higher than at any point in time before the crisis, this is consistent with the suggestion that perhaps it is not that reserves matter more for risk taking after the GFC per se, but, rather, that reserves matte more for risk taking when reserve holdings are already high, as is the case after the GFC.

Table 6B again confirms that reserves matter more after the GFC compared to across the full sample, but only as far as magnitude of coefficient estimates goes. Interestingly, the Table 6B results suggest that the influence of reserves on the stock price risk indicator is more pronounced when the overall level of uncertainty is high.

Tables 7A and 7B pertain to the threshold model described in Equation (4), i.e. the threshold model where Chinese CDS spreads are used to indicate risk. The Table 7A results are similar to the Table 6A results just described, except once we include the US stock price control variable in our estimations we no longer maintain significance of the reserve variable regardless of whether we consider the full or the post-GFC sample and regardless of whether prevailing reserve levels are high or low. The results provided in Table 7B show a (marginally) significant effect of reserves on the CDS spread only for the post-GFC high uncertainty segment, even after controlling for both exchange rates and US stock prices, again suggesting that the influence of reserves on risk is more discernable after the GFC and when uncertainty is high.

2. 5. 4 The Daily Data Event Study

Table 8 shows the results of the daily data event study analysis of the January 2008 to October 2019 period for which reserve announcement surprises can be constructed. The top panel pertains to the daily data event study estimation of the stock price risk indicator with reserve announcement surprises in place of ΔRES_t, i.e. the daily data event study version of Equation (1). As the panel shows, the reserve variable coefficient estimates are consistently positive and highly significant, at the 1% level, regardless of whether or not we control for exchange rates and US stock prices. Even the magnitudes of the three reserve variable coefficient estimates are very similar. These are strong findings as they after addressing potential reverse causality endogeneity concerns further confirm that an increase in reserve holdings is systematically and significantly associated with an increase in the stock price risk indicator.

In complete tandem, the bottom panel results, pertaining to the daily data event study estimation of the CDS risk indicator and the daily data event study version of Equation (2), similarly strengthen the evidence that an increase in reserve holdings is associated with a systematic and significant decrease in the CDS risk indicator, thereby again supporting the suggestion that reserve accumulation leads to an increase in risk taking.

Finally, our intraday results are reported in Table 9 and pertain to the intraday event study version of Equation (1) without control variables. While all but one of 9 coefficient estimates are positive, consistent with the suggestion that an increase in reserves is associated with an increase in stock prices and thus increased willingness to assume risk, only one of these estimates is significant (the Shanghai SE Composite Index for the 1-minute window). As noted earlier, our intraday analysis effectively addresses both omitted variable and reverse causality endogeneity concerns but is restricted by the very low number of reserve announcements made during market hours. In that sense the consistency with respect to the sign of the reserve surprise coefficient estimates is quite remarkable, as is the significant effect of reserves with respect to one of the stock market indices for the 1-minute window.

Overall, our results provide very consistent evidence across monthly frequency estimations, and across daily and intraday event study estimations, that PBC reserve accumulation after the GFC is systematically associated with an increase in willingness to take on more stock market risk (as domestic stock prices on average rise in response to reserve accumulation) and more sovereign credit default risk (as prices and thus demand for sovereign default insurance on average decline in response to reserve accumulation), thereby supporting the suggestion that reserve accumulation comes at the additional cost of an increase in risk taking. Although a very different study with respect to methodology, data, and time-period focus, our findings are nevertheless consistent with those of Tong and Wei (2019). By contrast, our findings are different from those of Fatum and Yetman (2020) and their lack of systematic evidence that reserve accumulation influences risk taking as per their focal risk measure of implied volatility of currency options. However, our findings are not at odds with their stock price and CDS spread risk indicator based results to the extent that for these two measures Fatum and Yetman (2020) do not reject that reserve accumulation matters for risk taking.

2. 6 Robustness

In this section, we check the robustness of our estimation. We use the stock return as the proxy for risk-taking, as an investor might interpret the increase of foreign reserves as a good signal of the export business. In addition, the monetary base variable could also affect the stock return; hence, we control the monetary base to see if our result is robust or not.

We conduct the additional estimation in terms of (1) the different proxy of risk-taking and (2) the effect of the monetary base.

2.6.1 The Different Proxy of Risk-Taking

In our main analysis, we use the stock return and sovereign CDS spread as the proxy of risk-taking, but these measures could not capture the risk-taking of the investors. Therefore, we use a different measure for robustness checks.

First, we use the leverage of the firm as the risk-taking. CEIC provides the quarterly based data of debt of non-financial corporations over GDP, so we use the changes of debt of non-financial corporations as the dependent variable for capturing the firm's leverage. Especially, Tong and Wei (2019) regress the firm's leverage on the change of foreign reserve by using the panel data, therefore using the leverage of the corporation as the dependent variable is in line with Tong and Wei (2019).

Next, we use the stock index constructed by the financial sectors. This is because the risk-taking of the investors could be more reflected in the stock of the financial sectors. Especially, MSCI provides the index constructed of the financial sectors, therefore we use the return of the financial stock as the proxy of the risk-taking.

To capture risk-taking one may focus on the shift from safe asset to risky asset. Past studies on household portfolios, such as Liao et al. (2017) and Cooper and Zhu (2018), used data from the China Household Finance Survey, but the household data from this survey suffers from low frequency, therefore we use the market sentiment index created by J. P. Morgan, called the J. P. Morgan China A-shares Sentiment Index. This index is an aggregate measure that takes into account typically-used indicators ranging from technical indicators to flows, investor confidence, and derivatives positioning. This indicator includes monthly based data starting from 2007 and is available from Bloomberg.

Tables 10, 11, and 12 show the estimation result when we used the change of the firm's leverage, financial stock return, and sentiment index as a dependent variable. Table 10 shows that the reserves have a significant effect on the firm's leverage at the 5% level. Table 11 indicates that the reserves have a significant effect on the return of the financial stock. Table 12 shows that the reserves have a significant effect on the investor sentiment index firm's leverage with the 1% or 5% level. These estimations are consistent with the actual results we obtained.

2.6.2 The Effect of the Monetary Base

After 2009, the monetary base has increased in China, while capital flow into China also increased from GFC to 2014. To prevent the appreciation of the currency, the Chinese government conducted the intervention by selling CNY and buying USD, which increased the foreign reserve in China. In this sense, China's foreign reserve might have accumulated not by risk-taking but by the increase of monetary base.

To control this effect, we include the change of monetary base of China as a control variable. Table 13 shows the estimation results when we use the stock return and CDS spread as a dependent variable. This result shows the reserve has a significant effect on the stock return and CDS premium even if we control the monetary base. Table 13 shows the results based on the sub-sample. These results are also consistent with the previous results. Especially, it should be emphasized that the reserve still affects the stock return and CDS spread when we use Post GFC sample, which includes the period of the intervention conducted by the Chinese government.

2.6.3 Using the Reserve over Foreign Debt

In our analysis, we use the foreign reserve over GDP as the main explanatory variable; however, using the foreign reserves over China's foreign debt might be appropriate since foreign reserves could be considered as buffers when a government is likely to default. In fact, East Asian countries only started to accumulate foreign reserves after the East Asian Financial Crisis. We obtained the quarterly data of USD-denominated Chinese foreign debt and linearly interpolated this into monthly data.

Table 14 shows the estimation result when we use USD-denominated Chinese foreign debt as the denominator of foreign reserves. This table shows the foreign reserves significantly affect stock return at the 10% level. However, we could not obtain a significant result when we control the change of the currency and the return of US stocks. In addition, we could not obtain a significant result when we use the CDS as the dependent variable.

2. 7 Extensions

In this section we consider the influence of reserves on risk for other Asian emerging economies, address if Chinese reserve accumulation increases domestic market uncertainty, and analyze separately the post-July 2005 floating CNY regime.

First, to provide more context to our investigation we extend our monthly frequency time-series estimations described in Equations (1) and (2) to consider the influence of reserve accumulation on risk taking for Indonesia, South Korea, Malaysia, Philippines, and Thailand. Tables 15 (domestic stock price as risk indicator) and 16 (local currency sovereign CDS as risk indicator) present the results. When we make use of the domestic stock price risk indicator, we find that the results for Indonesia are particularly similar to those of China, and when we employ the local currency sovereign CDS risk indicator the results for South Korea are particularly similar to those of China. Overall, these results suggest that while we do not find systematic evidence to support that reserve accumulation increases risk taking to the same extent as in the case of China, we nevertheless find indications that reserve accumulation has qualitatively similar risk consequences for other Asian emerging economies and thus that unintended increases in risk taking as a result of holding large amounts of reserves is not unique to China.

Second, we address if Chinese reserve accumulation increases domestic stock market uncertainty by estimating equation (1) at the monthly and the daily frequency with the China ETF volatility index ("Chinese VIX") as the dependent variable.[28] Using monthly data our results suggest that an increase in reserve accumulation reduces market uncertainty when we include either no control variables or only the exchange rate variable. Once we control for US stock prices the influence of reserves is no longer significant. When we carry out daily data event study estimations of the effects of reserve announcement surprises we find no systematic influence of reserves on market uncertainty, regardless of whether or which control variables are included. Overall, these estimations do not point to a systematic link between reserves and domestic market uncertainty.

Third and final, we redo the monthly frequency analysis on a reduced sample that excludes the August 2001 to June 2005 period of fixed CNY/USD exchange rates. We do so to ensure that the absence of significant reserve variable coefficient estimates pre-GFC is not due to the fixed exchange rate regime that describes most of the pre-GFC period. As it turns out, our previously described results remain unchanged.[29]

Tables 15 also shows the negative relationship between the foreign exchange and stock return. This is consistent with previous literature, such as Tsai (2012). According to Tsai (2012) and Liang et al. (2013), if the impact of an external parameter influences the stock market to go up, the domestic investors' wealth increases, raising the demand for the currency. The demand for money then increases and drives the interest rate to rise, consequently absorbing the inflow of foreign capital and causing the domestic currency

[28] The China ETF volatility index (VXFXI) series starts in March 2011 and is available from the Chicago Board of Trade.

[29] Results pertaining to the VXFXI and the post-June 2005 estimations are available upon request.

to appreciate.

2. 8 Conclusion

We consider if the Chinese accumulation of reserves is associated with unintended consequences in the form of increased private sector risk taking over the 2001 to 2019 period. Using sovereign CDS spreads and stock index prices as indicators of private sector risk taking we first estimate monthly frequency models of the effects of reserve accumulation on our risk taking indicators. Our results strongly suggest that as reserve holdings increase so does the willingness of the private sector to take on more risk. When we compare the effects of reserves on risk taking across sub-samples, our results show that the effects are noticeably more pronounced after the GFC while largely absent prior to and during the GFC. Our monthly frequency threshold models confirm that reserves matter more for risk taking after the GFC when reserve levels are consistently high.

We incorporate survey expectations of Chinese reserve announcements to identify the surprise component of reserve announcements and, in turn, estimate event study models at both daily and intraday frequencies to assess the effects of reserve surprises on the risk indicators. Doing so allows us to effectively address omitted variable as well as reverse causality endogeneity concerns and obtain more precise estimates of the effects of reserve accumulation. The reserve surprise estimations provide further, and even stronger, evidence that reserve accumulation is significantly and systematically associated with risk indicator changes consistent with the suggestion that as reserve holdings increase so does private sector risk taking.

Our results are important in that they point to an unintended consequence of reserve accumulation that is not considered in standard studies of reserve accumulation and costs of holding reserves. Moreover, reserve accumulation driving up risk taking is an unintended consequence that seems particularly counterproductive when a main objective of reserve accumulation is to provide insurance in the event of financial crises and increased risk taking in and of itself makes such crises more likely.

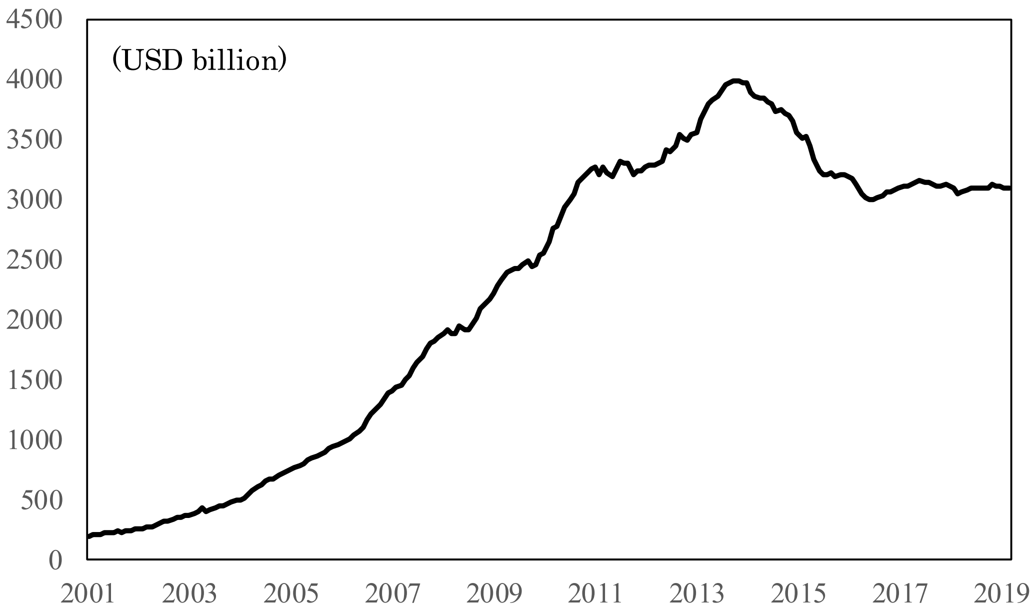
Importantly, our evidence supporting the notion that reserve accumulation is associated with increased risk taking and potentially costly by making crises more likely does not in any way suggest that this unintended cost outweighs or off-sets the benefits of holding large amounts of reserves. Indeed, our results do not call into question the validity of the precautionary savings motive for reserve accumulation or, for that matter, that reserves for other reasons and via other mechanisms may deter or reduce the probability of crises. Rather, our study suggests that more reserves are associated with private sector willingness to hold more risk which, in and of itself, may attenuate the benefits of accumulating reserves.

Future research is necessary to investigate the relationship between the foreign reserves and foreign exchange system in China after 2015. In particular, the CNY continued to appreciate after 2015. During this period, the Chinese government intervened in the foreign exchange market by purchasing USD. However, after 2015, the CNY started to depreciate, and the Chinese government might change the intervention, which should be related to the foreign reserves. As far as I know, no empirical research has addressed this issue. To conduct this research, we have to obtain minute by minute CNY data.

Other future research is needed to decompose the VIX into the proxy of risk aversion and uncertainty. The difference between the squared VIX and an estimate of the conditional variance is often called the variance premium. Bekaert and Hoerova (2014) show that the variance premium is indeed increasing in risk aversion in realistic calibrated example economies; therefore, this premium can be used as a proxy for risk-taking. To compute the variance premium, high-frequency data is also needed to compute the realized measure.

We can also extend our analysis using different models. We used Hansen (2000) to capture whether reserve levels are relatively high or relatively low. However, a different model could be considered. For example, the smooth transition model can capture the gradual changing effect of reserves on the risk-taking measure.

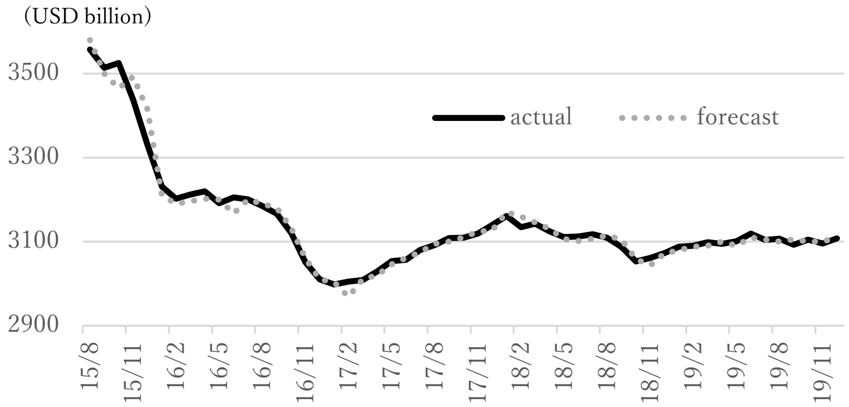
Figure 1 Reserves: China



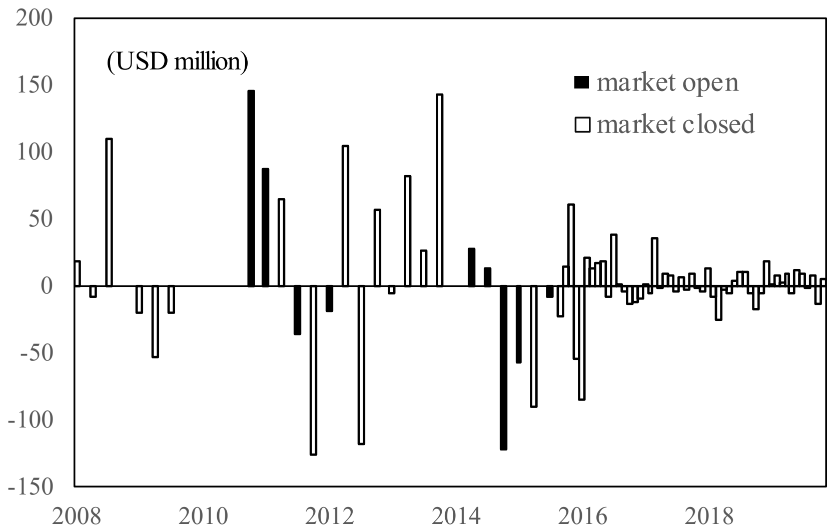
Source: Bloomberg

Figure 2 Reserve Announcement Surprises: China

(a) The time series of actual and forecast data of reserves

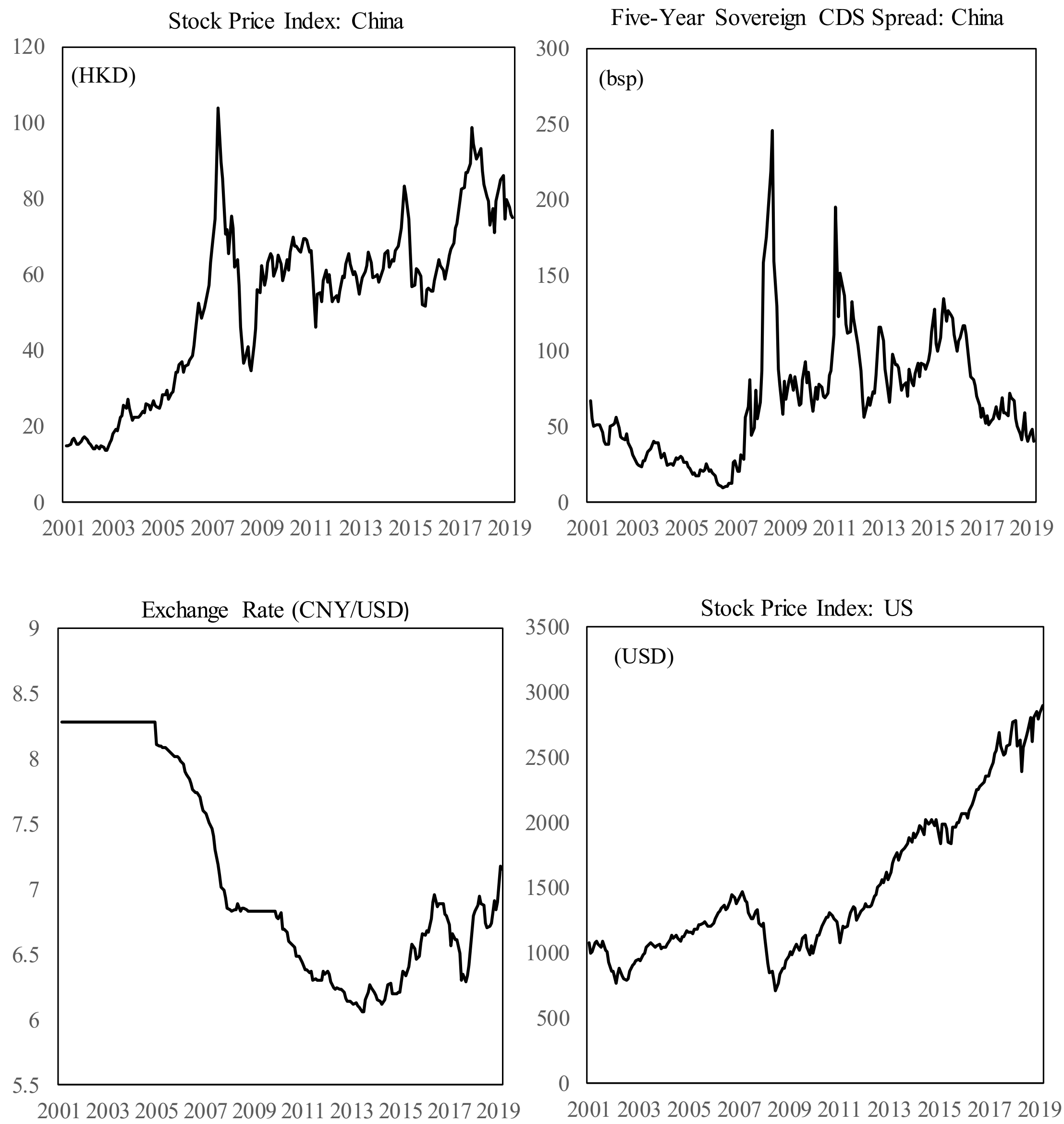


(b) The time series of surprise: market open and market closed



Source: Own calculations based on data from Bloomberg

Figure 3 Risk Indicators and Control Variables



Source: Bloomberg and Markit

Table 1 Descriptive Statistics: July 2001 to October 2019

	Start of Period	End of Period	Mean	Max	Min	Standard Deviation
Reserves: China (USD billion)	195.8	3092.4	2210.5	3993.2	195.8	1253.8
Stock Price Index: China (HKD)	1.9	75.0	53.1	103.9	13.7	22.2
CDS Spread (bps)	67.6	40.8	68.3	245.8	9.8	39.8
CNY/USD Exchange Rate	8.28	7.15	7.10	8.28	6.05	0.79
Stock Price Index: US (USD)	989.9	2891.2	1506.3	2891.2	700.7	569.7

Source: Bloomberg and Markit

Table 2 Baseline Estimations (Full Sample): Stock Price Index and CDS

Dependent Variable (Risk Indicator): ΔS_t

From August 2001 to October 2019			
ΔRES	1.25***	1.09***	0.45*
	(3.72)	(3.28)	(1.82)
ΔCNYUSD		-1.87***	-1.33***
		(-3.50)	(-3.48)
ΔUSS			0.97***
			(8.93)
Constant	0.75	0.65	0.39
	(1.58)	(1.43)	(1.05)
R2	0.09	0.13	0.42
obs	218	218	218

Dependent Variable (Risk Indicator): ΔCDS_t

From August 2001 to October 2019			
ΔRES	-2.87***	-2.77***	-1.33**
	(-3.81)	(-3.61)	(-2.52)
ΔCNYUSD		1.17	-0.02
		(1.35)	(-0.03)
ΔUSS			-2.17***
			(-6.71)
Constant	0.53	0.59	1.16
	(0.52)	(0.59)	(1.45)
R2	0.10	0.11	0.42
obs	218	218	218

Notes: 1. *t* statistics in parentheses.
2. ***, **, and * denote significant at the 1%, 5%, and the 10% levels, respectively.

