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Information content and market liquidity in the fixed income market: Evidence from the swaption market

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ABSTRACT

In this paper, I investigate the relationship between market liquidity and the information content of implied volatility (IV) in the fixed income market. For its part, financial regulation including Basel III relies heavily on historical volatility (HV) in capturing the financial risk of financial institutions. One of the main reasons for this is that many countries may not necessarily obtain a meaningful measure of IV in their option markets because of the lack of liquidity. Using US dollar and Japanese yen swaption data, I find that the information content of IV critically depends on the measure of liquidity. This finding empirically justifies the use of HV instead of IV as a financial risk measure, especially in countries where option market liquidity is low.

1. Introduction

Several existing studies (Canina and Figlewski, 1993; Szakmary et al., 2003; Yu et al., 2010) find that implied volatility (IV) has more information content than historical volatility (HV). However, most financial regulation including Basel III continues to rely heavily on HV instead of IV in capturing the financial risk faced by financial institutions. While some financial regulations also employ IV as a measure of financial risk—for example, in the computation of the initial margins for over-the-counter (OTC) derivatives—HV remains by far the more popular measure of market volatility.

One of the main reasons for the reliance of financial regulation on HV is that many countries cannot obtain a meaningful measure of IV because of the lack of liquidity in their options markets. This is critical because the information content of IV depends on how actively investors trade options. For example, if investors do not trade very actively, the option price does not fully reflect investor opinion. In this sense, whether the option price has information content tightly connects to market liquidity, and many countries do not necessarily have sufficiently liquid traded option markets to compute meaningful measures of IV.

For example, even though the Japanese government bond market is one of the world's largest fixed income markets, the IV of the Japanese yen (JPY) option market does not work as a meaningful measure of interest rate risk (Hattori, 2017). In these circumstances and given global financial regulation should regulate not only advanced but also developing economies, HV may well be a better and more internationally consistent measure to capture financial risk. Nonetheless, even though the relationship between IV and market liquidity is crucial for global financial regulation, it is yet uninvestigated in the literature.

This paper addresses this gap in the literature, especially focusing on interest rate risk. Because governments restrict banks from bearing equity risk, the most critical risk for financial institutions to manage should be interest rate risk. In this paper, I use the IV from

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interest rate swap options or swaptions as one of the most popular derivative contracts in fixed income markets. I then extend the traditional approach to evaluate the information content of IV following the established literature (Canina and Figlewski, 1993; Szakmary et al., 2003; Yu et al., 2010).

In general, these studies test whether IV includes all information about future volatility and whether HV has no information beyond the information already included in IV by regressing future realized volatility on IV and HV and evaluating whether the coefficients of IV and HV are significant. I include market liquidity and its interaction with IV in the model to detect how liquidity affects the predictive power of IV. Using US dollar (USD) and JPY swaption data, I find that the information content of IV empirically depends on market liquidity. Given that global financial regulation should employ a consistent method, this finding supplies a justification for the use of HV in this regard.

The remainder of this paper is organized as follows. Section 2 describes the swaption market and market liquidity. Section 3 discusses the model and empirical result. Section 4 concludes.

2. Swaption market and market liquidity

2.1. Swaption

A swaption is one of the most liquid interest rate options in the OTC market, being an option in which the underlying asset is an interest rate swap. In turn, an interest rate swap is a swap agreement where a contractor swaps a fixed for a floating rate payment or vice versa. The important feature is that swaptions trade in the OTC market, and for this reason, they are customizable for each contract.

In June 2012, Chicago Board Options Exchange introduced the CBOE Interest Rate Swap Volatility Index (SRVIX), which is based on 1-year over-the-counter (OTC) swaptions on 10-year US Dollar interest rate swaps. Mele and Obayashi (2012) discuss the model-free valuation formulas for variance swap of interest rate swaps, while Mele and Obayashi (2014) provide an overview of how volatility pricing and indexing methodologies work for options, including interest rate swap. Mele et al. (2015) show that SRVX significantly reacts to different events and risk factors from CBOE's VIX, thereby providing investors with complementary diversification, hedging, and risk-taking tools. In addition, Bank of America Merrill Lynch also calculates and disseminates the Swaption Merrill Option Volatility Estimate (SMOVE), which measures the implied volatility of US non-Treasury swaptions (See Fassas and Siriopoulos, 2021). However, this study relies not only on USD but also JPY; therefore, I use the swaptions based on USD and JPY.