Table 3 Baseline Estimations (Sub-Samples): Stock Price Index

Dependent Variable (Risk Indicator): ΔS_t

Pre GFC Sample From August 2001 to July 2007			
ΔRES	-0.48	-0.40	-0.52
	(-0.97)	(-0.73)	(-1.30)
ΔCNYUSD		-4.95**	-3.66*
		(-2.46)	(-1.75)
ΔUSS			0.81***
			(4.74)
Constant	3.08***	2.33*	2.52
	(2.77)	(1.86)	(2.68)
R2	0.02	0.07	0.29
obs	71	71	71
GFC Sample From August 2007 to December 2008			
ΔRES	3.20	4.61***	-0.60
	(1.43)	(2.89)	(-0.27)
ΔCNYUSD		8.29*	5.12
		(1.81)	(1.38)
ΔUSS			1.88***
			(3.54)
Constant	-2.05	3.05	5.86
	(-0.62)	(0.81)	(1.63)
R2	0.11	0.22	0.56
obs	17	17	17
Post GFC Sample From January 2009 to October 2019			
ΔRES	2.59***	2.23***	1.05***
	(7.76)	(6.35)	(2.90)
ΔCNYUSD		-1.96***	-1.54
		(-4.77)	(-5.56)
ΔUSS			0.73***
			(6.51)
Constant	1.99***	1.87***	0.52
	(4.13)	(4.10)	(1.11)
R2	0.31	0.41	0.54
obs	129	129	129

Notes: Same as Table 2.

Table 4 Baseline Estimations (Sub-Samples): CDS

Dependent Variable (Risk Indicator): ΔCDS_t

Pre GFC Sample			
From August 2001 to July 2007			
ΔRES	-0.09	-0.09	-0.03
	(-0.39)	(-0.38)	(-0.12)
ΔCNYUSD		-0.03	-0.65
		(-0.02)	(-0.40)
ΔUSS			-0.39**
			(-2.01)
Constant	-0.22	-0.23	-0.32
	(-0.37)	(-0.36)	(-0.47)
R2	0.00	0.00	0.11
obs	71	71	71

GFC Sample			
From August 2007 to December 2008			
ΔRES	-9.06**	-10.39**	-1.39
	(-2.09)	(-2.35)	(-0.51)
ΔCNYUSD		-7.78	-2.30
		(-0.99)	(-0.39)
ΔUSS			-3.25***
			(-6.60)
Constant	8.57*	3.78	-1.07
	(1.76)	(0.56)	(-0.18)
R2	0.32	0.35	0.72
obs	17	17	17

Post GFC Sample			
From January 2009 to October 2019			
ΔRES	-6.52***	-6.30***	-2.34*
	(-4.77)	(-4.35)	(-1.94)
ΔCNYUSD		1.20	-0.21
		(1.33)	(-0.22)
ΔUSS			-2.46***
			(-4.90)
Constant	-4.48	-4.40	0.10
	(-2.98)	(-2.93)	(0.08)
R2	0.25	0.26	0.45
obs	129	129	129

Notes: Same as Table 2.

Table 5 Baseline Estimations (Sub-Samples)

Dependent Variable (Risk Indicator): ΔS_t

From August 2015 to October 2019			
ΔRES	2.94***	1.73**	0.78
	(3.70)	(2.26)	(1.63)
ΔCNYUSD		-2.32***	-1.66***
		(-5.00)	(-6.87)
ΔUSS			0.95***
			(11.04)
Constant	3.06***	2.59***	0.92*
	-2.93	(3.28)	(1.79)
R2	0.22	0.52	0.80
obs	50	50	50

Dependent Variable (Risk Indicator): ΔCDS_t

From August 2015 to October 2019			
ΔRES	-4.36***	-3.38**	-1.99*
	(-3.64)	(-2.52)	(-1.81)
ΔCNYUSD		1.93*	0.97
		(1.95)	(1.07)
ΔUSS			-1.39***
			(-3.65)
Constant	-4.91***	-4.52***	-2.08
	(-3.02)	(-2.95)	(-1.48)
R2	0.19	0.27	0.49
obs	50	50	50

Notes: Same as Table 2.

Table 6A Stock Price Index and Reserve Amount Thresholds

Dependent Variable (Risk Indicator): ΔS_t
Threshold variable: RES_{t-1}

	From August 2001 to October 2019			From January 2009 to October 2019		
ΔRES (High)	3.72***	3.42***	1.19	2.37***	2.52***	1.84**
	(6.08)	(5.60)	(1.27)	(4.38)	(4.26)	(2.29)
ΔCNYUSD (High)		2.88	1.58		2.15	2.09
		(1.13)	(0.87)		(1.39)	(1.37)
ΔUSS (High)			0.94***			0.37
			(2.92)			(1.17)
Constant (High)	-0.70	1.56	-1.15	-0.93	-0.53	-0.83
	(-0.68)	(1.59)	(-0.91)	(-1.10)	(-0.54)	(-0.78)
R2 (High)	0.46	0.32	0.58	0.48	0.50	0.54
obs (High)	40	62	36	24	24	24
ΔRES (Low)	0.76**	0.30	0.29	2.76***	2.27***	1.09***
	(2.24)	(0.94)	(1.11)	(7.21)	(5.87)	(2.63)
ΔCNYUSD (Low)		-2.67***	-1.74***		-2.20***	-1.68***
		(-6.64)	(-4.35)		(-5.62)	(-6.48)
ΔUSS (Low)			0.95***			0.76***
			(7.37)			(6.27)
Constant (Low)	1.30***	1.20***	0.91**	2.76***	2.66***	0.99*
	(2.59)	(2.72)	(2.22)	(4.96)	(5.14)	(1.79)
R2 (Low)	0.04	0.19	0.40	0.31	0.46	0.58
obs (Low)	177	155	181	104	104	104
SupF(1|0)	18.10***	23.53***	13.01	11.34*	18.14**	11.18
SupF(2|1)	6.40	7.48	13.60	4.35	10.61	4.90
Threshold	0.435	0.405	0.438	0.447	0.447	0.447

Notes: Same as Table 2.

Table 6B CDS and Reserve Amount Thresholds

Dependent Variable (Risk Indicator): ΔS_t
Threshold variable: VIX_{t-1}

	From August 2001 to October 2019			From January 2009 to October 2019		
ΔRES (High)	3.38***	1.95***	0.93***	2.62***	3.84***	2.40***
	(4.78)	(4.27)	(2.81)	(7.69)	(5.56)	(3.40)
ΔCNYUSD (High)		-0.39	0.33		-7.48**	-6.61***
		(-0.22)	(0.24)		(-2.51)	(-4.08)
ΔUSS (High)			0.96***			0.74***
			(6.80)			(3.34)
Constant (High)	-0.74	-0.25	-0.17	1.58***	2.28	0.37
	(-0.45)	(-0.32)	(-0.27)	(3.09)	(1.34)	(0.26)
R2 (High)	0.50	0.17	0.50	0.34	0.77	0.87
obs (High)	22	98	91	114	13	13
ΔRES (Low)	0.91***	0.22	0.00	3.04*	1.57***	0.54
	(2.69)	(0.52)	(0.01)	(1.79)	(4.47)	(1.49)
ΔCNYUSD (Low)		-2.84***	-2.05***		-2.09***	-1.63***
		(-6.62)	(-5.97)		(-4.93)	(-5.73)
ΔUSS (Low)			0.94***			0.73***
			(5.25)			(5.99)
Constant (Low)	0.90*	1.41***	0.88**	5.90***	1.37***	0.11
	(1.86)	(3.02)	(1.95)	(4.26)	(2.95)	(0.23)
R2 (Low)	0.05	0.24	0.37	0.24	0.34	0.48
obs (Low)	195	119	126	14	115	115
SupF(1|0)	11.29**	11.99	10.12	8.00	17.69**	16.69**
SupF(2|1)	4.07	11.12	6.55	5.96	17.48**	8.97
Threshold	29.15	17.47	18.07	11.99	14.19	26.05

Notes: Same as Table 2.

Table 7A Stock Price Index and Market Uncertainty Thresholds

Dependent Variable (Risk Indicator): ΔCDS_t
Threshold variable: RES_{t-1}

	From August 2001 to October 2019			From January 2009 to October 2019		
ΔRES (High)	-8.55***	-9.01***	-1.83	-7.52**	-7.50**	-1.55
	(-4.42)	(-4.34)	(-1.24)	(-2.38)	(-2.34)	(-0.68)
ΔCNYUSD (High)		-5.27	-0.03		2.23	-2.74
		(-1.10)	(-0.02)		(0.52)	(-0.84)
ΔUSS (High)			-3.22***			-3.82***
			(-6.89)			(-3.61)
Constant (High)	1.66	0.01	1.66	5.54**	5.84*	2.67
	(0.61)	(0.00)	(0.93)	(2.04)	(1.76)	(1.00)
R2 (High)	0.31	0.32	0.58	0.39	0.43	0.55
obs (High)	62	62	81	25	26	46
ΔRES (Low)	-0.76**	-0.53	-0.37	-6.38***	-6.06***	-1.24
	(-2.24)	(-1.57)	(-1.20)	(-5.14)	(-4.40)	(-1.08)
ΔCNYUSD (Low)		2.43***	1.75**		1.93**	1.17
		(3.05)	(2.32)		(2.16)	(1.36)
ΔUSS (Low)			-0.76***			-1.40***
			(-3.91)			(-3.71)
Constant (Low)	-0.74	-0.87	-0.35	-7.15***	-7.20***	-0.60
	(-1.07)	(-1.29)	(-0.60)	(-4.02)	(-3.88)	(-0.41)
R2 (Low)	0.03	0.10	0.27	0.26	0.27	0.33
obs (Low)	155	155	136	103	102	82
SupF(1|0)	37.29***	38.54***	32.91**	19.40*	20.89*	9.76
SupF(2|1)	5.69	3.85	12.63	18.18**	21.43***	8.21
Threshold	0.405	0.405	0.393	0.447	0.400	0.399

Notes: Same as Table 2.

Table 7B CDS and Market Uncertainty Thresholds

Dependent Variable (Risk Indicator): ΔCDS_t
Threshold variable: VIX_{t-1}

	From August 2001 to October 2019			From January 2009 to October 2019		
ΔRES (High)	-12.57***	-12.11***	-5.85	-13.31***	-14.81***	-5.62*
	(-5.34)	(-4.54)	(-1.52)	(-3.26)	(-3.62)	(-1.79)
ΔCNYUSD(High)		29.03	30.64		30.89*	25.29**
		(0.87)	(1.43)		(1.75)	(2.50)
ΔUSS (High)			-2.46**			-4.76***
			(-2.19)			(-3.10)
Constant (High)	7.19	8.28	5.52	-9.30	-3.21	9.08
	(1.14)	(1.33)	(0.89)	(-0.97)	(-0.31)	(1.25)
R2 (High)	0.48	0.50	0.64	0.48	0.57	0.75
obs (High)	22	22	22	13	13	13
ΔRES (Low)	-1.25***	-1.10***	-0.53	-3.50***	-2.98***	-0.63
	(-3.18)	(-2.86)	(-1.62)	(-4.54)	(-3.52)	(-0.73)
ΔCNYUSD (Low)		1.46*	0.47		1.91**	0.85
		(1.72)	(0.68)		(2.28)	(1.04)
ΔUSS (Low)			-1.55***			-1.68***
			(-7.45)			(-5.09)
Constant (Low)	-0.08	0.00	0.65	-2.49**	-2.31	0.57
	(-0.12)	(0.00)	(1.08)	(-2.35)	(-2.23)	(0.50)
R2 (Low)	0.04	0.06	0.33	0.15	0.18	0.37
obs (Low)	195	195	195	115	115	115
SupF(1|0)	116.73***	99.34***	30.29*	27.13*	30.86**	81.38***
SupF(2|1)	8.03	6.21	5.42	1.16	2.99	6.62
Threshold	29.15	29.15	29.15	26.05	26.05	26.05

Notes: Same as Table 2.

Table 8 Daily Data Estimations: Reserve Announcement Surprises

Dependent Variable (Risk Indicator): ΔS_t

RESSURP	0.50***	0.47***	0.45***
	(3.32)	(3.29)	(3.18)
ΔFX		-0.82	-0.65
		(-1.17)	(-1.07)
ΔUSS			0.41**
			(2.34)
Constant	0.07	0.09	0.06
	(0.49)	(0.61)	(0.45)
R2	0.13	0.15	0.22
obs	76	76	76

Dependent Variable (Risk Indicator): ΔCDS_t

RESSURP	-0.98***	-0.96***	-0.96***
	(-3.57)	(-3.47)	(-3.34)
ΔFX		0.46	0.35
		(0.42)	(0.33)
ΔUSS			-0.26
			(-1.17)
Constant	-0.37	-0.38	-0.36
	(-1.08)	(-1.10)	(-1.07)
R2	0.10	0.10	0.10
obs	76	76	76

Notes: Same as Table 2.

Table 9 Intraday Estimations: Reserve Announcement Surprises

CSI 300 Index

	1-minute	2-minute	5-minute
RESSURP	1.01	2.32	0.62
	(0.78)	(0.80)	(0.11)
Constant	-0.47	-1.99	-3.68
	(-0.29)	(-0.72)	(-0.55)
R2	0.04	0.06	0.00
obs	9	9	9

Shanghai SE Composite Index

	1-minute	2-minute	5-minute
RESSURP	2.04**	2.63	1.20
	(2.48)	(1.18)	(0.33)
Constant	-0.12	1.06	-0.94
	(-0.10)	(0.32)	(-0.17)
R2	0.21	0.05	0.00
obs	9	9	9

Shenzhen SE Composite Index

	1-minute	2-minute	5-minute
RESSURP	0.97	2.00	1.82
	(0.99)	(0.88)	(0.34)
Constant	0.19	-0.68	-2.03
	(0.14)	(-0.25)	(-0.31)
R2	0.05	0.05	0.01
obs	9	9	9

Notes: Same as Table 2.

Table 10 Estimations: Firm Leverage

	From September 2001 to September 2019
ΔRES	9.09**
	(2.03)
Constant	0.94***
	(3.06)
R2	0.00
obs	74

Notes: 1. *t* statistics in parentheses.
2. ***, **, and * denote significant at the 1%, 5%, and the 10% levels, respectively
3. The dependent variable is the firm leverage. The frequency is quarterly.

Table 11 Estimations: Financial Stock Return

	From August 2001 to October 2019		
ΔRES	1.53***	1.37***	0.68*
	(3.62)	(3.21)	(1.86)
ΔCNYUSD		-1.86***	-1.29**
		(-2.95)	(-2.54)
ΔUSSTOCK			1.05***
			(7.20)
Constant	0.72	0.62	0.35
	(1.22)	(1.08)	(0.69)
R2	0.08	0.10	0.30
obs	218	218	218

Notes: 1. *t* statistics in parentheses.
2. ***, **, and * denote significant at the 1%, 5%, and the 10% levels, respectively
3. The dependent variable is the financial stock return constructed by MSCI.

Table 12 Estimations: Investment Sentiment

	From January 2007 to October 2019		
ΔRES	3.50*	6.31**	5.02**
	(1.97)	(2.02)	(2.21)
ΔCNYUSD		-0.10	-0.06
		(-1.02)	(-0.66)
ΔUSSTOCK			0.028***
			(3.54)
Constant	-0.01	0.67	0.40
	(-0.17)	(1.00)	(0.62)
R2	0.02	0.04	0.11
obs	154	153	153

Notes: 1. *t* statistics in parentheses.
2. ***, **, and * denote significant at the 1%, 5%, and the 10% levels, respectively
3. The dependent variable is the investment sentiment constructed by JP morgan.

Table 13 Estimations: Controlling of Monetary Base

Dependent Variable (Risk Indicator): ΔS_t

	From August 2001 to October 2019	
ΔRES	1.24***	0.44*
	(3.64)	(1.79)
ΔCNYUSD		-1.33***
		(-3.48)
ΔUSSTOCK		0.97***
		(8.85)
ΔM	11.07	5.15
	(0.20)	(0.13)
Constant	0.61	0.33
	(0.88)	(0.60)
R2	0.08	0.42
obs	218	218

Dependent Variable (Risk Indicator): ΔCDS_t

	From August 2001 to October 2019	
ΔRES	-2.80***	-1.26**
	(-3.80)	(-2.35)
ΔCNYUSD		-0.09
		(-0.12)
ΔUSS		-2.17***
		(-6.74)
ΔM	-76.24	-79.8
	(-0.44)	(-0.59)
Constant	1.42	2.09
	(0.76)	(1.35)
R2	0.10	0.41
obs	218	218

Notes: 1. *t* statistics in parentheses.

2. ***, **, and * denote significant at the 1%, 5%, and the 10% levels, respectively

3. △M is the change of monetary base in China

Table 14 Estimations: Using the Reserve over Foreign Debt

Dependent Variable: Stock

	From Januart 2002 to October 2019		
ΔRES	0.73*	0.59	0.29
	(1.64)	(1.31)	(0.77)
ΔCNYUSD		-2.18***	-1.42***
		(-4.11)	(-3.68)
ΔUSSTOCK			1.02***
			(9.29)
Constant	0.97**	0.81*	0.42
	(1.99)	(1.75)	(1.11)
R2	0.01	0.07	0.40
obs	214	214	214

Dependent Variable: CDS

	From August 2001 to October 2019		
ΔRES	-1.95	-1.82	-1.15
	(-1.41)	(-1.31)	(-1.13)
ΔCNYUSD		1.91**	0.18
		(2.19)	(0.24)
ΔUSS			-2.32***
			(-6.65)
Constant	-0.03	0.11	1.00
	(-0.03)	(0.11)	(1.22)
R2	0.02	0.03	0.40
obs	214	214	214

Notes: Same as Table 2.