Early studies such as Szakmary et al. (2003) test information content using IV based on futures options. However, because there is standardization in the maturity of exchange futures (i.e., the delivery month), the maturity of futures options changes every day, which results in a maturity mismatch. In response, later studies have carefully addressed this problem. For example, Yu et al. (2010) use equity IV in OTC markets to avoid the problem. As an alternative, and as a swaption is an OTC derivative, I can also avoid this mismatched problem.

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, whereas normal Vol assumes that interest rates follow a normal distribution. As Patel et al. (2018) describe, each model has its pros and cons. Black's model is the most accepted, especially for the swaption market before the 2010s, but assumes a lognormal distribution, and therefore cannot work under negative interest rate regimes. In fact, broker dealers have begun to stop quoting prices using Black's model owing to the negative yield. Furthermore, data for IV based on the shifted Black model are quite limited with the specifications of the model not always provided. Compared with these models, the data for normal volatility are consistently available through providers such as Bloomberg. Therefore, I use normal Vol for this analysis. As in earlier studies (e.g., Duyvesteyn and Zwart, 2015), I use IV from the at the money swaptions.

2.3. Liquidity in the fixed income market

To examine how low liquidity in the swaption market could affect information content, I employ the measure proposed by Hu et al. (2013) to capture market liquidity. The intuition is simple. If an investor is well-capitalized, they supply ample liquidity to the market, thus making the yield curve smooth. However, if investors have limited capital, their arbitrage is insufficient, making the yield curve noisy. Therefore, I can interpret the deviation from the model-implied yield curve as a proxy of market liquidity. I obtain the noise measure in the US and Japan from Hu et al. (2013) and Hattori (2021), respectively.

3. Model and estimation result

3.1. The data

I obtain a dataset of swap rates and swaptions from Bloomberg. I focus on 5-, 10-, and 20-year swap rates and swaptions for USD and JPY. I use the Bloomberg Composite Rates (CMP) as the data source.[1]

3.2. The model

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

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

where $RV_{t:\,t+\tau}$ is future RV from t to $t + \tau$.

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

Hypothesis 1. : *IV includes all information about future volatility; the historical volatility (or the GARCH volatility forecast) contains no information beyond the information already included in IV.*

To test this hypothesis, the literature commonly uses the following model:

$$RV_{t:t+\tau} = \alpha + \beta IV_{t:t+\tau} + \beta' HV_{t-\tau:t} + e_t, \tag{2}$$

where HV is defined as the lag of RV computed from $t - \tau$ to t, $IV_{t:\,t+\tau}$ is normal volatility (IV) traded at t, $IV_{t:\,t+\tau}$ is observed at t by investors and e_t is the error term. Under this hypothesis, I expect $\beta \neq 0$ and $\beta_3' = 0$.

To evaluate the effect of the liquidity condition for the information contained in the swaption, I include the liquidity measure and its interaction in this model as follows:

$$RV_{t:t+\tau} = \alpha + \beta IV_{t:t+\tau} + \beta' HV_{t-\tau:t} + \gamma liquidity_t + \delta liquidity_t \times IV_{t:t+\tau} + u_t, \tag{3}$$

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, I construct the intersection of IV with liquidity ($liquidity_t \times IV_{t:\,t+\tau}$). Because the noise measure increases when liquidity deteriorates, I expect δ to take a negative value when the IV has more information under the high-liquidity condition. I test the information content of one-month ahead future volatility, setting τ as 20, and specifying swaptions with a one-month maturity.

3.3. The result

First, I confirm the estimation result from Eq. (2), which is shown in Table 1. Standard errors are adjusted using Newey and West (1987). For USD, the coefficients for IV are statistically significant at the 1% level, and the coefficients of HV are not statistically significant, which suggests that Hypothesis 1 does hold in the USD swaption market. However, for JPY, the IV coefficients for the 5- and 10-year swap rates are statistically significant at the 1% level, but the IV coefficients for 20-year swap rates are not statistically significant. Moreover, the HV coefficients for the 5-, 10- and 20-year swap rates are statistically significant at the 1% level, which suggests that Hypothesis 1 does not hold in the JPY market. This result is consistent with Hattori (2017).