Table 15 Baseline Estimations for Comparison Countries: Stock Price Indices

Dependent Variable (Risk Indicator): $\Delta LOCSTOCK_t$

	Indonesia (Full Sample) From May 2004 to October 2019			Indonesia (Post GFC) From January 2009 to October 2019		
ΔLOCRES	0.88***	0.47***	0.40***	0.88***	0.51***	0.44***
	(4.79)	(4.11)	(4.01)	(6.55)	(3.82)	(3.63)
ΔLOCUSD		-1.22***	-0.94***		-1.19***	-0.95***
		(-7.40)	(-6.27)		(-6.53)	(-5.64)
ΔUSS			0.46***			0.39***
			(5.18)			(4.04)
Constant	1.38***	1.67***	1.34***	1.01**	1.31***	0.87***
	(3.45)	(4.97)	(4.23)	(2.47)	(3.65)	(2.57)
R2	0.21	0.45	0.51	0.23	0.45	0.51
obs	185	185	185	129	129	129

	South Korea (Full Sample) From August 2001 to October 2019			South Korea (Post GFC) From January 2009 to October 2019		
ΔLOCRES	1.08***	0.64**	0.31	1.04***	0.34	0.16
	(3.87)	(2.22)	(1.45)	(3.26)	(1.60)	(0.81)
ΔLOCUSD		-0.55***	-0.07		-0.85***	-0.44***
		(-4.39)	(-0.53)		(-7.92)	(-3.71)
ΔUSS			0.86***			0.57***
			(8.79)			(5.64)
Constant	0.70*	0.77**	0.45	0.45	0.51	-0.01
	(1.84)	(2.11)	(1.49)	(1.24)	(1.58)	(-0.04)
R2	0.10	0.17	0.42	0.14	0.38	0.52
obs	218	218	218	129	129	129

	Malaysia (Full Sample) From August 2001 to October 2019			Malaysia (Post GFC) From January 2009 to October 2019		
ΔLOCRES	0.41***	0.29**	0.22**	0.32**	0.14	0.09
	(2.95)	(2.12)	(1.97)	(2.40)	(1.24)	(0.87)
ΔLOCUSD		-0.58***	-0.33***		-0.52***	-0.35***
		(-6.14)	(-3.27)		(-5.65)	(-3.55)
ΔUSS			0.35***			0.24***
			(4.58)			(2.77)
Constant	0.42*	0.46*	0.29	0.52**	0.55**	0.26
	(1.69)	(1.95)	(1.29)	(2.02)	(2.32)	(1.13)
R2	0.08	0.16	0.28	0.06	0.21	0.29
obs	218	218	218	129	129	129

Notes: 1. *t* statistics in parentheses.

2. ***, **, and * denote significant at the 1%, 5%, and the 10% levels, respectively

3. LOCSTOCK is the MSCI stock price index for a given comparison country. LOCRES is the amount of reserves (USD million) held by a given comparison country. LOCUSD is the exchange rate in local currency per USD for a given comparison country.

Table 15 Baseline Estimations for Comparison Countries: Stock Price Indices - continued

Dependent Variable (Risk Indicator): $\Delta LOCSTOCK_t$

	Philippines (Full Sample) From August 2001 to October 2019			Philippines (Post GFC) From January 2009 to October 2019		
ΔLOCRES	0.39*	0.15	0.14	0.75**	0.42	0.44
	(1.88)	(0.84)	(0.82)	(2.28)	(1.38)	(1.48)
ΔLOCUSD		-1.28***	-0.87***		-1.19***	-0.79***
		(-5.06)	(-3.58)		(-4.49)	(-2.74)
ΔUSS			0.47***			0.34***
			(4.48)			(3.40)
Constant	0.78**	0.82**	0.61*	1.06***	1.16***	0.77**
	(2.07)	(2.34)	(1.81)	(2.79)	(3.34)	(2.28)
R2	0.02	0.14	0.25	0.08	0.23	0.30
obs	218	218	218	129	129	129

	Thai (Full Sample) From August 2001 to October 2019			Thai (Post GFC) From January 2009 to October 2019		
ΔLOCRES	0.74***	-0.08	-0.02	1.03***	0.29*	0.12
	(4.22)	(-0.37)	(-0.10)	(5.40)	(1.73)	(0.59)
ΔLOCUSD		-2.02***	-1.42***		-1.64***	-1.35***
		(-6.27)	(-5.76)		(-8.40)	(-5.68)
ΔUSS			0.67***			0.44***
			(6.19)			(4.15)
Constant	0.74*	0.59	0.38	0.92**	0.82**	0.40
	(1.83)	(1.63)	(1.19)	(2.41)	(2.49)	(1.28)
R2	0.07	0.25	0.43	0.19	0.40	0.50
obs	218	218	218	129	129	129

Notes: 1. *t* statistics in parentheses.
2. ***, **, and * denote significant at the 1%, 5%, and the 10% levels, respectively
3. LOCSTOCK is the MSCI stock price index for a given comparison country. LOCRES is the amount of reserves (USD million) held by a given comparison country. LOCUSD is the exchange rate in local currency per USD for a given comparison country.

Table 16 Baseline Estimations for Comparison Countries: CDS Spreads

Dependent Variable (Risk Indicator): $\Delta LOCCDS_t$

	Indonesia (Full Sample) From May 2004 to October 2019			Indonesia (Post GFC) From January 2009 to October 2019		
ΔLOCRES	-5.39**	-2.34**	-1.76**	-4.54***	-2.01*	-1.36
	(-2.47)	(-2.40)	(-2.26)	(-3.91)	(-1.76)	(-1.44)
ΔLOCUSD		9.02***	6.38***		8.25***	6.01***
		(3.91)	(3.44)		(5.31)	(4.46)
ΔUSS			-4.32***			-3.65***
			(-5.33)			(-4.65)
Constant	-2.47	-4.54**	-1.53	-3.22	-5.31**	-1.19
	(-0.91)	(-2.19)	(-0.78)	(-1.20)	(-2.23)	(-0.58)
R2	0.17	0.46	0.59	0.16	0.43	0.58
obs	185	185	185	129	129	129

	South Korea (Full Sample) From August 2001 to October 2019			South Korea (Post GFC) From January 2009 to October 2019		
ΔLOCRES	-4.74***	-2.60	-1.80**	-4.73***	-2.35***	-1.86***
	(-3.89)	(-2.20)	(-1.98)	(-4.47)	(-3.60)	(-3.07)
ΔLOCUSD		2.67***	1.48***		2.88***	1.79***
		(5.04)	(2.85)		(6.81)	(3.74)
ΔUSS			-2.08***			-1.51***
			(-4.68)			(-4.74)
Constant	2.11	1.75	2.53**	0.25	0.05	1.45
	(1.55)	(1.41)	(2.14)	(0.20)	(0.04)	(1.47)
R2	0.15	0.28	0.40	0.24	0.47	0.56
obs	218	218	218	129	129	129

	Malaysia (Full Sample) From August 2001 to October 2019			Malaysia (Post GFC) From January 2009 to October 2019		
ΔLOCRES	-1.77**	-0.65	-0.10	-3.10***	-1.31	-0.76
	(-2.39)	(-1.00)	(-0.21)	(-2.76)	(-1.55)	(-1.08)
ΔLOCUSD		5.45***	3.71***		5.13***	3.29***
		(6.68)	(4.95)		(5.83)	(4.19)
ΔUSS			-2.47***			-2.71***
			(-7.25)			(-6.16)
Constant	-0.32	-0.70	0.46	-2.2	-2.50*	0.74
	(-0.25)	(-0.64)	(0.51)	(-1.23)	(-1.68)	(0.59)
R2	0.06	0.32	0.54	0.11	0.40	0.59
obs	218	218	218	129	129	129

Notes: 1. *t* statistics in parentheses.
2. ***, **, and * denote significant at the 1%, 5%, and the 10% levels, respectively
3. LOCCDS is the five-year sovereign CDS series for a given comparison country. LOCRES is the amount of reserves (USD million) held by a given comparison country. LOCUSD is the exchange rate in local currency per USD for a given comparison country.

Table 16 Baseline Estimations for Comparison Countries: CDS Spreads- continued

Dependent Variable (Risk Indicator): $\Delta LOCCDS_t$

	Philippines (Full Sample) From August 2001 to October 2019			Philippines (Post GFC) From January 2009 to October 2019		
ΔLOCRES	-2.12**	-0.45	-0.38	-1.88*	0.42	0.26
	(-1.98)	(-0.45)	(-0.39)	(-1.93)	(0.56)	(0.33)
ΔLOCUSD		8.91***	5.63***		8.22***	4.58***
		(5.39)	(4.65)		(6.14)	(4.52)
ΔUSS			-3.79***			-3.09***
			(-5.15)			(-5.70)
Constant	-1.74	-2.07	-0.39	-2.55	-3.24**	0.26
	(-0.79)	(-1.04)	(-0.21)	(-1.33)	(-2.04)	(0.20)
R2	0.02	0.19	0.39	0.02	0.33	0.55
obs	218	218	218	129	129	129

	Thai (Full Sample) From August 2001 to October 2019			Thai (Post GFC) From January 2009 to October 2019		
ΔLOCRES	-1.92**	0.05	-0.17	-3.62***	-1.38	-0.29
	(-2.39)	(0.05)	(-0.27)	(-3.21)	(-1.21)	(-0.35)
ΔLOCUSD		4.87***	2.62***		4.98***	3.10
		(4.40)	(3.55)		(3.49)	(3.13)
ΔUSS			-2.50***			-2.78***
			(-7.44)			(-6.37)
Constant	-0.06	0.29	1.07	-1.36	-1.04	1.60
	(-0.05)	(0.25)	(1.06)	(-0.87)	(-0.70)	(1.22)
R2	0.05	0.17	0.44	0.15	0.26	0.51
obs	218	218	218	129	129	129

Notes: 1. *t* statistics in parentheses.

2. ***, **, and * denote significant at the 1%, 5%, and the 10% levels, respectively

3. LOCCDS is the five-year sovereign CDS series for a given comparison country. LOCRES is the amount of reserves (USD million) held by a given comparison country. LOCUSD is the exchange rate in local currency per USD for a given comparison country.

Chapter 3

The Information Content of the Implied Volatility of Interest Rates: Evidence from US Dollar, Euro, and Japanese Swaption

3. 1 Introduction

This chapter first analyzes the information content of implied volatility (IV) based on the swaption for major currencies, including the US dollar (USD), Euro (EUR), and Japanese Yen (JPY). Many papers have discussed the information content of IV using equity options (such as Day and Lewis, 1992; Canina and Figlewski, 1993; Christensen and Prabhala, 1998) and foreign exchange (such as Jorion, 1995). Szakmary et al. (2003) study the IV of futures options, and this empirical study includes interest rate options, such as Treasury bonds or UK long gilt. However, although swaption itself has been analyzed in terms of the volatility risk premium (Fornari, 2005; Fornari, 2010; Duyvesteyn and Zwart, 2015) and other subjects (Fornari, 2004), there is no existing study on IV swaption, which is among the most widely used IV in bond markets.

Swaption is the interest rate swap option, and it is one of the most popular derivative contracts. According to the Bank for International Settlement (BIS), for the first half of 2015, the notional outstanding amounts of interest swaps (Over-The-Counter, OTC) were USD106.8 trillion for USD swaps, USD87.2 trillion for EUR swaps, and USD41.4 trillion for JPY swaps. On the other hand, the notional outstanding amounts of interest rate options (OTC) were USD15.6 trillion for USD options, USD16.8 trillion for EUR options, and USD2.6 trillion for JPY options, which were smaller than interest rates swaps but still quite large.

I believe that this chapter contributes to both academics and practitioners, including traders and risk managers. This chapter’s contribution is twofold. First, understanding IV based on the interest rate is important for risk management. Recently, the market size for fixed-income securities has increased, mainly because of government deficits. Particularly, financial institutions, such as commercial banks and insurance companies, have primarily invested in fixed income securities because of regulations or for the purposes of asset liability management (ALM). Therefore, the main purpose of risk management for financial institutions is to manage risk related to fixed income securities. Many studies test the information content of asset volatility, and this type of analysis should not be restricted to equity and foreign exchange markets.

Second, the bond market is an OTC market, except for futures. In OTC markets, financial contracts are not standardized but are customized; therefore, I can obtain the exact maturity (expiry) of an option. However, futures option maturities change, causing a maturity mismatch problem, and earlier studies suffered from this problem. For example, Day and Lewis (1992) examine the one-week ahead predictive power of IV based on options that have a much longer remaining life. However, later studies treated this problem carefully. For example, Yu et al. (2010) use equity IV in OTC markets to avoid this problem. Here, I use the same strategy using IV based on swaption.

The remainder of this chapter is organized as follows. I describe the data and related factors in section 3.2. I present the definition of volatility and hypothesis in section 3.3. Section 3.4 presents the results of the predictive power of IV, including a robustness check. Section 3.5 shows further analysis, and section 3.6 presents the conclusions.

3. 2 Data

3.2.1 Swaption

A swaption is one of the most liquid interest rate options in the OTC market. A swaption is an option in which the underlying is an interest rate swap. An interest rate swap is a swap agreement where a contractor swaps a fixed-rate payment with a float-rate payment, or vice versa. In a swaption, the typical floating-rate payment is based on the 3-month or

6-month LIBOR. There are two types of swaptions: a payer swaption and receiver swaption. The former corresponds to a put option, while the latter corresponds to a call option.

The important feature is that swaptions are traded in the OTC market. Of course, there are bond options, such as Treasury bond futures or JGB futures, but these financial contracts are standardized because these are traded in stock exchanges, such as the Osaka Exchange market. On the other hand, a swaption is an OTC financial product; therefore, it is customized for each contract. In other words, I can obtain the exact maturity of the option. For example, I can acquire a 1-month maturity swaption every business day as long as I obtain the data from the swaption.

3.2.2 Normal Model (Bachelier Model)

Black Vol is the IV based on Black (1976), which assumes that the interest rate process has a lognormal distribution. On the other hand, normal Vol assumes that the interest rate follows a normal distribution. As Patel et al. (2018) describe, each model has its pros and cons. Black's model is the most commonly accepted, especially for the swaption market before the 2010s, but this model assumes a lognormal distribution; therefore, it cannot work under negative rate regimes. In fact, broker-dealers have begun to stop quoting prices using Black's model due to the negative yield. Some brokers use the Shifted Black model after a yield goes into negative territory, although it requires a parameter modification. Furthermore, data for IV based on the shifted Black model are quite limited, and the specifications of the model are not always disclosed. Compared with these models, the normal volatility does not require parameter modification and the data are consistently available through providers such as Bloomberg. Therefore, I use normal Vol for this analysis. As in previous studies (e.g., Fornari, 2005; Duyvesteyn and Zwart, 2015), I use IV from the at the money (ATM) swaption.

In the normal model, the forward rate is modeled as follows:

$$dF_t = \sigma_N dW_t,$$

where W_t refers to a Brownian motion and σ_N refers to the volatility of the forward rate, which is called normal volatility. The formula of the European call option is as follows:

$$C = e^{-r\tau}\left[(F - K)N(d) + \sigma_N\sqrt{\tau}N(d)\right],$$

$$d = \frac{F - K}{\sigma_N\sqrt{\tau}},$$

where C refers to the premium of the call option, F the forward price, K the strike price, and τ the remaining time to maturity. $N(\cdot)$ is the cumulative distribution function of the standard normal distribution.

3.2.3 Data Source

I obtain a dataset of swap rates and swaptions from Bloomberg. I focus on 5, 10, and 20-year swap rates and swaptions. I use the Bloomberg Composite Rates (CMP) as the data source.[30] I examine one-month ahead future volatility; therefore, a swaption with a one-

[30] According to Bloomberg, the Bloomberg Composite Rates (CMP) is a "best market" calculation. At any given point in time, the composite bid rate is equal to the highest bid rate of all of the currently active,

month maturity is used in this analysis.

The IV of swaption from Bloomberg includes Black volatility (Black Vol) and normal volatility (normal Vol).[31] Jiang and Tian (2005) show that the model-free implied volatility subsumes all information contained in the Black–Scholes' implied volatility. Although the Black-Scholes formula has unrealistic assumptions, such as the price of the underlying asset following a geometric Brownian motion with constant drift and volatility, I rely on the normal Vol of the swaption because of data availability (Bloomberg only provides Black and normal volatility as the price data).

Figure 1 shows the time series of a 1-month maturity swaption's IV for USD, EUR, and JPY. This series has three features. First, the IV with a different tenure has a high correlation. Second, the IV increased sharply during the global financial crisis. Third, the average IV of the JPY was much lower than that of the USD and EUR, which reflects the low-yield and low-volatility environment in the JPY market.

3.2.4 Sampling Procedure

When I use consecutive observations in the time series of historical and future volatility, as Christensen and Prabhala (1998) noted, the estimated result could suffer from serial correlation because of overlapping samples. Therefore, I check the robustness of the result by taking a non-overlapping sample on a monthly basis based on Christensen and

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contributed, bank indications. I choose CMP depending on close time. I choose USD for New York time (CMPN), JPY for Tokyo time (CMPT), and EUR for London time (CMPL).

[31] Swaption is the option trade in OTC markets, and the source has to be determined. I use BBIR provided by Bloomberg, which is based on contributed market quotes of swaption volatilities from dealers and brokers. BBIR Vols are quoted as Black Vol, and BBIR normal Vols are determined from BBIR Black Vols.

Prabhala (1998) and Yu et al. (2010).

To construct the non-overlapping data, I sample monthly data from the daily sample. I create monthly data from weekly data, which produces four datasets. To realize whether the results are sensitive to the sampling procedure, I use four different monthly samples and check whether the results are robust.

3. 3 Methodology

3.3.1 Hypotheses

I test the information content of IV based on previous studies (Canina and Figlewski, 1993; Szakmary et al., 2003; Yu et al., 2010) and present the following three hypotheses.

H1. IV is an unbiased estimator of future realized volatility (RV).

H2. IV has more explanatory power than the historical volatility (or the GARCH volatility forecast) for forecasting future RV.

H3. IV includes all information regarding future volatility; the historical volatility (or the GARCH volatility forecast) contains no information beyond the information already included in IV.

To test the hypotheses above, I regress three models commonly used in previous studies.

$$RV_{t:t+\tau} = \alpha_1 + \beta_1 IV_{t:t+\tau} + e_t, \quad (1)$$

$$RV_{t:t+\tau} = \alpha_2 + \beta_2 RV_{t-\tau:t} + e_t, \quad (2)$$

$$RV_{t:t+\tau} = \alpha_3 + \beta_3 IV_{t:t+\tau} + \beta_3' RV_{t-\tau:t} + e_t, \quad (3)$$

where $RV_{t:t+\tau}$ is future RV from t to $t+\tau$. $RV_{t-\tau:t}$ is the historical volatility (HV), where we use lag of RV, computed from $t-\tau$ to t; $IV_{t:t+\tau}$ is normal volatility (IV) traded at t; and e_t is an error term. Since $IV_{t:t+\tau}$ is the option price at time t (τ is the remaining time to maturity), $IV_{t:t+\tau}$ is observed at t by investors. I use one-month IV maturity and compute $RV_{t:t+\tau}$ matching the remaining life of the IV. Since we use 20 business days as a one-month, we set τ as 20. I repeat the same regressions, replacing $RV_{t-\tau:t}$ with the GARCH volatility forecast. For estimating (1) to (3), I use the daily data from January 2007 to December 2015 and weekly data from January 2005 to December 2015 for the robustness check (as I explain later).

If H1 holds, IV is an unbiased predictor of RV; therefore, $\alpha_1 = 0$ and $\beta_1 = 1$ should be expected in regression (1). If H2 holds, a higher R^2 is expected from regression (1) than regression (2). If H3 holds, $\beta_3{}' = 0$ should be expected when IV is already included in the model.

3.3.2 Realized Volatility, Historical Volatility, and GARCH

I have the daily swap rate: R_t $(t = 0,1,2,\ldots,n)$, and I construct the difference of the swap rate: $r_t = R_t - R_{t-1}$.[32] I estimate RV ($RV_{t:t+\tau}$) as the sum of their squares below.

$$RV_{t:t+\tau} = \sqrt{\sum_{i=1}^{\tau} r_{t+i}^2}. \tag{4}$$

[32] Since the swap rate could take the negative value, I take the difference instead of log difference.

The IV is annual, based on market convention; therefore, I annualize RV for estimation. I use 250 trading days as one year and 20 trading days as one month.

Following the previous literature, such as Szakmary et al. (2003), I use GARCH to forecast volatility using the GARCH (1,1) model as follows:

$$\varepsilon_t = \sigma_t z_t, \tag{5}$$

where $\sigma_t > 0$ holds and stochastic parameter z_t satisfies $z_t \sim N(0,1)$, and

$$\sigma_t^2 = \omega_0 + \beta_0 \sigma_{t-1}^2 + \alpha_0 \varepsilon_{t-1}^2, \tag{6}$$

where $\omega_0 > 0$ and $\beta_0, \alpha_0 \geq 0$ holds.

Following Engle and Bollerslev (1986), a daily s-step ahead volatility forecast can be computed as follows:

$$\hat{\sigma}_{t+s}^2 = \hat{\omega}_0 \sum_{i=0}^{s-2} (\hat{\alpha}_0 + \hat{\beta}_0)^i + (\hat{\alpha}_0 + \hat{\beta}_0)^{s-1} \hat{\sigma}_{t+1}^2, s = 2, .., N. \tag{7}$$

The volatility forecasts (GARCH forecast volatility) are computed by aggregating the s-step-ahead daily forecasts as follows:

$$\hat{\sigma}_{t:t+\tau}^2 = \sum_{s=1}^{\tau} \hat{\sigma}_{t+s}^2, \tag{8}$$

where τ is the number of days ahead of the forecast, and $\hat{\sigma}_{t:t+\tau}^2$ is the forecast variance at time t over the next τ days. I test the information content of one-month ahead future volatility, setting τ as 20. This forecast variance is multiplied by $250/\tau$ to annualize it. The parameters are estimated using the data from the last five years, and I compute forecast variance based on the estimates.[33]

The descriptive statistics for the RV and IV are shown in Table 1. This table shows that the mean values of RV and IV of USD and of EUR are approximately 100 bps and 60–80 bps, respectively. However, the mean values of JPY are 30–50 bps, which are relatively lower. The standard deviations of JPY are also relatively lower.

Table 2 shows the descriptive statistics of the interest rate swap. First, the table shows the level of interest rate following the non-stationary process. However, the first difference of the interest rate swap follows the stationary process. Second, the kurtosis of the first difference of each interest rate swap is over 3, which suggests that the first difference of the interest rate swap has a fat tail when compared to the normal distribution. Third, there is no autocorrelation in the first difference of the swap rate.[34] Table 3 shows the estimation results when I estimate GARCH using the daily data. First, this table shows that the coefficients are significant at the 1 % level. Second, $\hat{\alpha}_0 + \hat{\beta}_0$ is closer to 1; therefore, the persistency of the volatility of the swap rate is high.

3. 4 Empirical Results

3.4.1 Overlapping Data

Table 4 shows the results for the predictive power of IV, GARCH (1,1), and historical

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[33] The parameters in the GARCH model are estimated applying ε_t as r_t because the change of swap rate is not different from zero and do not have autocorrelation, according to the Ljung-Box test.

[34] LB (5) of US interest rate swap shows the nulls are rejected but this result is not robust when we use subsample for the rolling estimation.

volatility ($RV_{t-\tau:t}$) in forecasting the RV ($RV_{t:t+\tau}$), which includes the estimates, t-statistics, and adjusted-R^2 in eq. (1) to (3). I report the regression results after correcting the standard errors of the coefficients for heteroscedasticity and autocorrelation according to the Newey and West (1987) method.

First, I test H1 using eq. (1). When $\alpha_1 = 0$ and $\beta_1 = 1$ is tested in the Wald-test, the null hypothesis is rejected for every currency and maturity except for 5-year and 10-year USD, as shown in Table 5. This finding does not fully accord with H1, which is consistent with existing studies such as Jordan (1995) and Szakmary et al. (2003).

On the other hand, in the first rows of each currency and tenor in Table 4, I report the coefficients, their t-statistics, and adjusted-R^2 from eq. (1). Table 4 shows that $\hat{\beta}_1$ is 0.69~0.87 for USD, 0.60~0.63 for EUR, and 0.58~0.76 for JPY, which are far less than 1. Regardless of the type of currency, the coefficients for IV are statistically significant at the 1% level, which suggests that IV contains information on future RV. However, H1 is a more restrictive statement; it requires not only the slope coefficients are non-zero but also the slope coefficient is one and constant term is zero. This result suggests IV is a biased forecast of the RV.

Second, I test H2 using eq. (2). The results are displayed in the second row of each currency and tenor in Table 4. As seen in eq. (1), regardless of the type of currency, the coefficients for the GARCH volatility forecast and historical volatility are also statistically significant at the 1% level, although IV is a better predictor according to adjusted-R^2 except in the case of JPY. I also confirm that the result is consistent with the Diebold and Mariano test (Diebold and Mariano 1995), using the realized volatility and the forecast of the IV and lag of RV. Table 6 shows the result of the Diebold and Mariano test, based on mean square error, and I confirm the IV is the better variable, except for

JPY. The information content of the model is greater when the tenor is shorter, according to adjusted-R^2.

Finally, I test H3 by regressing RV on IV and GARCH volatility forecast (historical volatility), as specified in eq. (3). The results are shown in the coefficients displayed in the third row of each currency and tenor. For USD and EUR, the coefficient for IV is statistically significant at the 1% level, while the coefficient of GARCH forecast and lag of RV are not statistically significant. However, for JPY, the GARCH forecast and historical volatility are statistically significant at the 1% level, while the coefficient for IV is not always statistically significant. This implies that the GARCH volatility forecast and historical volatility contain information on future RV, even if IV is controlled. The information content of the model is higher when the tenor is shorter, according to adjusted-R^2, which confirms H1 and H2.

One of the reasons the GARCH volatility forecast and historical volatility in the JPY market also have predictive power could be related to liquidity. The notional amount of the JPY swaption is lower than that of the USD and EUR swaptions, as shown in section 1. This suggests that the liquidity of the yen swaption could be lower. If the liquidity of the swaption market is lower, fewer investor opinions are reflected in the swaption premium, lowering the predictive power for future volatility.

Table 7 shows the daily turnover of the interest derivative option, which was investigated by the Bank for International Settlement in 2013 (the "Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity in 2013" survey). The turnovers of USD and EUR were 116,754 and 26,278 million USD, although that of JPY only amounted to 7,333 million USD. In addition, there is anecdotal evidence of low liquidity in the swaption market in Japan. Mitsubishi UFJ Morgan Stanley suffered from huge losses, amounting to 80 billion JPY, because swaption traders manipulated their positions. Since the swaption in the JPY market is not liquid, a swaption trader could potentially manipulate the market price. I conduct an empirical analysis of this in Section 3.5.

For the estimation, the lag is set as 20 business days since the daily data of this estimation have a one-month overlap. Accordingly, I set the lag with the consideration of the data characteristics. The result is robust when I use the guideline for choosing lag, which is suggested by Stock and Watson (2018).[35] The result is also robust when we follow the recommendation of Lazarus et al. (2018). I show these results in the Appendix. Furthermore, I also conduct the robustness check with non-overlapping data in next section.

3.4.2 Non-overlapping Data

The result in Table 4 contains overlapping data. Although the standard errors are adjusted by the Newey and West (1987) method, I use non-overlapping data to construct monthly data to check the robustness of the results in eq. (3).

One problem with constructing monthly data is lowering the frequency of the data. I can extend the dataset from January 2005 for normal IV when I use weekly data. In this case, I can construct four datasets when I construct monthly data from the weekly data; therefore, I use four datasets to check the robustness of the results in Table 4.

In Table 8, I report the coefficients, their t-statistics, and adjusted-R^2 in eq. (3)

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[35] Stock and Watson (2018) show the guideline to use the formula, which is $0.75T^{1/3}$, where T is sample size. This formula is obtained from a formula in Andrews (1991), specialized for the case of a first-order autoregression with coefficient 0.25.

using weekly data from January 2005 to December 2015. In this case, the estimates depend on the datasets (first week, second week, third week, and fourth week), displayed in each row. I confirm the same result as in Table 4, which shows that IV is the only predictor of future volatility for USD and EUR, but the GARCH forecast and historical volatility have greater predictive power for the RV for JPY. The information content of the model is also greater when the tenor is shorter, according to adjusted-R^2, which is consistent with the results in Table 4.

3.4.3 During and after the Financial Crisis

To consider the problem of liquidity, I check whether the results could change when I use samples during and after the financial crisis (2008 to 2009). During the financial crisis, the problem of liquidity was widespread, and, even after the financial crisis, practitioners tended to insist that the liquidity of the OTC derivatives market was lower because of stricter regulation.

I estimate eq. (3) using the dataset for January 2008 to December 2009 for the financial crisis period and show the results in Table 9. During the financial crisis, the predictive power of the USD, EUR, and JPY markets was lower in terms of adjusted-R^2, and the coefficient of IV in the JPY market was statistically insignificant or negative, although the GARCH forecast and historical volatility remained significant at the 1% level. These results could be explained by the lack of liquidity during the financial crisis.

I estimate eq. (3) using the dataset for January 2010 to December 2015 for the period after the financial crisis. The result is similar to the results in Table 4. IV has predictive power, although the GARCH forecast and historical volatility can also predict future RV, except in the case of JPY. The predictive power of the model in the USD, EUR, and JPY markets was lower in terms of adjusted-R^2, although the degree is much larger compared with the adjusted-R^2 during the financial crisis. This is consistent with previous studies, such as Trebbi and Xiao (2019), which find no systematic evidence of deterioration in liquidity levels or structural breaks in the US fixed income market during periods of post-crisis regulatory interventions.

3. 5 Further analysis

3.5.1 Liquidity in the Fixed Income Market

To examine how low liquidity in the swaption market in Japan could affect the information content, I use the liquidity measure in Japan to conduct the empirical study. In this study, I use the noise measure, which is widely used in fixed income markets to capture liquidity. Following Hu et al. (2013), I construct the noise measure by fitting daily data for JGBs (Japanese Government Bonds) into a smooth yield curve using the approach of Svensson (1994), and I then computed the mean squared errors as the illiquidity measure, following eq. (9).

$$y(x,b) = \frac{1}{x}\int_0^x f(s)ds = \alpha_4 + \beta_4\left(\frac{1-\exp\left(-\frac{x}{\tau_1}\right)}{\frac{x}{\tau_1}}\right) + \gamma_4\left(\frac{1-\exp\left(-\frac{x}{\tau_1}\right)}{\frac{x}{\tau_1}} - \exp\left(-\frac{x}{\tau_1}\right)\right) + \delta_4\left(\frac{1-\exp\left(-\frac{x}{\tau_2}\right)}{\frac{x}{\tau_2}} - \exp\left(-\frac{x}{\tau_2}\right)\right), \quad (9)$$

where x is the remaining maturity, and $b = (\alpha_4\ \beta_4\ \gamma_4\ \delta_4\ \tau_1\ \tau_2)$ are the parameters to be estimated. The parameters must satisfy conditions $\alpha_4 > 0, \alpha_4 + \beta_4 > 0, \tau_1 > 0, \tau_2 > 0$ (Svensson 1994; Hu et al. 2013).We consider $y_t^i(x_t, b_t)$ as the theoretical yield for the security i at time t, and minimize the deviation between the theoretical and actual yields to estimate the parameters based on eq. (9).[36] We construct the noise measure using the model-implied and actual yields (y_t^i), as follows:

$$Noise_t = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}[y_t^i - y_t^i(x_t, b_t)]^2}. \quad (10)$$

To compute the noise measure in Japan, I use bonds with a maturity between 1 month and 10 years to estimate the parameters, whereas I use only bonds with a maturity between 1 year and 10 years to construct the noise measure. In addition, I employ a filter, where any bonds with four standard deviations away from the model yield are excluded from the construction of the noise measure. The data is obtained from Hattori (2021).

Table 10 shows the descriptive statistics of the noise measure based on the JGB data, which clearly indicate this measure increased from 2008 to 2009. This proves that liquidity in the fixed income market deteriorated during the financial crisis.

The regression

To evaluate the effect of the liquidity condition for the information contained in the swaption, we first divide the sample with above and below noise measure averages and then regress the RV on the IV and GARCH/lag of RV, following eq. (3). If the liquidity affects the information of the IV, the coefficient of the IV is not significant when the liquidity is low. Second, we regress the equation as below:

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[36] Hu et al. (2013) minimize the weighted sum of the squared deviations between the actual and the model-implied prices, divided by MaCaulay's duration. We use the actual yield and model-implied yields directly because the fitness of this approach is better in the JGB market.

$$RV_{t:t+\tau} = \alpha_5 + \beta_5 IV_{t:t+\tau} + \beta'_5 RV_{t-\tau:t} + \gamma_5 liquidity_t + \delta_5 liquidity_t \times IV_{t:t+\tau} + e_t, \qquad (11)$$

where $liquidity_t$ is the liquidity captured by the noise measure. For the noise measure, the liquidity increases when liquidity deteriorates. To see how liquidity affects the information content of the IV, we construct the intersection of IV with liquidity ($liquidity_t \times IV_{t:t+\tau}$). Since the noise measure increases when liquidity deteriorates, we expect δ_5 to be a negative value when the IV contains more information under the high liquidity condition.

Table 11 shows the regression result when we divide the sample with below and above noise measure averages, following eq. (3). When the liquidity is below the average, the coefficient of the IV of 10 and 20 years is no longer significant, while it remains significant when liquidity is above the average. In addition, the R-square of 10 and 20 years above average is around 0.3 but that below average is only 0.2. This simple regression suggests that liquidity affects the information contained in IV, especially for the 10-year and 20-year swaption.

Table 12 shows the estimation result following eq. (11). This table indicates that the intersection of the IV with liquidity has a significantly negative impact on the RV. This suggests that the information content of the IV is affected by the liquidity condition.

3.5.2 The Interaction of the IV among USD, EUR and JPY

Thus far, we conducted country-specific predictive regressions. In this section, I discuss how the IV of the USD affects the RV of the JPY. We conducted the regression below:

$$RV_{JPY,t:t+\tau} = \alpha_6 + \beta_6 IV_{US,t-1:t+\tau-1} + e_t, \qquad (12)$$

where $RV_{JPY,t:t+\tau}$ refers to the future RV of the JPY from t to $t+\tau$ while $IV_{US,t-1:t+\tau-1}$ refers to the implied volatility of the USD with maturity $t-1$ to $t+\tau-1$.

Table 13 shows the estimation result. This result suggests the IV of the USD significantly predicts that of the JPY. This implies that the US option price contains information to predict the future volatility of the JPY rates market.

3. 6 Conclusion

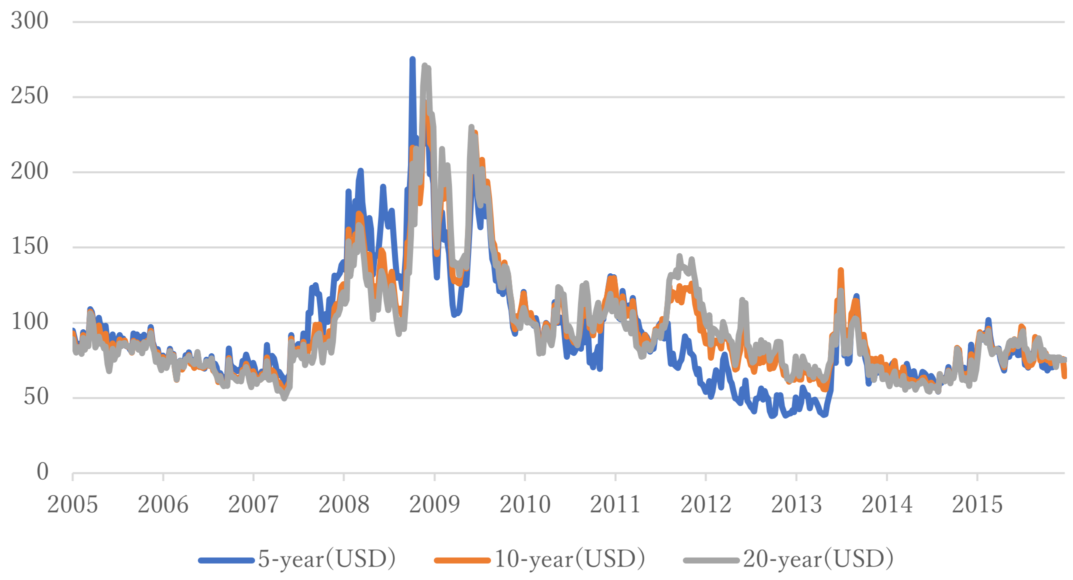
This chapter estimates the information content of IV for the fixed income market using swaption data. The results of IV based on equity or foreign exchange show stronger predictive power for future RV based on USD and EUR swaptions. I suggest that liquidity could also be an important factor in predicting future volatility. For the JPY swaption, the information content of IV is lower, and the GARCH forecast and lag of RV have stronger predictive power for future volatility.

The implications of these conclusions for risk managers are clear and important. With exposure to the interest risk of the USD and EUR, risk managers are advised to check the IV of these currencies. However, if there is some exposure to interest rate risk of the JPY, the GARCH forecast volatility and lag of RV should also be checked. If there is some suspicion that the market has a liquidity-related problem, these checks are even more important.

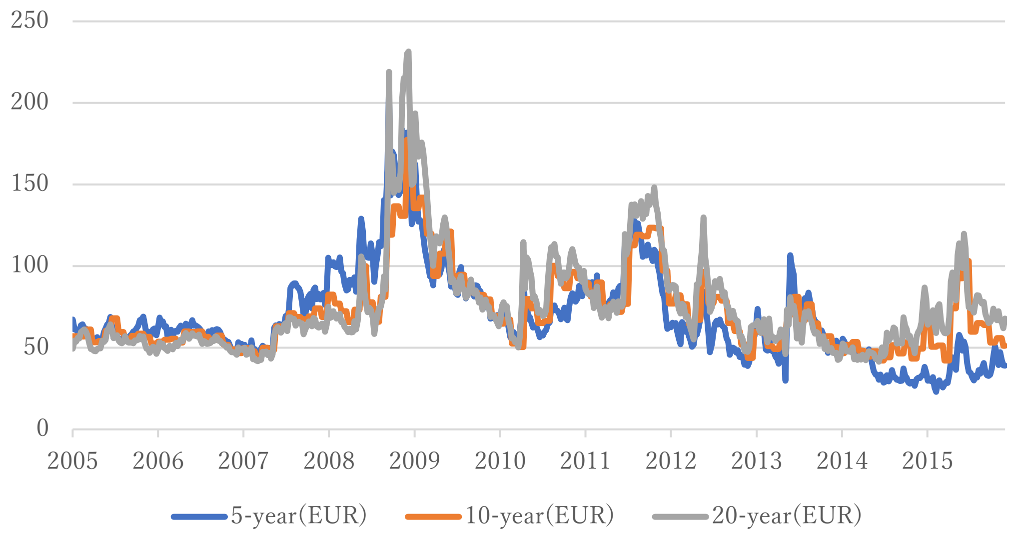
In our analysis, we use 1-month ATM swaption because of data availability. However, the Chicago Board Option Exchange（CBOE） has started to compute model-free interest rate swap volatility indexes. According to studies that have used stock price, using a model-free IV leads to more information than Black-Scholes IV. In addition, as described, the first difference of the interest rate swap does not follow a normal process. Therefore, future research should use model-free IV to test whether this could lead to more information.

Figure 1 Time series of the IV of swaptions

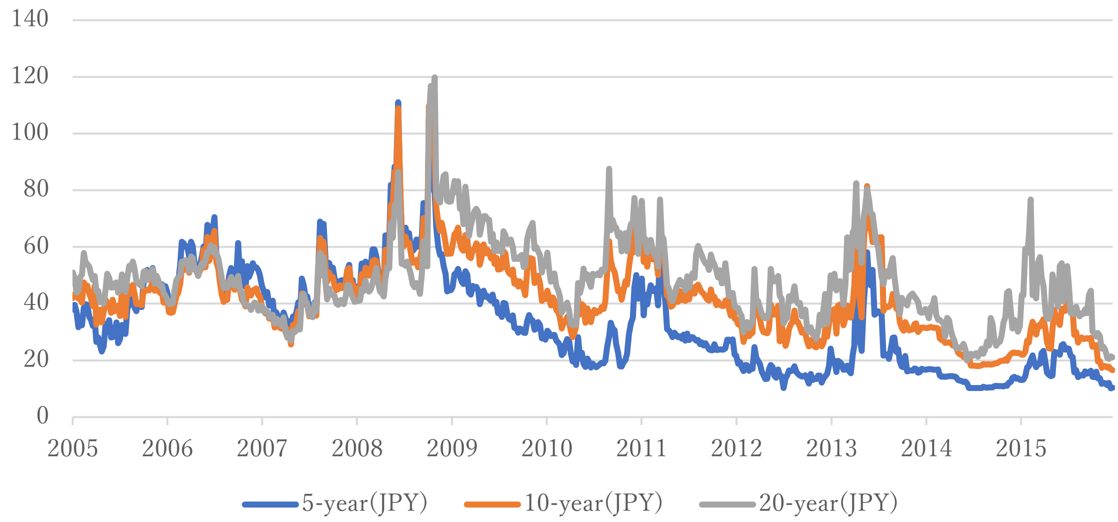
(i) USD



(ii) EUR



(iii) JPY



Note: These time series are based on weekly data.

Source: Bloomberg

Figure 2 Time series of the noise measure in JGB market

Note: The data is obtained from Hattori (2021).

Table 1 Descriptive statistics of realized volatility and implied volatility

(1) Realized volatility

		Obs	Mean	Std.Dev.	Min	Max
USD	5-year	2,349	93.0	45.9	23.3	292.9
	10-year	2,349	97.7	43.5	27.5	298.6
	20-year	2,349	94.5	38.3	27.3	250.5
EUR	5-year	2,349	60.9	24.8	16.4	160.6
	10-year	2,349	65.2	23.0	24.8	160.0
	20-year	2,347	68.4	31.2	29.3	266.0
JPY	5-year	2,349	26.3	17.4	4.3	112.9
	10-year	2,349	35.3	16.8	7.6	115.3
	20-year	2,348	39.4	19.0	9.6	164.3

(2) Implied volatility

		Obs	Mean	Std.Dev.	Min	Max
USD	5-year	2,349	96.6	42.2	35.9	290.6
	10-year	2,349	101.4	37.8	51.6	252.5
	20-year	2,349	101.2	39.1	48.9	276.1
EUR	5-year	2,349	71.7	31.1	23.0	211.5
	10-year	2,349	75.4	25.8	38.9	177.5
	20-year	2,347	80.4	32.1	40.5	232.8
JPY	5-year	2,349	30.7	17.4	10.0	111.1
	10-year	2,349	41.7	15.2	15.7	110.5
	20-year	2,348	48.0	15.6	18.6	126.3

Note: These tables show the descriptive statistics of Realized volatility and implied volatility.