One of the reasons why the HV in the JPY market also has predictive power could be related to liquidity. 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. The previous works show that liquidity is typically related to volatility (Farmer et al., 2004; Weber and Rosenow, 2006).

Table 2 shows the daily turnover of the interest derivative option, which was investigated by the Bank for International Settlement in 2019 (the “Triennial Central Bank Survey of Foreign Exchange and Over-the-counter (OTC) Derivatives Markets in 2019”). The turnovers of USD and EUR were 139,877 and 283,208 million USD, although that of JPY only amounted to 9,526 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.

To address the liquidity effect on the information content of IV, I conduct the regression based on Eq. (3). Table 3 shows the

[1] 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 the currently active, contributed, bank indications. I select CMP depending on the closing time, with USD for New York time (CMPN), JPY for Tokyo time (CMPT), and EUR for London time (CMPL).

[2] Given that the swap rate can take a negative value, I take the difference instead of the log difference.

Table 1
Estimation results.

Year	USD α	β	β'	Obs
5	8.240	0.981	-0.110	2,406
	(1.91)	(7.45)	(-1.02)	
10	13.839	0.789	0.039	2,406
	(2.15)	(6.04)	(0.40)	
20	23.699	0.617	0.089	2,406
	(4.97)	(5.97)	(1.00)	
	JPY			
Year	α	β	β'	Obs
5	4.811	0.329	0.454	2,406
	(3.39)	(4.92)	(8.35)	
10	10.382	0.186	0.498	2,406
	(4.29)	(2.60)	(5.10)	
20	15.303	0.103	0.499	2,405
	(5.31)	(0.82)	(2.98)	

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 10.

Table 2
Turnover of interest rate derivatives (options).

	2019
USD	139,877
EUR	283,208
GBP	7,010
AUD	2,120
JPY	9,526
CAD	994
SEK	1,158
NZD	224
CNY	1,609
NOK	1,526
KRW	1,140
CHF	133
ZAR	268
MXN	69
Other currencies	1,743

Table 3
Estimation results.

Year	USD α	β	β'	γ	δ	Obs
5	-5.667	1.053	-0.124	7.578	-0.040	2,406
	(-0.83)	(7.09)	(-1.14)	(3.78)	(-3.30)	
10	3.433	0.704	0.003	14.404	-0.059	2,406
	(0.45)	(5.19)	(0.04)	(4.97)	(-4.07)	
20	8.292	0.716	-0.049	12.484	-0.053	2,406
	(1.25)	(5.81)	(-0.53)	(5.44)	(-4.80)	
	JPY					
Year	α	β	β'	γ	δ	Obs
5	-0.257	0.202	0.418	10.773	-0.064	2,406
	(-0.08)	(1.91)	(7.01)	(2.82)	(-1.24)	
10	0.501	0.193	0.416	18.961	-0.178	2,406
	(0.11)	(1.55)	(4.83)	(4.12)	(-2.35)	
20	-3.587	0.359	0.419	21.333	-0.251	2,405
	(-0.68)	(2.43)	(3.05)	(4.17)	(-3.22)	

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 10.

estimation result, and the coefficients of HV are not statistically significant for USD but significant for JPY, which confirms that Hypothesis 1 does hold in the USD swaption market, but Hypothesis 1 does not hold in the JPY market. In this table, the coefficients of liquidity (γ) for USD and JPY are positive and significant at the 1% level, which suggests that variation in the liquidity premium increases the realized volatility. This table also shows the interaction coefficient (δ) has a significantly negative impact on RV except for the 5-year JPY. As I described, this result can be interpreted as meaning that the IV has more information under the high-liquidity condition. For USD, the interaction coefficient (δ) is significant at the 1% level, while for JPY, that of the 10-year JPY is significant at the 5% level and that of the 20-year JPY is significant at the 1% level.

4. Conclusion

In this paper, I investigate the relationship between market liquidity and the information content of IV in the fixed income market. Using USD and JPY swaption data, I find that the information content of IV empirically depends on the measure of liquidity. This justifies the use of HV instead of IV as a financial risk measure, especially when the liquidity of the option market is low.

Declaration of Competing Interest

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