Table 2 Descriptive statistics of interest rate swap rate

		PP test		Difference					
		Level	Difference	Mean	Std. Dev.	Skewness	Kurtosis	LB(1)	LB(5)
USD	5-year	-1.950 (0.31)	-66.624 (0.00)	-0.001	0.065	0.106	5.608	0.065	0.000
	10-year	-1.9 (0.33)	-66.635 (0.00)	-0.001	0.065	0.083	5.574	0.066	0.000
	20-year	-1.794 (0.38)	-66.719 (0.00)	-0.001	0.061	0.124	4.891	0.061	0.000
EUR	5-year	-0.572 (0.88)	-66.049 (0.00)	-0.001	0.042	0.282	5.191	0.162	0.019
	10-year	-0.657 (0.86)	-66.588 (0.00)	-0.001	0.041	0.201	4.617	0.068	0.017
	20-year	-0.579 (0.88)	-62.111 (0.00)	-0.001	0.043	0.049	8.212	0.295	0.016
JPY	5-year	-1.698 (0.43)	-65.721 (0.00)	0.000	0.023	0.482	8.792	0.325	0.834
	10-year	-1.707 (0.43)	-66.711 (0.00)	0.000	0.027	0.432	7.162	0.048	0.495
	20-year	-1.960 (0.30)	-65.199 (0.00)	0.000	0.030	0.208	9.417	0.632	0.767

Note: This table shows the descriptive statistics of the interest swap rate. The data period is from January 2000 to December 2015. LB (1) and LB (5) are the p-value of Ljung-Box statistic to test the null hypothesis of no autocorrelations up to 1 and 5 lags.

Table 3 Estimation result

	Year	ω_0	β_0	α_0
USD	5	0.136 (6.36)	0.955 (93.62)	0.042 (4.32)
	10	0.330 (34.35)	0.944 (349.74)	0.047 (19.54)
	20	0.379 (3.64)	0.941 (142.56)	0.048 (9.80)
EUR	5	0.045 (5.37)	0.963 (209.24)	0.036 (7.12)
	10	0.208 (104.05)	0.952 (317.30)	0.035 (12.03)
	20	0.842 (4.98)	0.854 (49.36)	0.097 (16.66)
JPY	5	0.018 (6.24)	0.917 (132.84)	0.083 (10.56)
	10	0.044 (1.42)	0.910 (75.82)	0.089 (7.56)
	20	0.064 (4.95)	0.921 (58.29)	0.075 (3.78)

Note: This table reports regression coefficients and t-statistics (in parentheses) for eq. (5) and (6) based on daily samples from January 2000 to December 2015.

Table 4 Forecasting RV with IV, GARCH (1,1), and HV

			IV				GARCH						HV				
	Year		α_1	β_1	α_2	β_2	α_3	β_3	β_3'	Adjust-ed R^2	α_2	β_2	α_3	β_3	β_3'	Adjust-ed R^2	Obs
USD	5	(1)	8.634	0.874						0.645							2348
			(1.72)	(14.36)													
		(2)			8.012	0.890				0.576	28.724	0.706				0.477	2348
					(1.47)	(13.37)					(5.63)	(12.07)					
		(3)					8.161	0.837	0.041	0.645			7.798	0.776	0.113	0.649	2348
							(1.60)	(7.66)	(0.43)				(1.53)	(9.30)	(1.57)		
	10	(1)	13.553	0.830						0.519							2348
			(1.73)	(9.50)													
		(2)			14.118	0.823				0.427	32.234	0.670				0.450	2348
					(1.71)	(9.12)					(5.39)	(9.84)					
		(3)					14.825	0.896	-0.078	0.520			14.435	0.692	0.135	0.523	2348
							(1.90)	(5.25)	(-0.51)				(1.84)	(4.57)	(1.25)		
	20	(1)	24.644	0.690						0.496							2348
			(3.98)	(10.49)													
		(2)			14.457	0.822				0.393	32.386	0.658				0.433	2348
					(1.89)	(10.15)					(6.43)	(11.87)					
		(3)					26.073	0.723	-0.049	0.496			23.264	0.536	0.180	0.503	2348
							(3.97)	(5.14)	(-0.32)				(4.06)	(4.79)	(1.98)		
EUR	5	(1)	15.676	0.631						0.626							2348
			(4.74)	(12.49)													
		(2)			4.233	0.905				0.516	17.657	0.710				0.504	2348
					(1.02)	(13.02)					(5.94)	(13.47)					
		(3)					17.150	0.672	-0.070	0.626			15.192	0.598	0.047	0.626	2348
							(4.75)	(7.10)	(-0.62)				(4.70)	(6.82)	(0.53)		
	10	(1)	18.110	0.624						0.491							2348
			(4.67)	(11.55)													
		(2)			12.206	0.796				0.323	25.817	0.605				0.370	2348
					(2.21)	(9.36)					(7.00)	(10.28)					
		(3)					23.862	0.752	-0.231	0.497			17.867	0.599	0.033	0.491	2348
							(4.66)	(8.24)	(-1.77)				(4.57)	(7.52)	(0.43)		
	20	(1)	20.279	0.598						0.379							2346
			(2.94)	(6.10)													
		(2)			23.610	0.650				0.195	30.017	0.563				0.318	2346
					(2.50)	(4.44)					(4.43)	(5.10)					
		(3)					26.888	0.736	-0.257	0.389			20.113	0.482	0.139	0.384	2346
							(3.70)	(5.71)	(-2.00)				(2.94)	(5.17)	(1.17)		
JPY	5	(1)	3.062	0.757						0.573							2348
			(1.82)	(11.95)													
		(2)			0.844	0.881				0.587	5.535	0.780				0.610	2348
					(0.59)	(16.15)					(5.14)	(17.23)					
		(3)					0.890	0.328	0.531	0.602			3.511	0.292	0.519	0.626	2348
							(0.58)	(3.11)	(5.18)				(2.41)	(3.38)	(7.38)		
	10	(1)	8.101	0.653						0.347							2348
			(2.83)	(8.88)													
		(2)			1.244	0.901				0.420	11.057	0.682				0.458	2348
					(0.37)	(9.23)					(4.33)	(8.65)					
		(3)					1.165	0.124	0.766	0.423			9.095	0.127	0.588	0.462	2348
							(0.34)	(1.42)	(5.56)				(3.42)	(1.62)	(5.43)		
	20	(1)	11.598	0.579						0.225							2347
			(4.12)	(9.78)													
		(2)			6.940	0.776				0.284	15.552	0.602				0.359	2347
					(1.47)	(6.53)					(3.81)	(5.29)					
		(3)					5.712	0.156	0.626	0.290			14.518	0.045	0.573	0.359	2347
							(1.33)	(1.57)	(3.46)				(3.99)	(0.30)	(3.04)		

Note: This table reports regression coefficients and t-statistics (in parentheses) for Eq. (1) to (3) based on daily samples from January 2007 to December 2015. I use the Newey and West (1987) method to adjust the standard errors to compute t-statistics. The lag is selected as 20.

Table 5 Wald-test ($\alpha_1 = 0,\ \beta_1 = 1$)

USD			EUR			JPY		
5-year	10-year	20-year	5-year	10-year	20-year	5-year	10-year	20-year
2.37	2.05	12.12	51.66	44.03	19.22	12.91	20.27	35.57
(0.09)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: This table reports Wald-statistics for the joint of the hypothesis ($\alpha_1 = 0,\ \beta_1 = 1$). The parenthesis is p-value. I use the Newey and West (1987) method to adjust the standard errors to compute the Wald statistics. The lag is selected as 20.

Table 6 Diebold and Mariano Test

USD			EUR			JPY		
5-year	10-year	20-year	5-year	10-year	20-year	5-year	10-year	20-year
-2.833	-2.186	-2.288	-3.382	-3.998	-2.776	0.291	1.369	0.985
(0.00)	(0.03)	(0.02)	(0.00)	(0.00)	(0.01)	(0.77)	(0.17)	(0.32)

Note: This table reports Diebold and Mariano test (Diebold and Mariano 1995), based on Mean Square Error. The parenthesis is p-value.

Table 7 Turnover of interest rate derivatives (options)

USD	116,754
EUR	26,278
GBP	7,809
JPY	7,322
AUD	1,687
ZAR	792
KRW	691
SEK	512
CAD	375
MXN	62
CHF	44
NOK	14
NZD	4

Note: Daily averages, in millions of US dollars

Source: BIS

Table 8 Forecasting RV with IV, GARCH (1,1), and HV with non-overlapping data

				IV	GARCH			IV	HV		
	Year	week	α_3	β_3	β_3’	Adjusted R^2	α_3	β_3	β_3’	Adjusted R^2	Obs
USD	5	first week	10.391	0.725	0.123	0.580	11.861	0.902	-0.072	0.579	144
			(1.71)	(4.59)	(0.83)		(1.89)	(3.67)	(-0.29)		
		second week	3.486	0.896	0.040	0.684	3.822	0.942	-0.010	0.684	143
			(0.65)	(6.22)	(0.34)		(0.66)	(6.13)	(-0.10)		
		third week	3.998	0.973	-0.044	0.681	3.066	1.017	-0.082	0.682	143
			(0.67)	(7.89)	(-0.42)		(0.49)	(7.65)	(-0.94)		
		fourth week	9.008	0.840	0.032	0.618	9.181	0.931	-0.064	0.619	143
			(1.88)	(5.75)	(0.26)		(1.75)	(5.47)	(-0.45)		
	10	first week	16.689	0.930	-0.134	0.506	14.317	0.789	0.029	0.504	144
			(2.31)	(4.26)	(-0.66)		(1.93)	(3.93)	(0.19)		
		second week	8.201	0.836	0.053	0.572	9.709	0.774	0.105	0.574	143
			(1.28)	(3.88)	(0.29)		(1.30)	(4.14)	(0.82)		
		third week	11.407	0.988	-0.129	0.566	9.804	0.792	0.084	0.566	143
			(1.54)	(4.79)	(-0.72)		(1.28)	(4.43)	(0.59)		
		fourth week	15.299	0.930	-0.115	0.496	13.980	0.756	0.074	0.496	143
			(2.44)	(3.38)	(-0.47)		(1.96)	(4.18)	(0.55)		
	20	first week	27.224	0.800	-0.148	0.506	21.929	0.635	0.080	0.504	144
			(3.42)	(4.85)	(-0.74)		(4.12)	(4.54)	(0.60)		
		second week	16.116	0.679	0.101	0.559	17.928	0.624	0.146	0.564	143
			(2.64)	(4.32)	(0.55)		(3.83)	(4.28)	(1.05)		
		third week	26.372	0.809	-0.139	0.522	21.415	0.609	0.123	0.523	143
			(3.24)	(3.94)	(-0.54)		(4.32)	(4.14)	(0.81)		
		fourth week	22.083	0.637	0.076	0.464	22.785	0.558	0.160	0.470	143
			(3.68)	(3.78)	(0.42)		(4.42)	(3.90)	(1.20)		

			IV	GARCH			IV	HV		
	Year	week	α_3	β_3	β_3'	Adjust-ed R^2	α_3	β_3	β_3'	Adjust-ed R^2	Obs
EUR	5	first week	14.520	0.466	0.192	0.573	18.619	0.542	0.043	0.569	144
			(3.10)	(3.40)	(1.00)		(4.32)	(5.66)	(0.40)		
		second week	18.508	0.796	-0.228	0.607	15.125	0.748	-0.127	0.606	143
			(3.49)	(6.45)	(-1.42)		(3.29)	(7.05)	(-1.05)		
		third week	15.693	0.670	-0.036	0.607	15.637	0.704	-0.078	0.608	143
			(3.49)	(5.27)	(-0.23)		(3.71)	(6.84)	(-0.65)		
		fourth week	15.359	0.709	-0.082	0.655	14.047	0.700	-0.054	0.655	143
			(3.13)	(5.09)	(-0.43)		(3.55)	(7.41)	(-0.52)		
	10	first week	21.367	0.592	-0.033	0.475	21.972	0.685	-0.156	0.481	144
			(4.49)	(6.77)	(-0.24)		(6.34)	(7.43)	(-1.46)		
		second week	24.372	0.912	-0.422	0.509	16.032	0.808	-0.186	0.502	143
			(4.04)	(6.49)	(-2.07)		(3.78)	(7.85)	(-1.62)		
		third week	18.813	0.738	-0.133	0.506	15.800	0.669	-0.010	0.504	143
			(3.82)	(5.26)	(-0.69)		(4.28)	(4.73)	(-0.07)		
		fourth week	16.442	0.670	-0.028	0.522	15.338	0.593	0.079	0.524	143
			(3.48)	(4.77)	(-0.15)		(4.26)	(5.87)	(0.84)		
	20	first week	23.809	0.532	0.005	0.367	24.126	0.555	-0.027	0.367	144
			(5.13)	(5.17)	(0.05)		(5.34)	(3.56)	(-0.16)		
		second week	26.981	0.836	-0.372	0.405	18.633	0.704	-0.101	0.384	143
			(4.98)	(3.39)	(-1.40)		(2.82)	(4.42)	(-0.76)		
		third week	28.955	0.862	-0.423	0.418	18.403	0.617	0.016	0.397	143
			(4.58)	(4.20)	(-1.64)		(3.57)	(4.34)	(0.10)		
		fourth week	15.853	0.587	0.083	0.412	18.179	0.547	0.096	0.414	143
			(2.14)	(3.97)	(0.44)		(3.00)	(3.56)	(0.75)		

				IV	GARCH			IV	HV		
	Year	week	α_3	β_3	β_3'	Adjust -ed R^2	α_3	β_3	β_3'	Adjust -ed R^2	Obs
JPY	5	first week	-0.329	0.478	0.432	0.678	2.380	0.413	0.457	0.694	144
			(-0.18)	(2.94)	(2.74)		(1.41)	(5.04)	(5.92)		
		second week	0.628	0.405	0.489	0.654	2.911	0.420	0.435	0.658	143
			(0.36)	(3.68)	(4.32)		(1.91)	(4.15)	(4.30)		
		third week	0.681	0.283	0.621	0.619	3.484	0.369	0.480	0.621	143
			(0.35)	(2.29)	(4.79)		(2.00)	(3.05)	(4.36)		
		fourth week	3.172	0.475	0.326	0.553	4.531	0.451	0.337	0.563	143
			(1.48)	(3.34)	(2.18)		(2.32)	(3.95)	(3.19)		
	10	first week	-0.838	0.309	0.621	0.502	5.707	0.334	0.471	0.516	144
			(-0.27)	(2.80)	(5.19)		(2.21)	(3.20)	(4.32)		
		second week	1.974	0.077	0.803	0.457	9.619	0.128	0.602	0.467	143
			(0.58)	(0.72)	(6.32)		(3.38)	(1.20)	(5.91)		
		third week	3.289	0.160	0.686	0.363	10.621	0.179	0.516	0.386	143
			(0.81)	(1.20)	(4.27)		(2.82)	(1.34)	(4.25)		
		fourth week	5.446	0.273	0.502	0.332	10.566	0.337	0.327	0.331	143
			(1.39)	(2.54)	(3.63)		(3.02)	(3.61)	(3.23)		
	20	first week	2.278	0.181	0.675	0.368	9.960	0.225	0.487	0.369	144
			(0.66)	(1.93)	(5.17)		(3.08)	(2.35)	(4.68)		
		second week	6.299	0.133	0.632	0.334	13.262	0.143	0.501	0.340	143
			(1.40)	(0.90)	(3.61)		(3.31)	(0.84)	(3.12)		
		third week	5.668	0.231	0.549	0.244	14.579	0.164	0.443	0.279	143
			(1.10)	(1.52)	(2.83)		(2.50)	(0.87)	(2.92)		
		fourth week	11.270	0.170	0.476	0.177	18.765	0.114	0.393	0.208	143
			(1.97)	(1.62)	(3.10)		(2.98)	(0.55)	(2.17)		

Note: These tables report regression coefficients and t-statistics (in parentheses) for eq. (3) based on monthly samples from January 2005 to December 2015. I use the Newey and West (1987) method to adjust the standard errors to compute t statistics. The lag is selected as 4, which is based on $0.75T^{1/3}$.

Table 9 Forecasting RV with IV, GARCH (1,1), and HV during/after the financial crisis

(i) During financial crisis (2008/1～2009/12)

Year			IV	GARCH			IV	HV		
		α_3	β_3	β_3'	Adjust-ed R^2	α_3	β_3	β_3'	Adjust-ed R^2	Obs
USD	5	72.977	0.698	-0.209	0.180	59.865	0.781	-0.215	0.188	523
		(2.81)	(4.58)	(-0.88)		(3.59)	(4.82)	(-1.34)		
	10	76.864	0.653	-0.201	0.133	72.985	0.486	0.004	0.128	523
		(3.96)	(3.58)	(-1.01)		(4.06)	(2.99)	(0.03)		
	20	78.145	0.545	-0.186	0.193	71.011	0.430	0.002	0.187	523
		(4.58)	(4.47)	(-1.12)		(4.60)	(3.97)	(0.01)		
EUR	5	39.175	0.463	-0.049	0.292	42.407	0.537	-0.182	0.306	523
		(3.20)	(4.28)	(-0.26)		(4.72)	(4.66)	(-1.30)		
	10	24.835	0.628	-0.083	0.430	22.209	0.514	0.092	0.431	523
		(3.39)	(4.92)	(-0.45)		(3.38)	(5.71)	(0.81)		
	20	31.215	0.688	-0.248	0.282	29.250	0.333	0.243	0.289	522
		(3.46)	(4.73)	(-1.32)		(3.26)	(3.15)	(1.33)		
JPY	5	3.801	0.238	0.592	0.372	11.507	0.185	0.513	0.393	523
		(0.97)	(1.83)	(5.12)		(2.88)	(1.46)	(5.87)		
	10	23.079	-0.269	0.861	0.136	39.813	-0.333	0.608	0.202	523
		(2.49)	(-1.44)	(4.03)		(4.49)	(-1.87)	(3.97)		
	20	52.271	-0.529	0.706	0.098	63.715	-0.672	0.631	0.210	523
		(6.21)	(-2.44)	(3.54)		(6.08)	(-2.62)	(3.07)		

(ii) After financial crisis (2010/1～2015/12)

	Year	IV	GARCH			IV	HV		
		α_3	β_3	β_3'	Adjust-ed R^2	α_3	β_3	β_3'	Adjust-ed R^2	Obs
USD	5	9.323	0.809	0.014	0.445	9.546	0.813	0.009	0.445	1565
		(1.97)	(9.93)	(0.19)		(2.15)	(10.22)	(0.12)		
	10	9.263	0.748	0.090	0.343	12.233	0.692	0.124	0.346	1565
		(1.39)	(5.82)	(0.76)		(1.87)	(5.53)	(1.43)		
	20	18.076	0.634	0.096	0.316	20.773	0.573	0.139	0.321	1565
		(2.73)	(5.47)	(0.80)		(3.50)	(5.11)	(1.65)		
EUR	5	17.986	0.929	-0.361	0.594	12.164	0.816	-0.152	0.587	1565
		(5.90)	(8.93)	(-2.72)		(5.05)	(11.71)	(-2.20)		
	10	31.858	0.861	-0.461	0.422	18.784	0.764	-0.170	0.408	1565
		(5.65)	(9.53)	(-3.17)		(5.38)	(9.69)	(-2.22)		
	20	(28.499)	(0.809)	(-0.346)	0.377	17.449	0.829	-0.231	0.374	1565
		(4.51)	(10.92)	(-2.77)		(4.51)	(8.65)	(-2.29)		
JPY	5	2.761	0.197	0.537	0.354	5.601	0.160	0.509	0.394	1565
		(1.98)	(2.09)	(4.49)		(4.71)	(1.85)	(5.80)		
	10	2.908	0.129	0.663	0.333	9.097	0.156	0.502	0.365	1565
		(1.20)	(1.29)	(4.71)		(4.73)	(1.77)	(5.42)		
	20	3.889	0.270	0.471	0.326	8.513	0.333	0.312	0.329	1565
		(1.64)	(2.55)	(3.95)		(3.55)	(3.91)	(4.41)		

Note: This table reports regression coefficients and t-statistics (in parentheses) for eq. (3). I use the Newey and West (1987) method to adjust the standard errors to compute t statistics. The lag is selected as 20.

Table 10 Descriptive statistics of the noise measure

	Mean	Median	Max	Min	Std	Skewness	Kurtosis	Obs
2005-2007	1.48	1.46	2.35	0.93	0.26	0.41	3.42	738
2008-2009	2.00	2.05	3.75	0.80	0.72	0.02	1.98	488
2010-2016	0.85	0.81	2.28	0.31	0.29	1.07	4.93	1716

Note: This table reports the descriptive statics of noise measure. The data is obtained from Hattori (2021).

Table 11 Estimation results: The regression with the divided sample

(i) Sample: liquidity is below the average

	GARCH				HV				
Year	α_3	β_3	β_3'	Adjust-ed R^2	α_3	β_3	β_3'	Adjust-ed R^2	Obs
5	5.715	0.279	0.503	0.378	8.994	0.321	0.397	0.381	769
	(4.08)	(4.87)	(9.14)		(6.25)	(6.38)	(9.74)		
10	15.254	-0.064	0.738	0.196	26.015	-0.059	0.515	0.219	769
	(6.09)	(-1.18)	(10.71)		(11.27)	(-1.15)	(8.64)		
20	25.943	-0.057	0.556	0.110	34.610	-0.200	0.542	0.195	765
	(9.81)	(-1.00)	(6.36)		(13.25)	(-2.67)	(6.32)		

(ii) Sample: liquidity is above the average

	GARCH				HV				
Year	α_3	β_3	β_3'	Adjust-ed R^2	α_3	β_3	β_3'	Adjust-ed R^2	Obs
5	2.014	0.219	0.562	0.386	8.994	0.321	0.397	0.381	1579
	(3.63)	(4.61)	(11.19)		(6.25)	(6.38)	(9.74)		
10	1.987	0.157	0.670	0.310	7.944	0.219	0.485	0.332	1579
	(2.00)	(3.91)	(12.34)		(9.85)	(6.38)	(13.46)		
20	5.622	0.272	0.451	0.281	10.100	0.298	0.337	0.298	1587
	(5.32)	(6.73)	(9.75)		(10.10)	(8.41)	(11.54)		

Note: This table reports regression coefficients and t-statistics (in parentheses) for eq. (3). I use the robust standard error to compute t statistics. The lag is selected as 20.

Table 12 Estimation results: The regression with the interaction

	GARCH						
Year	α_5	β_5	β_5'	γ_5	δ_5	Adjust -ed R^2	Obs
5	-5.100	0.224	0.496	11.908	-0.086	0.631	2348
	(-1.80)	(1.82)	(5.22)	(2.76)	(-1.65)		
10	-6.502	0.207	0.557	18.377	-0.173	0.491	2348
	(-1.49)	(1.53)	(4.32)	(3.96)	(-2.31)		
20	-7.470	0.372	0.427	20.380	-0.208	0.368	2348
	(-1.30)	(2.80)	(3.76)	(3.98)	(-3.13)		

	HV						
Year	α_5	β_5	β_5'	γ_5	δ_5	Adjust -ed R^2	Obs
5	-3.846	0.281	0.429	12.911	-0.109	0.640	2348
	(-1.34)	(2.47)	(5.83)	(3.01)	(-2.15)		
10	-3.473	0.271	0.437	20.752	-0.219	0.512	2348
	(-0.81)	(2.02)	(4.36)	(4.47)	(-3.00)		
20	-4.505	0.373	0.418	21.839	-0.258	0.399	2348
	(-0.80)	(2.25)	(2.58)	(4.02)	(-3.48)		

Note: This table reports regression coefficients and t-statistics (in parentheses) for eq. (11). I use the Newey and West (1987) method to adjust the standard errors to compute t statistics. The lag is selected as 20.

Table 13 Estimation result

	5-year	10-year	20-yar
α_6	4.151	16.725	20.346
	(1.27)	(4.17)	(5.30)
β_6	0.229	0.183	0.188
	(6.52)	(4.58)	(4.66)
Obs	2348	2348	2348

Note: This table reports regression coefficients and t-statistics (in parentheses) for eq. (12). I use the Newey and West (1987) method to adjust the standard errors to compute t statistics. The lag is selected as 20.

Appendix

A1 Forecasting RV with IV, GARCH (1,1), and HV

	Year		IV		GARCH						HV						
			α_1	β_1	α_2	β_2	α_3	β_3	β_3'	Adjust-ed R^2	α_2	β_2	α_3	β_3	β_3'	Adjust-ed R^2	Obs
USD	5	(1)	8.634	0.874						0.645							2348
			(2.03)	(16.90)													
		(2)			8.012	0.890				0.576	28.724	0.706				0.477	2348
					(1.80)	(16.28)					(7.00)	(14.86)					
		(3)					8.161	0.837	0.041	0.645			7.798	0.776	0.113	0.649	2348
							(1.91)	(8.01)	(0.43)				(1.85)	(9.63)	(1.59)		
	10	(1)	13.553	0.830						0.519							2348
			(2.11)	(11.56)													
		(2)			14.118	0.823				0.427	32.234	0.670				0.450	2348
					(2.05)	(10.89)					(6.10)	(11.01)					
		(3)					14.825	0.896	-0.078	0.520			14.435	0.692	0.135	0.523	2348
							(2.28)	(6.49)	(-0.62)				(2.23)	(5.50)	(1.42)		
	20	(1)	24.644	0.690						0.496							2348
			(4.81)	(12.62)													
		(2)			14.457	0.822				0.393	32.386	0.658				0.433	2348
					(2.19)	(11.59)					(7.30)	(13.21)					
		(3)					26.073	0.723	-0.049	0.496			23.264	0.536	0.180	0.503	2348
							(4.61)	(6.23)	(-0.38)				(4.78)	(5.65)	(2.23)		
EUR	5	(1)	15.676	0.631						0.626							2348
			(5.67)	(14.86)													
		(2)			4.233	0.905				0.516	17.657	0.710				0.504	2348
					(1.24)	(15.59)					(6.77)	(15.08)					
		(3)					17.150	0.672	-0.070	0.626			15.192	0.598	0.047	0.626	2348
							(5.76)	(7.92)	(-0.68)				(5.60)	(7.81)	(0.59)		
	10	(1)	18.110	0.624						0.491							2348
			(5.64)	(13.97)													
		(2)			12.206	0.796				0.323	25.817	0.605				0.370	2348
					(2.69)	(11.39)					(8.25)	(12.20)					
		(3)					23.862	0.752	-0.231	0.497			17.867	0.599	0.033	0.491	2348
							(5.61)	(9.81)	(-2.09)				(5.47)	(8.79)	(0.48)		
	20	(1)	20.279	0.598						0.379							2346
			(3.57)	(7.44)													
		(2)			23.610	0.650				0.195	30.017	0.563				0.318	2346
					(2.73)	(4.85)					(4.97)	(5.72)					
		(3)					26.888	0.736	-0.257	0.389			20.113	0.482	0.139	0.384	2346
							(4.30)	(6.95)	(-2.15)				(3.50)	(5.77)	(1.24)		
JPY	5	(1)	3.062	0.757						0.573							2348
			(2.23)	(14.70)													
		(2)			0.844	0.881				0.587	5.535	0.780				0.610	2348
					(0.71)	(18.96)					(6.00)	(19.71)					
		(3)					0.890	0.328	0.531	0.602			3.511	0.292	0.519	0.626	2348
							(0.71)	(3.51)	(5.79)				(2.89)	(3.80)	(8.07)		
	10	(1)	8.101	0.653						0.347							2348
			(3.44)	(10.77)													
		(2)			1.244	0.901				0.420	11.057	0.682				0.458	2348
					(0.43)	(10.99)					(4.95)	(9.93)					
		(3)					1.165	0.124	0.766	0.423			9.095	0.127	0.588	0.462	2348
							(0.40)	(1.59)	(6.44)				(3.99)	(1.86)	(6.17)		
	20	(1)	11.598	0.579						0.225							2347
			(4.85)	(11.30)													
		(2)			6.940	0.776				0.284	15.552	0.602				0.359	2347
					(1.67)	(7.30)					(4.23)	(5.88)					
		(3)					5.712	0.156	0.626	0.290			14.518	0.045	0.573	0.359	2347
							(1.52)	(1.75)	(3.86)				(4.76)	(0.35)	(3.45)		

Note: This table reports regression coefficients and t-statistics (in parentheses) for Eq. (1) to (3) based on daily samples from January 2007 to December 2015. I use the Newey and West (1987) method to adjust the standard errors to compute t statistics. The lag is selected as 10, which is based on $0.75T^{1/3}$.

A2 Forecasting RV with IV, GARCH (1,1), and HV

	Year		IV		GARCH						HV						
			α_1	β_1	α_2	β_2	α_3	β_3	β_3'	Adjust-ed R^2	α_2	β_2	α_3	β_3	β_3'	Adjust-ed R^2	Obs
USD	5	(1)	8.634	0.874						0.645							2348
			(1.58)	(13.41)													
		(2)			8.012	0.890				0.576	28.724	0.706				0.477	2348
					(1.33)	(12.38)					(4.82)	(11.03)					
		(3)					8.161	0.837	0.041	0.645			7.798	0.776	0.113	0.649	2348
							(1.49)	(7.54)	(0.47)				(1.38)	(9.74)	(1.81)		
	10	(1)	13.553	0.830						0.519							2348
			(1.68)	(9.10)													
		(2)			14.118	0.823				0.427	32.234	0.670				0.450	2348
					(1.83)	(10.21)					(6.30)	(13.20)					
		(3)					14.825	0.896	-0.078	0.520			14.435	0.692	0.135	0.523	2348
							(2.05)	(4.09)	(-0.43)				(1.82)	(3.82)	(1.10)		
	20	(1)	24.644	0.690						0.496							2348
			(4.11)	(11.00)													
		(2)			14.457	0.822				0.393	32.386	0.658				0.433	2348
					(1.86)	(10.47)					(6.37)	(13.07)					
		(3)					26.073	0.723	-0.049	0.496			23.264	0.536	0.180	0.503	2348
							(4.17)	(4.63)	(-0.29)				(4.52)	(4.46)	(1.74)		
EUR	5	(1)	15.676	0.631						0.626							2348
			(4.29)	(11.40)													
		(2)			4.233	0.905				0.516	17.657	0.710				0.504	2348
					(0.90)	(11.67)					(5.57)	(13.94)					
		(3)					17.150	0.672	-0.070	0.626			15.192	0.598	0.047	0.626	2348
							(3.99)	(7.05)	(-0.60)				(4.12)	(7.04)	(0.52)		
	10	(1)	18.110	0.624						0.491							2348
			(4.71)	(11.69)													
		(2)			12.206	0.796				0.323	25.817	0.605				0.370	2348
					(2.00)	(8.32)					(6.20)	(8.76)					
		(3)					23.862	0.752	-0.231	0.497			17.867	0.599	0.033	0.491	2348
							(4.55)	(7.23)	(-1.55)				(4.67)	(6.91)	(0.37)		
	20	(1)	20.279	0.598						0.379							2346
			(3.08)	(6.09)													
		(2)			23.610	0.650				0.195	30.017	0.563				0.318	2346
					(3.43)	(6.22)					(5.55)	(6.35)					
		(3)					26.888	0.736	-0.257	0.389			20.113	0.482	0.139	0.384	2346
							(4.71)	(4.41)	(-1.71)				(3.30)	(4.93)	(1.36)		
JPY	5	(1)	3.062	0.757						0.573							2348
			(1.66)	(11.77)													
		(2)			0.844	0.881				0.587	5.535	0.780				0.610	2348
					(0.53)	(16.39)					(4.69)	(18.99)					
		(3)					0.890	0.328	0.531	0.602			3.511	0.292	0.519	0.626	2348
							(0.54)	(3.21)	(5.15)				(2.40)	(3.74)	(8.06)		
	10	(1)	8.101	0.653						0.347							2348
			(2.38)	(8.29)													
		(2)			1.244	0.901				0.420	11.057	0.682				0.458	2348
					(0.38)	(10.33)					(4.85)	(10.98)					
		(3)					1.165	0.124	0.766	0.423			9.095	0.127	0.588	0.462	2348
							(0.35)	(1.24)	(5.60)				(3.44)	(1.62)	(6.86)		
	20	(1)	11.598	0.579						0.225							2347
			(3.21)	(8.70)													
		(2)			6.940	0.776				0.284	15.552	0.602				0.359	2347
					(1.57)	(8.26)					(4.84)	(7.68)					
		(3)					5.712	0.156	0.626	0.290			14.518	0.045	0.573	0.359	2347
							(1.37)	(1.47)	(4.14)				(3.24)	(0.29)	(3.99)		

Note: This table reports regression coefficients and t-statistics (in parentheses) for Eq. (1) to (3) based on daily samples from January 2007 to December 2015. I use the Newey and West (1987) method to adjust the standard errors to compute t statistics. The lag is selected as 63, which is based on Lazarus et al. (2018).

A3 Wald-test ($\alpha_1 = 0,\ \beta_1 = 1$)

USD			EUR			JPY		
5-year	10-year	20-year	5-year	10-year	20-year	5-year	10-year	20-year
2.03	1.79	12.64	41.24	38.66	13.88	10.46	16.83	30.08
(0.13)	(0.17)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: This table reports Wald-statistics for the joint of the hypothesis ($\alpha_1 = 0,\ \beta_1 = 1$). The parenthesis is p-value. I use the Newey and West (1987) method to adjust the standard errors to compute Wald statistics. The lag is selected as 10, which is based on $0.75T^{1/3}$.

A4 Wald-test ($\alpha_1 = 0,\ \beta_1 = 1$)

USD			EUR			JPY		
5-year	10-year	20-year	5-year	10-year	20-year	5-year	10-year	20-year
3.36	3.07	17.65	74.90	65.92	29.66	20.56	32.00	51.53
(0.04)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: This table reports Wald-statistics for the joint of the hypothesis ($\alpha_1 = 0,\ \beta_1 = 1$). The parenthesis is p-value. I use the Newey and West (1987) method to adjust the standard errors to compute Wald statistics. The lag is selected as 63, which is based on Lazarus et al. (2018).

Chapter 4

The Impact of Quantitative and Qualitative Easing on Term Structure: Evidence from Micro-level Data

4.1 Introduction

This chapter uses Japanese Government Bond (JGB) data to evaluate the impact of the quantitative and qualitative monetary easing (QQE) policy conducted by the Bank of Japan (BOJ) on term structure. I consider that the event of the implementation of the QQE policy should be an ideal situation to test the market segmentation theory (the preferred habitat theory), in which markets are segmented, investors demand bonds of a specific maturity, and the interest rate is determined by the supply and demand of bonds of that particular maturity.[37] The distinct feature of this study is that the micro-level panel data of JGBs are used for the first time to empirically show that the exogenous demand shock significantly affects the JGB price.

After the theoretical contributions by Greenwood and Vayanos (2014) and Vayanos and Vila (2021), several academic papers testing the market segmentation theory have emerged. As D'Amico and King (2013) point out, the implementation of quantitative easing (QE) is an event that provides the opportunity to perform an experiment for identifying the exogenous demand shock on the term structure. As the BOJ insists, the scale of bond purchasing following QQE has been unprecedented and even larger than that of the other central banks' QE; thus, it is quite natural to use the event of the BOJ's QQE to identify the impact of the demand factor on the JGB price.

For identification, I take advantage of the institutional change in BOJ's market operations, which is unique to the BOJ's policy. Before March 2017, the BOJ notified the market participants at 10:10 a.m. whether it would conduct an operation or not. Thus, investors faced uncertainty about the operation until the day of operation. However, the

[37] This description is based on Gürkaynak and Wright (2012).

market suffered excessive volatility during January and February 2017 because of miscommunications between the BOJ and the market participants. Therefore, after March 2017, the BOJ decided to publish detailed schedules of its planned asset purchases in advance and to inform market participants of the dates of its bond-buying operations. Following this policy change, the open market operation schedule is predetermined and cannot be institutionally changed by the BOJ; therefore, I can interpret the purchases by the BOJ as an exogenous shock, which suggests that this is an ideal situation for empirically testing the market segmentation theory.

In this chapter, I focus on the flow effect of QQE because the daily flow data enables us to control for the possible shift of the JGB supply curve. The Ministry of Finance, Japan discloses the JGB Issuance Plan every December, and this plan outlines the annual issuance of JGB. Of course, the supply of JGB could be modified based on the supplementary budget and the auction for enhanced liquidity, although I can completely control the supply curve shift as long as I focus on the daily flow data.[38] Blanchard and Perotti (2002) take advantage of the detailed institutional information, using quarterly data to control for the endogeneity of the policy effect, and an identification follows a similar approach.

After the theoretical work of Vayanos and Vila (2021), many papers have pursued the supply/demand effect on the term structure of the interest rate. Some papers use Japan's case (Fukunaga et al. 2015; Sudo and Tanaka 2018), although there is no

[38] Auctions for enhanced liquidity are the JGB auctions at which the Ministry of Finance, Japan issue the JGB that were previously issued in the past based on the investor's demands. The purpose of this auction is to enhance the liquidity of the JGB market. For further detail see *Debt Management Report* by the Ministry of Finance, Japan.

study using micro-level data to investigate the market segmentation theory. Literature using micro-level data has developed recently, and this includes the cases of the Federal Reserve Board (FRB) and European Central Bank (ECB). D'Amico and King (2013) interpret the Federal Reserve's 2009 program as a natural experiment for testing the stock and flow effect on the term structure. Kandrac and Schlusche (2013) look at both price and liquidity of Treasury securities. Song and Zhu (2018) use Federal Reserve reverse auction purchase data.[39] Schlepper et al. (2017) investigates the scarcity effect, using intraday transaction-level data for German government bonds, purchased under the public sector purchase program of the ECB.

I show that the BOJ's purchase significantly affects the JGB price, which is consistent with previous research. Lou et al. (2013) discuss how anticipated and repeated shock affect the Treasury yield under dealers' limited risk-bearing capacity and end-investors' imperfect capital mobility. Since the BOJ also provides anticipated and repeated shock to the JGB market through the open market operation, our result is consistent with Vayanos and Vila (2021), who discuss that local demand and supply can distort Treasury yields due to market segmentation.[40] I show that anticipated and repeated demand shock significantly affects the JGB price, which is consistent with the story of preferred habitat theory.

On the other hands, the estimated effect is considerably small. This result should

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[39] Other markets such as the Mortgage Backed Securities and Treasury Inflation Protected Securities have also been analyzed (Christensen and Gillan 2016).

[40] Quantitative easing could affect the asset price in the other mechanism of preferred habitat theory. For example, Kandrac and Schlusche (2013) point out an ourtright purchase by the central bank could affect the price through impaired liquidity. Kandrac and Schlusche (2013) also mention the uncertainty around the outcomes of each purchase or sale operation could affect the treasury price.

be reasonable as the BOJ conducts its QQE policy in normal time. As Vayanos and Vila (2021) describe, the extent of the market segmentation depends on the investors' attitude to risk. The FRB conducted its QE policy during the financial crisis, which amplified the effect, while the BOJ implemented its QQE policy in a stable period, which should be a natural situation where the impact of the QQE is considerably small.

The remainder of this chapter is organized as follows. Section 4.2 overviews QQE and the market microstructure of the open market operation. Section 4.3 presents the identification strategy and the model. Section 4.4 reports the estimation results and implications of the empirical analyses. Section 4.5 concludes.

4.2 Quantitative and Qualitative Easing in Japan

4.2.1 Description of Quantitative and Qualitative Easing in Japan

In April 2013, the BOJ introduced its QQE policy with the aim of achieving a 2% inflation rate as measured by the CPI as soon as possible. As I describe in the introduction, this policy consists of two easing processes: i.e., quantitative and qualitative easing.[41]

The QE means that the BOJ sets the target in terms of quantity. The BOJ decided to change the main operating target for its money market operations from the uncollateralized overnight call rate (i.e., interest rates) to the monetary base (i.e., quantity) and conduct money market operations so that the monetary base will increase at an annual pace of about 60–70 trillion yen.[42] This almost doubles the monetary base in two years.

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[41] This description is based on the BOJ's press release (https://www.boj.or.jp/en/announcements/release_2013/k130404a.pdf) and the speech by the Governor of the BOJ, Haruhiko Kuroda (https://www.boj.or.jp/en/announcements/press/koen_2013/data/ko130412a1.pdf).

[42] This number is based on the April 2013 release.

To do this, the BOJ will purchase JGBs so that its outstanding holdings of JGBs on its balance sheet will increase at an annual pace of about 50 trillion yen, which more than doubles its holdings of JGBs in two years.

The qualitative easing means that the BOJ purchases unconventional assets, such as longer maturity bonds, exchange-traded funds (ETFs), and Japan real estate investment trusts (J-REITs). In terms of the JGBs, the BOJ began to purchase the whole range of JGBs, including 40-year bonds. The average remaining maturity of the BOJ's JGB purchases will be extended from about three years to about seven years, which is equivalent to the average maturity of the outstanding amount of JGBs issued.[43]

In October 2014, the BOJ will accelerate the pace of increase in the monetary base. The BOJ will conduct money market operations so that the monetary base will increase at an annual pace of about 80 trillion yen (an addition of about 10–20 trillion yen compared with the past). In January 2016, the BOJ introduced its QQE with a negative interest rate policy by applying a negative interest rate of minus 10 basis points (bps) to current accounts held by financial institutions at the BOJ. Subsequently, in September 2016, the BOJ introduced a QQE with yield curve control (YCC) policy, under which it controls the yield curve through its market operations.

The scale of the BOJ's QQE has been unprecedented and even larger than that of the other central banks' QE. Table 1 shows the comparison between QQE and QE1–3 (by the FRB) in terms of the asset purchase on a monthly basis. Considering the flow effect of the central bank's demand, the BOJ has purchased around 0.9% of the outstanding total amount during QQE period while the FRB purchased 0.47%–0.83%

[43] This number is based on the April 2013 release.

(this range depends on QE1–3). For this comparison, I exclude the nonmarketable treasury for the outstanding of the treasury.[44]

4.2.2 QQE with Yield Curve Control Conducted by the Bank of Japan

As previously noted, the BOJ introduced the QQE with YCC policy in September 2016.[45] Two challenges to monetary policy in Japan are considered by the BOJ. Firstly, despite unprecedentedly large-scale monetary easing, a reduction in observed inflation has pushed down inflation expectations in the wake of the substantial decline in crude oil prices. Secondly, the BOJ realizes that when short-term interest rates are negative and long-term interest rates have fallen to extremely low levels, there could be side effects or costs that weaken the functioning of financial intermediation and may reduce monetary easing effects. The BOJ introduced this new monetary policy framework to solve these challenges.

According to the BOJ's announcement, its QQE with YCC policy consists of two major components: (1) an inflation-overshooting commitment and (2) YCC. In its inflation-overshooting commitment, the BOJ commits itself to expanding the monetary base until the year-on-year rate of increase in the observed CPI exceeds the price stability target of 2% and stably remains above this target. The BOJ makes strong efforts to influence the perception of inflation. In YCC, the BOJ will control the short- and long-term interest rates. A new operation called "Sashine-ope" was introduced by the BOJ to

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[44] In Japan, there is a nonmarketable government bond for retail investors although the share of the retail investor holding JGB only amounts to about 1%.

[45] The description in this section is based on the BOJ's press releases and seminars, such as https://www.boj.or.jp/en/announcements/release_2016/k160921a.pdf and http://www.boj.or.jp/en/announcements/press/koen_2016/ko161009a.htm/.

control the entire yield curve.[46] Under this new operation, the BOJ conducts outright purchases of JGBs with yields designated by the BOJ to facilitate YCC.

After March 2017, the BOJ announced its open market operation in advance during the following month for outright purchases of JGBs.[47] Based on its experience in conducting open market operations for about half a year under YCC, the BOJ aimed to avoid excessive changes in interest rates in the markets through enhancing transparency. I describe the details of these operations in the following section.

4.2.3 Market Microstructure of Open Market Operation Implemented by the Bank of Japan

This section describes the market microstructure of the open market operation implemented by the BOJ. To ensure the transparency of its conduct of market operations, the BOJ releases the "Outline of Outright Purchases of Japanese Government Securities" for the following month in advance on the last business day of each month.[48] This outline includes information on the outright purchases of JGBs, such as purchase size and frequency of purchases during the following month.

Auction Style

The BOJ conducts multiple-security auction as in the case of the FRB. In conducting its open market operation, the BOJ announces that it will buy JGBs within a specific maturity bucket (e.g., less than 1-year, 1–3 years, 3–5 years, 5–10 years, 10–25 years, over 25

[46] For the details of fixed-rate purchase operations, see Hattori and Yoshida (2020b).

[47] For further details, see https://www.boj.or.jp/en/research/brp/ron_2017/data/ron170714a.pdf.

[48] For further details, see https://www.boj.or.jp/en/research/brp/ron_2017/data/ron170714a.pdf.

years).[49] As with the FRB's operation, the BOJ's operation uses an auction style in which the primary dealers or some financial institutions have the right to participate. In the conventional auction, the BOJ purchases JGBs by the target amount, based on the differentials between bid rates and the reference rates.[50] For example, if the BOJ announces 1–5 years as the targeted maturity zone, the financial institutions (including primary dealers) have the right to offer the prices of JGB within the targeted maturity.

One of the important differences between the BOJ and the FRB is that the BOJ does not use a specific algorithm to purchase the bonds. In the case of FRB, the Desk purchases securities from among the submitted bids based on a confidential algorithm.[51] However, the BOJ uses a much simpler rule: i.e. based on these prices and the reference prices (the previous day's closing prices), computed by the Japan Securities Dealers Association (JSDA), the BOJ purchases the JGBs from the cheapest offer up to the prices that reach the targeted amount of the purchase.

The market participants often mention that they could tend to sell on-the-run JGBs, which is usually called BOJ trade. The BOJ trade is to purchase JGBs at the auction from the Ministry of Finance, Japan, and immediately sell them on to the BOJ. This suggests that the on-the-run JGB could be in higher demand in the operation. Therefore, I control this effect in the regression (see Section 3 for further details).

Announcement Schedule

[49] The BOJ can offer multiple maturity buckets. For example, the BOJ simultaneously offered to buy JGBs with maturities of 1–3 years, 3–5 years, and 5–10 years on December 2, 2016.

[50] For further details, see Bank of Japan (2016) and Maeda et al. (2005).

[51] See D'Amico and King (2013) for the detail.

The other important characteristic of the open market operation is the announcement schedule. Before March 2017, the BOJ notified the market participants at 10:10 a.m. whether it would purchase JGB or not. At that time, the BOJ let the participants know the targeted zone of the JGB. However, because of miscommunication between the BOJ and the market participants, the market suffered excessive volatility during January and February 2017. Therefore, the BOJ decided to release a detailed schedule in advance of the dates on which it is to purchase JGB.

The Amount and Frequency of Each Operation

Table 2 shows the descriptive statistics of the open market operation conducted by the BOJ across five maturity categories (1–3 years, 3–5 years, 5–10 years, 10–25 years, and over 25 years). This table shows that the average amounts of the open market operation range from 93 billion JPY to 436 billion JPY. The time series of the amount of the open market operation offered by the BOJ with the five maturity categories is shown in Figure 1, which confirms that the amounts of the operation in each maturity category move stably.

Table 2 also indicates that the BOJ conducts operations 5–6 times a month for each maturity segment.

4.3 Identification and Model

4.3.1 Preferred Habitat and Local (Net) Supply Effect

According to Greenwood and Vayanos (2014) and Vayanos and Vila (2021), the theoretical and empirical work about how the demand and supply of government bonds affect term structures has emerged. In Vayanos and Vila (2021), preferred habitat investors invest in the government bond with a specific maturity. On the other hand, arbitrageurs invest in the bond with different maturities, but since arbitrageurs are risk-averse, the risk aversion prevents arbitrageurs from making an arbitrage of entire yield curves.

According to D'Amico and King (2013), Greenwood and Vayanos (2014) have argued that Treasury supply may affect the terms structure by changing the total quantity of duration risk that arbitrageurs must hold—when debt in public hands increases or shifts toward longer maturities, investors are more exposed in terms of interest rates, which requires higher premiums to bear the extra risk. As I described, the BOJ announces the timing of the JGB purchase before purchasing JGBs, but the announcement itself does not affect the quantity of duration risk. In this sense, we need the exogenous shock, which actually changes the demand of the BOJ instead of just announcing the operation schedule.

If the BOJ decreases the demand of JGB by purchasing it, this shock affects the entire term structure if arbitrageurs are nearly risk-neutral. D'Amico and King (2013) name the former effect as "duration effect". On the other hand, the demand shock on the specific maturity affects the yield of the specific maturity as long as the risk aversion of arbitrageurs is close to infinity. D'Amico and King (2013) name the latter effect as the "local (net) supply effect."[52] In reality, the risk aversion of arbitrageurs is midway between risk neutral and infinitely risk averse; therefore, D'Amico and King (2013) conjecture that yields should be determined by the combination of the duration effect and local (net) supply effect.

D'Amico and King (2013) emphasize that a non-zero effect on the local (net)

[52] D'Amico and King (2013) originally name "local supply effect" but in this paper, I use "local (net) supply effect" to avoid the confusion among the demand and supply effect on the JGB.

supply is necessary to test the preferred habitat theory. For example, Vayanos and Vila (2021) present a one-factor model in which yield could be affected solely by the behavior of arbitrageurs. In this sense, even if the demand of the JGB changes exogenously, and it affects the entire yield curve, this does not necessarily test the preferred habitat theory. In other words, it is essential to identify the exogenous shifts in the local (net) supply of government bonds to test the preferred habitat theory. As I described, the BOJ started to purchase the JGBs exogenously after YCC. Therefore, we take advantage of this period.

4.3.2 Identification

This paper interprets the QQE policy as an exogenous shock on the specific yield. As described in Section 2.2, the basic rule of open market operation is the same as the Federal Reserve's operation.[53] As D'Amico and King (2013) point out, at the daily frequency, the BOJ is unlikely to have responded meaningfully to price changes in specific securities or sector. In particular, after March 2017, the BOJ preannounces the detailed schedule for its open market operation; therefore, the BOJ cannot institutionally respond to the price changes and I can interpret the BOJ's purchases as an exogenous shock. Thus, I restrict the analysis to the period after March 2017 and do not use instrumental variable estimation following D'Amico and King (2013), although I control the fixed and time effects using the panel data.[54]

I can institutionally control the possible shift of the JGB supply curve when I

[53] In terms of the auction, the major difference is that the FRB purchases the treasury based on a confidential algorithm while the BOJ use the reference price based on JSDA. For further detail, see D'Amico and King (2013) or the website of the Federal Reserve of New York.

[54] D'Amico and King (2013) control for endogeneity using the instrumental variable approach when they estimate the "stock effect."

focus on the flow effect at the daily base. The Ministry of Finance, Japan could possibly respond to the price change for changing the supply of the JGB by controlling the issuance of the JGBs. However, the JGB issuance plan determines the outline of the issuance amount of JGB at the end of every December. The Ministry of Finance, Japan does not have the option of changing the JGB supply daily. Thus, as long as I increase the frequency of data captures and use institutional information about the annual budget-based schedule, I can control the possible shift of the JGB supply curve. Blanchard and Perotti (2002) take advantage of detailed institutional information, using quarterly data for controlling the endogeneity of the policy effect. The identification of this paper follows a similar approach.

The notable feature of this paper is its use of the micro-level data from the JGB market. The advantage of the micro-level data for evaluating the effect folds into two parts. First, as mentioned in section 4.2.2, the BOJ buys JGB with specific maturity, so this feature provides different demand shocks to the individual securities on specific days. Second, the micro-level data enables us to construct panel data using the JGB prices for each maturity. Most analyses of JGB that focus on monetary policy uses the par rate or zero coupon yield, an estimate based on micro-level JGB data. However, I can control the fixed effect of individual securities when I use micro-level JGB data.

4.3.3 Identification under YCC

One of the features of this analysis is to focus on the YCC. Under the YCC, the BOJ sets the target to the yield of 10-year JGB. In this sense, this policy can be interpreted that the BOJ endogenizes the purchase of the operation instead of the interest rate, which is the traditional monetary policy. Actually, Hattori and Yoshida (2020b) empirically show the

BOJ has started to make its bond purchase endogenous to market yield. Figure 2 shows the time series of 5-year to 10-year JGB purchases by the BOJ. This figure shows that the fluctuation of the JGB purchases widened after YCC. However, most of the fluctuations are stable, and the BOJ changed the amount at the end of the month. In this sense, the BOJ predetermines the schedule of the operation at the end of the month. Therefore, I could exclude the possibility of endogenous operation as long as the daily data is used.

4.3.4 Model

I model the effect of QQE on the yield curve based on D'Amico and King (2013), Kandrac and Schlusche (2013), and Schlepper et al. (2017), as below:

$$R_{n,t} = \gamma \cdot q_{n,t} + \delta_t + \alpha_n + \varepsilon_{n,t}, \tag{1}$$

where $R_{n,t}$ is the daily gross return of securities n at time t ($R_{n,t} = P_{n,t}/P_{n,t-1}$), δ_t and α_n are the time and fixed effects, and $\varepsilon_{n,t}$ is the error term.

I focus on the daily return because the BOJ conducts the open market operation for almost all business days except the dates of the JGB auctions and the BOJ's monetary policy meeting. Thus, on the next business day, the Ministry of Finance will issue JGBs or the BOJ will purchase the JGBs, which suggests that the supply and demand of the JGBs could change due to the next operation or supply.[55]

Following Schlepper et al. (2017), I use a purchase dummy indicating the

[55] In every month, the Ministry of Finance issues 2-, 5-, 10-, 20-, 30-year JGBs with T-bills while the monetary policy meeting takes 2 days.

operation ($q_{n,t}$).[56] I construct the dummy variable that takes the value one if the JGBs are in the targeted maturity segment and zero otherwise. For example, if the BOJ offers to buy JGBs with maturities of 1–5 years, the dummy variable takes one for the 4.5-year JGB and zero for 10-year JGB.

In addition, I construct the variables that take the yen value of the purchase if the JGBs are within the targeted zone and zero otherwise. For example, the BOJ offers to buy JGBs with maturities of 1–5-years and plans to purchase 400 billion yen in total; therefore, the 4.5-year JGB takes 400 billion yen and the 10-year JGB takes zero. This modification allows us to capture the heterogeneous effect of the operation in terms of the BOJ's offered amount.

To capture the nonlinear effect of the amount offered by the BOJ, I add the square term ($q_{n,t}^2$), as follows:

$$R_{n,t} = \gamma_1 \cdot q_{n,t} + \gamma_2 \cdot q_{n,t}^2 + \delta_t + \alpha_n + \varepsilon_{n,t}. \quad (2)$$

I construct the variable referring to the amount offered by the BOJ from the BOJ's website (Money Market Operations Conducted by the Bank of Japan).

4.3.5 Controlling Variables

For checking the robustness of the estimates in Section 4.3.2, I include the additional variables ($Controls_{n,t}$), as follows:

[56] D'Amico and King (2013) analyze the effect of QE using actual purchase data; however, the BOJ does not release the actual daily purchase quantity or value, unlike the FRB. The BOJ only releases the amounts of individual JGBs it holds every 10 days through its websites.

$$R_{n,t} = \gamma \cdot q_{n,t} + Controls_{n,t} + \delta_t + \alpha_n + \varepsilon_{n,t}. \quad (3)$$

$$R_{n,t} = \gamma_1 \cdot q_{n,t} + \gamma_2 \cdot q_{n,t}^2 + \beta \cdot Controls_{n,t} + \delta_t + \alpha_n + \varepsilon_{n,t}. \quad (4)$$

The Substitution Effect: The Other Segment and ETFs

First, I include the variables to evaluate the degree of the substitution effect across the JGBs. There is a possible substitution effect where the investors react by purchasing those JGBs that the BOJ does not purchase on the operation day. Thus, following D'Amico and King (2013), I define the narrow substitute bucket to include the JGBs maturing within two years. In eq. (3), I construct a dummy variable that takes one if the individual securities are in the narrow substitute bucket and zero otherwise. For example, if the BOJ offers to buy JGBs with maturities of 1–5-years, the dummy variable takes one for 6-year JGBs and zero for 8-year JGBs. In eq. (4), I construct variables that take the yen value of the purchase if the JGBs are within the substitute bucket and zero otherwise.

The effect of ETF purchase

Second, I consider the substitution effect of ETFs and J-REITs. Under QQE, the BOJ purchases ETFs and J-REITs on the same day as JGB purchases. Figure 3 shows the time series of the ETFs and J-REITs purchased by the BOJ. The BOJ purchases ETFs every business day although it increases the purchase amount from around 1 billion yen to 70–80 billion yen once or twice a week. In addition, this graph shows that the amount of ETFs purchased by the BOJ overwhelms that of the J-REITs (The number of J-REITs purchased only amounts to about 1% of the ETFs purchased). Figure 4 shows the share of listed equity over the total asset, hold by the Japanese financial institutions. This indicates that the shares of the listed stocks among Japanese financial institutions are around 2% to 3%.

The Surprise Effect: The Change in Purchased Amounts Compared with the Prepurchase by the BOJ

Although the operation schedule is preannounced, it is possible for a certain amount of surprise in connection with the operation. The BOJ releases purchase amounts within a certain range; therefore, the BOJ has some room to change the amounts. Thus, the estimation result might contain the effect of the surprise of the purchase size by the BOJ.

Ideally, we can control the surprise of the purchase amount if we can obtain the expectation data of BOJ purchases. If we can obtain expectation data for the BOJ purchase, we can determine the level of surprise in the operation change by computing the deviation between the expectation data and the actual number, which should not be contemporaneously correlated to an error term. However, there is no expectation data of BOJ purchases. The analysts in financial institutions has predicted the purchase amount, but the number cannot be obtained through data providers such as Bloomberg.

Figure 1 depicts the BOJ's purchase amount from March 2017 to March 2018, which shows that the BOJ's purchase was sufficiently stable, although the BOJ sometimes changed the amount. Therefore, we assume that the market participants expect the amount of the operation to be the same as before. Thus, we calculate the amounts of changes compared with the prior operation and include the change to control the surprise effect.

The on-the-run effect (so-called BOJ trade)

As described in section 4.2.3, the market participants often mention that the BOJ could tend to buy on-the-run JGBs (so-called BOJ trade). To control this effect, I include the interactions of on-the-run dummy and operation dummy to absorb the heterogeneity related to the on-the-run JGBs.

4.4 Data Description

I obtain the JGB data from the Reference Statistical Prices [Yields] for OTC (Over-The-Counter) Bond Transactions compiled by the JSDA. The JSDA collects bond prices and coupons daily from 18 main securities firms and provides the micro-level data on its website. This data source includes the price and maturity. I use all JGBs except T-bill and JGBs with less than 1-year.[57]

The BOJ releases the result of the operation through their website (Money Market Operations Conducted by the Bank of Japan).[58] Using this information, I construct the operation and substitution dummies. I exclude the unlimited purchase operation called sashine-ope because (1) the BOJ rarely conducts this operation and (2) the situation where the BOJ conducts this operation is considered as a special situation; e.g. JGB prices drop sharply.

For making the on-the-run dummy, I refer to the website of the Ministry of Finance, Japan, which releases the past records of JGB issuance. There are 2-year, 5-year, 10-year, 20-year, 30-year, and 40-year JGBs issued by Ministry of Finance, Japan;

[57] Even after March 2017, the schedule of the open market operation for less than 1-year JGBs is not disclosed.

[58] For further details, see http://www.boj.or.jp/en/statistics/boj/fm/ope/index.htm/.

therefore, there are 6 on-the-run JGBs daily.

I use the data from March 2017 to March 2018 when the BOJ decided to make its preannouncements for the open market operation. As I describe in section 4.2.3, the BOJ cannot endogenously choose the timing of the operation in this period. Table 3 shows the descriptive statistics of the JGBs that I use in the analysis.

4. 5 Estimation Results

4.5.1 Regression Results: Basic Model

Table 4 shows the estimation results using eq. (1) and (2). The dependent variable is the daily gross return (basis points) of JGBs. I test whether the open market operation implemented by the BOJ has a positive causal effect on the term structure or not. I use White (1980)'s robust standard error instead of HAC standard error because we only use the data in the operation dates.

The first column of Table 4 shows that the estimate of the operation effect ($\hat{\gamma}$) is significantly positive, which shows that the flow effect of the QQE policy had a causal impact on the term structure. However, the estimate of the operation effect ($\hat{\gamma}$) is only 0.354, which means the JGB price only increases by 0.354 bps (0.00354%) if the JGBs are targeted by the BOJ operation. As I describe in Section 1, the small effect of the operation on the JGB price should be reasonable because the BOJ conducts its QQE policy in normal time. R-square is 0.523, which suggests our model can describe more than half of the return of JGBs.

The second column of Table 4 shows that the coefficient of the operation (γ_1) is significantly positive, which is consistent with the results based on eq. (2). In addition, the coefficient of the square term (γ_2) is significantly negative, which means that the effect of the operation decreases when the BOJ offers a larger amount for the operation. The estimate of the effect of the operation ($\hat{\gamma}_1$) is 7.247, which means that the JGB price increases 7.247bps (0.0715%) when the BOJ offers one trillion JPY. R-square is 0.524, which is almost the same results using eq. (1).

4.5.2 Robustness Check

(i) Control variables

I check the substitution effect based on eq. (3) and (4). β_1, β_2, β_3, and β_4 represent the coefficients of control variables ($Controls_{n,t}$) related to (i) the substitution effect across the JGBs (ii) the substitution effect of ETFs, (iii) the change of the JGB purchase by the BOJ, and (iv) the on-the run effect, respectively.

Tables 5 and 6 show the estimation results based on eq. (3) and (4). Table 5 shows that the estimates of the effect ($\hat{\gamma}$) are basically significantly positive in columns (1) to (4), which is consistent with the results of Table 4, while the estimates are still positive but not significant in column (5).

The substitution effect across the JGB (β_1) is not significant, while the effect of ETFs (β_2) has a significantly negative effect on the JGB prices. As I described, Japanese financial institutions tend to hold the listed equities. Since the BOJ tend to purchase ETF when the stock price drop (see Harada and Okimoto (2019) and Hattori and Yoshida (2020a)), this drop could reduce the capacity of the risk-taking of the arbitrageur from the capital losses, which could potentially affect the JGB return. However, this result is not robust when we restrict the data after September 2017. Again, the BOJ institutionally predetermined the schedule of purchasing the BOJ, therefore we should obtain an unbiased estimate of the JGB purchase. The coefficient of the JGB purchase does not change even if we include the stock purchase by the BOJ.

The coefficient related to the changes of purchase (β_3) has significant negative effects on the JGB prices. This is not consistent with the preferred habitat theory. This might be because I include data from July to August 2017. During this period, the volatility of the JGB yield increased, and the rise in the JGB yield exceeded 0.1%, which is the target of the BOJ in YCC. To stabilize the JGB yield, the BOJ changed the operation drastically. Specifically, the BOJ conducted unlimited purchasing called sashine-ope during this period (see Hattori and Yoshida, 2020b for details). Figure 1 shows the change in the amount purchased by the BOJ during this period. In this sense, the BOJ was able to endogenize the amount purchased by the BOJ. Therefore, this might contain the risks that the BOJ tends to increase its JGB purchase when the JGB price declines. Since figure 1 shows the amount of the purchase has changed during April, we also conduct a robustness check by using the data after September 2017, when the amount of purchase was considerably stable.

The on-the-run dummies are not significant. This result indicates that there is no heterogeneous effect on on-the-run JGBs.

Table 6 shows the estimates of the effect ($\hat{\gamma}_1, \hat{\gamma}_2$) are significantly positive in the column (1) to (5) which is consist with the results of Table 4. Table 6 also shows that the effects of the control variables are also consistent with the result of Table 4. In this case, the substitution effect across the JGB (β_1) is significant, but still very small compared to the coefficient of the own purchase.

(ii) The different period (September 2017 to March 2018)

As I described in the previous section, this analysis is based on the period of YCC, and the BOJ might endogenize the amount of the operation under YCC. Therefore, as I described, I use our data from September 2017 to March 2018, when the BOJ only changed the amount of purchase in the end of the month. Table 7 shows the estimation result with the data from September 2017 to March 2018. This table shows the coefficients of operation are significantly positive. The result is robust when the control variables are included. This result is consistent with our baseline results. Furthermore, the coefficient of the changes in purchase is positively significant, in contrast with our main results. The positive coefficient should be in accordance with the preferred habitat theory.

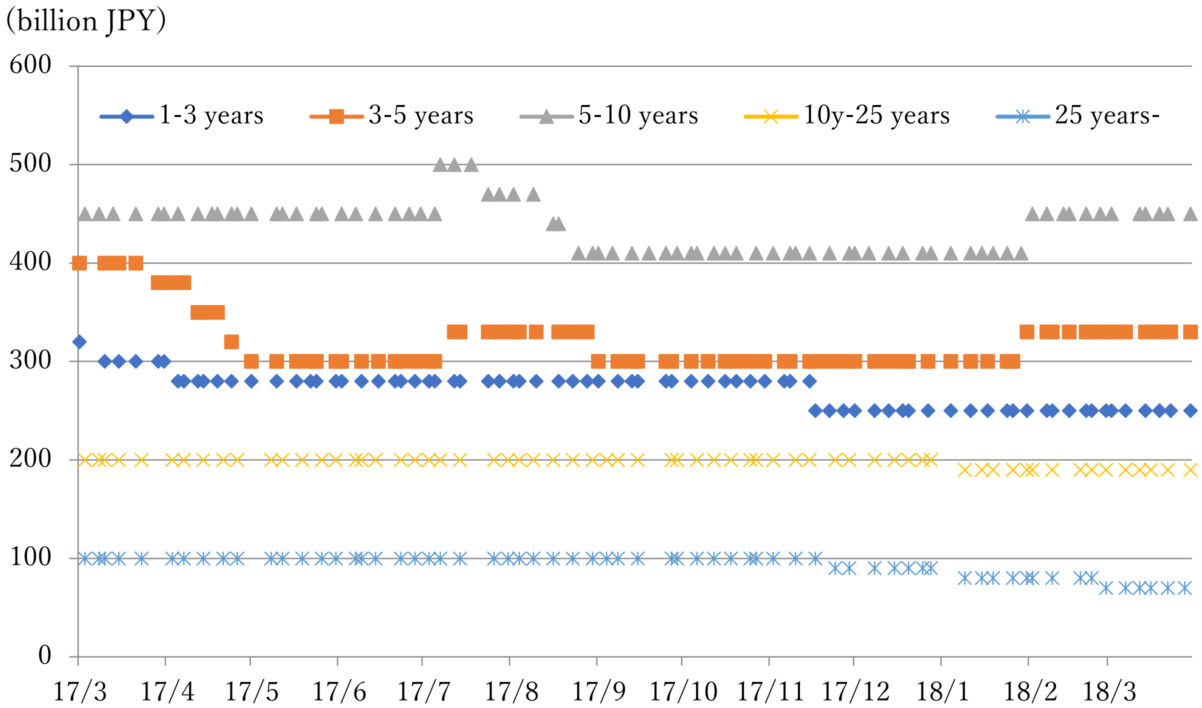
The coefficient of the ETF is positively significant when eq. (3) is used with all control variables although the coefficient is not significant when eq. (4) is used with all control variables. This result could be consistent with preferred habitat theory if the BOJ purchased ETFs held by financial institutions, which could mitigate the risk taking of the financial institution. On the other hand, although the effect of ETFs on equity prices is investigated by Barbon and Gianinazzi (2019), the effect of ETF purchases on other asset prices has not been addressed in the literature. Therefore, future analysis is needed.

As I describe, since Figure 1 shows the amount of the purchases changed in April and from July to August, we restrict the data to after September 2017. Even if we only drop the data from July and September, the result is basically consistent with the main result.

4.6 Conclusion

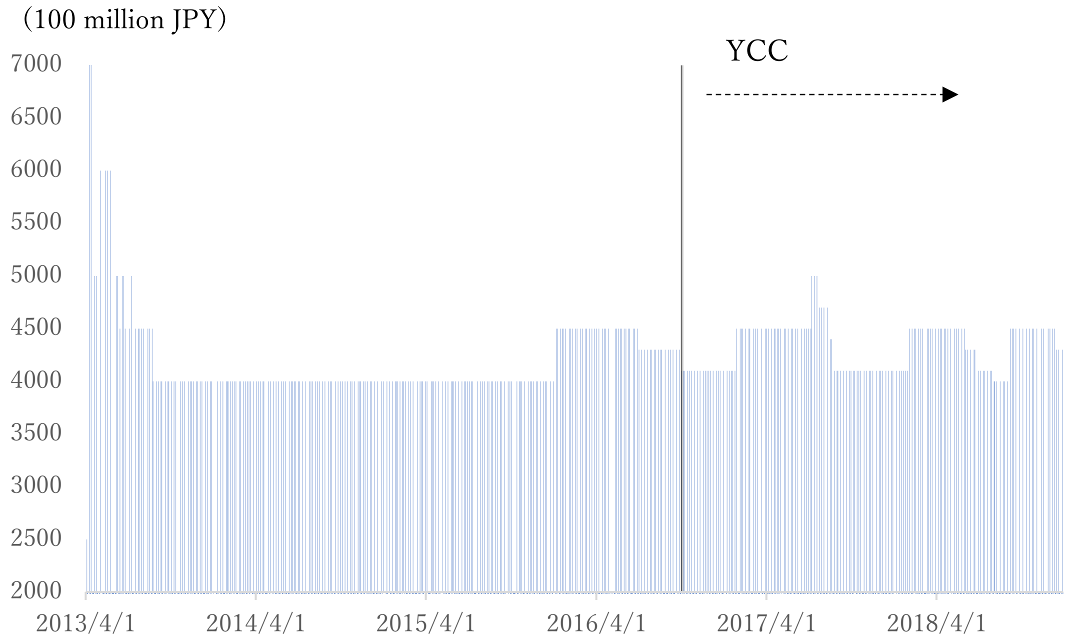
This chapter investigates how the QQE policy affects the yield curve, taking advantage of micro-level panel data for the causal inference. Using the BOJ case, I focus on the flow effect of the monetary policy, which is rarely documented in existing research. The uniqueness of this paper is to pay explicit attention to the institutional change of policy announcement by the BOJ. The BOJ announced the dates of their bond-buying operation after March 2017; thus, I can interpret the demand by the BOJ through QQE as an exogenous shock. In addition, the usage of the daily data enables us to control for the possible shift of the supply curves. Utilizing this ideal setup, I empirically show that the impact of demand factors on the term structure significantly affects the JGB price, which supports the market segmentation theory.

Figure 1 The amount of the open market operation offered by the BOJ



Note: This figure shows the amount of the open market operation offered by the BOJ, which indicates the amount of open market operation within a specific maturity bucket (e.g., 1–3 years, 3–5 years, 5–10 years, 10–25 years, and over 25 years).

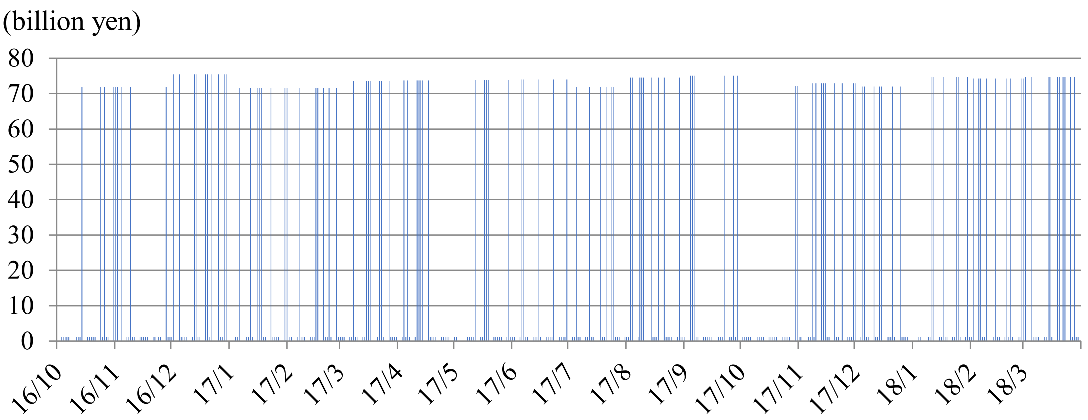
Figure 2 The amount of the JGB purchase (5-10 year) by the BOJ



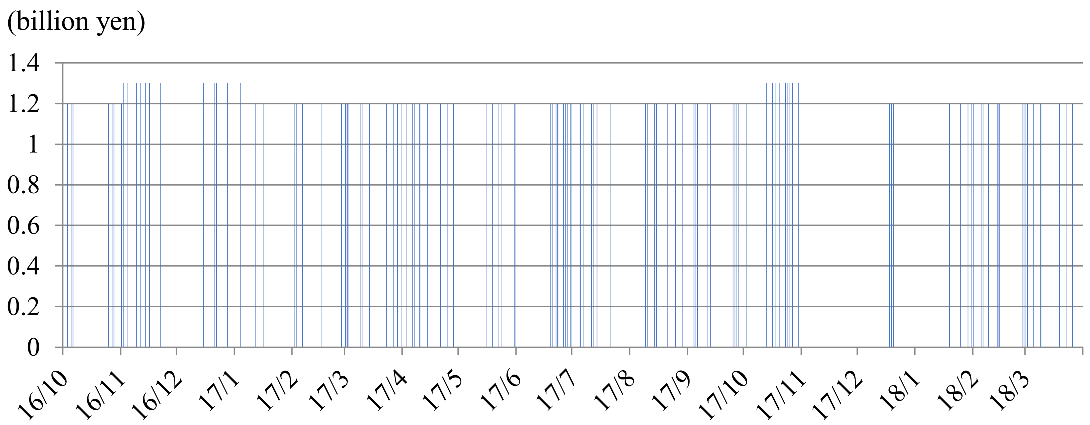
Note: This figure shows the amount of the open market operation offered by the BOJ, which indicates the amount of open market operation within 5–10 years.

Figure 3 The amount of the open market operation related to the ETFs and J-REITs

(1) ETFs purchased by the BOJ



(2) J-REITs purchased by the BOJ



Note: This figure shows the amount of the open market operation related to the ETFs and J-REITs.

Figure 4 The share of the listed stock over total asset, held by the Japanese financial institutions

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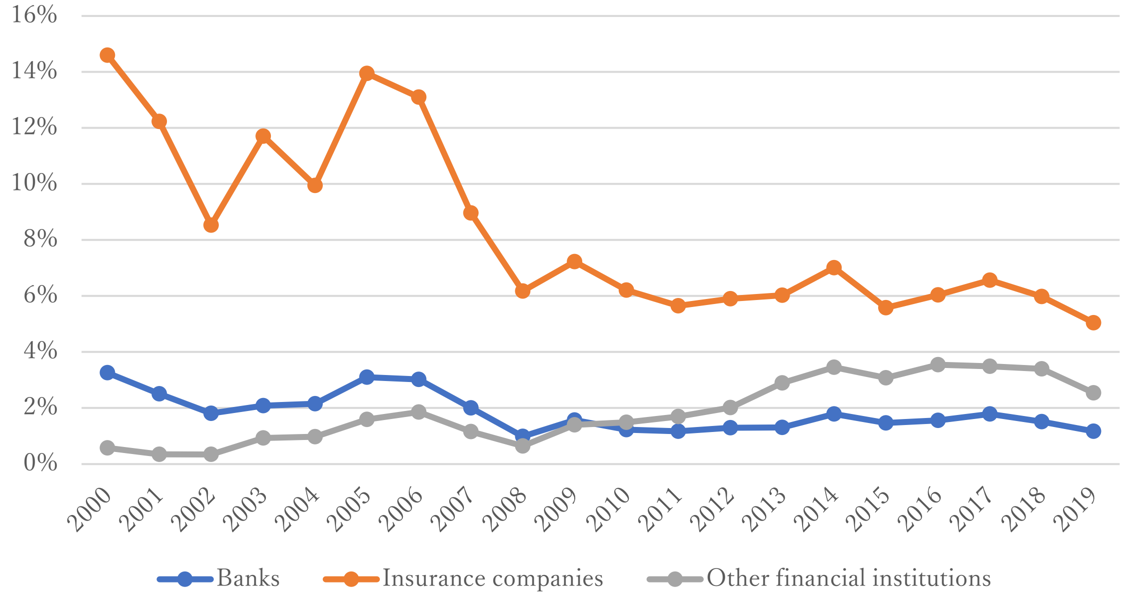

Source: Bank of Japan

Table 1 The comparison of QQE (BOJ) and QE (FRB): Purchase of government bonds

	FRB			BOJ
	QE1	QE2	QE3	QQE
Period	March 2009 ～September 2009	November 2010 ～June 2011	January 2013 ～December 2013	April 2013～
Purchase (monthly):1	50	75	54	7.8
Outstanding: 2	6,496	9,061	11,504	887
Ratio (1/2)	0.77%	0.83%	0.47%	0.88%

Note: The currency unit is billion USD for QE1–3 and trillion JPY. The purchase by the BOJ is the monthly average from March 2017 to March 2018. The outstanding value for the US Treasury consists of marketable bonds (not including nonmarketable bonds). The outstanding is the average balance.
Sources: Ministry of Finance, Japan, BOJ, FRB, Treasury direct.

Table 2 Descriptive statistics of the open market operation conducted by the BOJ across five maturity categories

	Short-term		Medium-term	Long-term	
	1-3 years	3-5 years	5-10 years	10-25 years	25 years-
Total Amount	21,170	24,980	34,030	12,850	6,070
Average Amount (per operation)	271	320	436	198	93
total number of operation	78	78	78	65	65
Average number of operation in month	6	6	6	5	5

Note: This table shows the descriptive statistics of the operation conducted by the BOJ. The unit of the amount is billion JPY.

Table 3 Descriptive statistics of JGBs in the operation dates

Number of observations	35,311
Average number of JGBs	302.3
Average remaining maturity	10.4
Average yield (%)	0.001

Note: This table shows the descriptive statistics of JGB. The data is based on the operation data from March 2017 to March 2018.

Table 4 Estimation results

		(1)	(2)
γ	Own purchase	0.354	
		(4.01)	
γ_1	Own purchase		7.147
			(6.35)
γ_2	Own purchase square		-20.149
			(-6.63)
	# Obs	35311	35311
	# bonds	309	309
	Adj. R^2	0.523	0.524

Note: The table shows regression results based on eq. (1) and (2). The dependent variable is the gross returns (basis points) of JGBs. The independent variables in eq. (1) are the own purchase while that in eq. (2) are own purchase and its squares. The t-statistic is in the parentheses. The standard error is based on White (1980).

Table 5 The estimation results

		(1)	(2)	(3)	(4)	(5)	(6)
γ	Own purchase	0.354	0.315	0.354	0.211	0.357	0.135
		(4.01)	(2.84)	(4.01)	(2.44)	(4.03)	(1.23)
β_1	Purchasese of near substitutes		-0.122				-0.252
			(-0.83)				(-1.71)
β_2	Purchases of ETF			-0.032			0.000
				(-18.00)			(19.16)
β_3	Changes of purchase				-0.015		-0.015
					(-12.12)		(-12.17)
β_4	on-the-run dummy					-0.371	-0.476
						(-0.54)	(-0.70)
	# Obs	35311	35311	35311	35311	35311	35311
	# bonds	309	309	309	309	309	309
	Adj. R^2	0.523	0.523	0.523	0.526	0.523	0.526

Note: The table shows regression results based on eq. (3). The dependent variable is the gross returns (basis points) of JGBs. The independent variables are the own purchase, the substitution effect across the JGBs, the substitution effect of ETF, the surprise effect, and the on-the run effect. The t-statistic is in the parentheses. The standard error is based on White (1980).

Table 6 The estimation results

		(1)	(2)	(3)	(4)	(5)
γ_1	Own purchase	6.803 (6.00)	7.147 (6.35)	5.158 (4.57)	7.182 (6.37)	4.798 (4.22)
γ_2	Own purchase square	-21.207 (-6.98)	-20.149 (-6.63)	-15.587 (-5.07)	-20.221 (-6.64)	-16.854 (-5.47)
β_1	Purchase of near substitutes	0.000 (-4.30)				0.000 (-4.85)
β_2	Purchases of ETF		-0.017 (-10.93)			0.000 (0.08)
β_3	Changes of purchase			-0.015 (-11.91)		-0.015 (-11.96)
β_4	on-the-run dummy				-0.373 (-0.54)	-0.493 (-0.72)
	# Obs	35311	35311	35311	35311	35311
	# bonds	311	311	311	311	311
	Adj. R^2	0.524	0.524	0.527	0.524	0.527

Note: The table shows regression results based on eq. (4). The dependent variable is the gross returns (basis points) of JGBs. The independent variables are the own purchase, its squares, the substitution effect across the JGBs, the substitution effect of ETF, the surprise effect, and the on-the run effect. The t-statistic is in the parentheses. The standard error is based on White (1980).

Table 7 The estimation result

(i) The result based on eq. (3).

		(1)	(2)	(3)	(4)	(5)	(6)
γ	Own purchase	0.718	0.682	0.718	0.744	0.726	0.751
		(6.75)	(5.06)	(6.75)	(7.08)	(6.80)	(5.66)
β_1	Purchase of near substitutes		-0.114				-0.002
			(-0.68)				(-0.01)
β_2	Purchases of ETF			-0.001			0.007
				(-2.82)			(7.26)
β_3	Changes of purchase				0.018		0.018
					(11.07)		(11.15)
β_4	on-the-run dummy					-0.983	-0.944
						(-1.05)	(-1.00)
	# Obs	19,288	19,288	19,288	19,288	19,288	19,288
	# bonds	289	289	289	289	289	289
	Adj. R^2	0.582	0.582	0.582	0.505	0.582	0.584

Note: The table shows regression results based on eq. (3). The dependent variable is the gross returns (basis points) of JGBs. The independent variables are the own purchase, the substitution effect across the JGBs, the substitution effect of ETF, the surprise effect, and the on-the run effect. The t-statistic is in the parentheses. The standard error is based on White (1980).

(ii) The result based on eq. (4).

		(1)	(2)	(3)	(4)	(5)	(6)
γ_1	Own purchase	8.257	8.067	8.257	9.894	8.363	9.829
		(5.76)	(5.59)	(5.76)	(6.94)	(5.82)	(6.83)
γ_2	Own purchase square	-19.903	-20.906	-19.903	-24.913	-20.144	-26.008
		(-5.01)	(-5.27)	(-5.01)	(-6.27)	(-5.06)	(-6.52)
β_1	Purchase of near substitutes		0.000				0.000
			(-2.76)				(-2.44)
β_2	Purchases of ETF			0.033			-0.002
				(26.80)			(-1.79)
β_3	Changes of purchase				0.018		0.018
					(11.49)		(11.51)
β_4	on-the-run dummy					-0.990	-0.995
						(-1.06)	(-1.06)
	# Obs	19,288	19,288	19,288	19,288	19,288	19,288
	# bonds	289	289	289	289	289	289
	Adj. R^2	0.581	0.581	0.581	0.584	0.524	0.584

Note: The table shows regression results based on eq. (4). The dependent variable is the gross returns (basis points) of JGBs. The independent variables are the own purchase, its squares, the substitution effect across the JGBs, the substitution effect of ETF, the surprise effect, and the on-the run effect. The t-statistic is in the parentheses. The standard error is based on White (1980).

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