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【要旨】

本論文は、スワップションから得られるインプライド・ボラティリティ（IV）の予測力を主要通貨（米ドル、ユーロ、円）で検証した最初の論文である。株式や為替などといったアセットクラスでは IV を用いたボラティリティの予測の検証が多数行われているものの、金利については先物市場の分析などにとどまり、未だ十分な研究がなされていない。財政赤字を背景に債務残高が拡大する中で、金利リスクの管理は特に金融機関にとって重要な問題であり、市場参加者にとっても IV の予測力の検証は有益である。本論文が見出したことは、米ドルとユーロについては GARCH やヒストリカルボラティリティ（HV）よりスワップションから得られる IV の予測力が高いというものであり、これは株式などに係る先行研究と整合的な結果である。もっとも、円については IV だけでなく GARCH や HV が予測力を持つことが確認された。その一因として米ドルやユーロに対して、円のスワップションの流動性が相対的に低いことが考えられる。

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The predictive power of the implied volatility of interest rates: Evidence from US Dollar, Euro, and Japanese Yen

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Abstract

This is the first paper to analyze the predictability of implied volatility based on swaption for the major currencies US Dollar (USD), Euro (EUR), and Japanese Yen (JPY). Managing interest rate risk is of huge importance for risk management in financial institutions, and swaption is an over-the-counter contract and well-used instrument that enables us to test whether the option contains the information required to predict future realized volatility. Our result shows that implied volatility has greater power to predict future realized volatility compared with the GARCH prediction or HV for the USD and EUR, which is consistent with the equity or futures options markets. However, the GARCH forecast and HV have stronger predictive power for JPY because of the lack of liquidity.

JEL Classifications: G13, G14, G120, G130, G140
Keywords: Implied volatility, Predictive power, GARCH, Interest rate, Swaption

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1. Introduction

This is the first paper to analyze the predictability of implied volatility (IV) based on swaption for major currencies including the US dollar (USD), Euro (EUR) and Japanese Yen (JPY). Many papers have discussed the predictability of IV based on 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) studied IV of futures options, and this empirical study includes the interest rate option, such as Treasury bonds or UK long gilt. However, there is no existing study on IV swaption, which is among the most widely used IVs in the bond markets although swaption itself has been analyzed in terms of the volatility risk premium (Fornari, 2005; Fornari, 2010; Duyvesteyn and Zwart, 2015) or other subjects (Fornari, 2004).

Swaption is the interest rate swap option and 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 rates options (OTC) were USD15.6 trillion for USD options, USD16.8 trillion for EUR option, and USD2.6 trillion for JPY options, which was smaller than interest rates swap but still large.

We consider our paper to contribute to academicians and practitioners including traders and risk managers. This paper's substantial contribution is threefold. First, the predictability of IV based on the interest rate is important for risk management, which shares the same motivation as IV analysis based on equity options. Recently, the market for fixed-income securities has increased mainly because of government deficits. Particularly, financial institutions, such as commercial banks and insurance companies, mainly invest in fixed income securities because of regulation or asset liability management (ALM). Therefore, the main purpose of risk management for financial institutions is to manage the risk related to fixed income securities. Many papers test the predictability 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. Because of OTC markets, financial contracts are not standardized but are customized; therefore, we can obtain the exact maturity (expiry) of the option. On the other hand, futures option maturities change causing a maturity mismatch problem, and earlier studies suffered from this problem. For example, Day and Lewis (1992) examined the one-week ahead predictive power of IV based on options that have a much longer remaining life. However, the later studies treated this problem carefully. For example, Yu et al. (2010) used equity IV in OTC markets to avoid this problem, and we could use the same strategy using IV based on swaption.

Third, the bonds have term structures, and we test whether the result could be different when the tenor (length of contract) of the underlying changes. Of course, the interest rate risk (duration risk) itself is different when the tenor changes, but the liquidity or cost of taking the position could change depending on tenor. Additionally, recently, the preferred habitat theory has found favor among practitioners but also among academicians (such as Greenwood and Vayanos (2014). According to this theory, the markets are segmented, which means that investors purchase bonds of a specific maturity. Therefore, the interest rate is influenced by the supply and demand of bonds of a particular maturity. This implies that the predictability of the interest rate of a particular maturity has substantial influence on a financial institution's risk management. The empirical studies on swaption, such as Fornari (2005, 2010), verify whether or not the result depends on the tenor.

The remainder of this paper is organized as follows. We describe our data and the related factors in section 2. We present the definition of volatility and our hypothesis in section 3. Section 4 presents the results of the predictive power of IV compared with HV including the robustness check. Section 5 presents our conclusions.

2. Data

2.1. Data source

We obtain a dataset of swap rates and swaption from Bloomberg. Our sample contains USD, EUR and JPY data from January 2005 to December 2015 (weekly) and from January 2007 to December 2015 (daily). We use daily data for the estimation and weekly data for the robustness check (as we explain later). We focus on 5, 10, and 20 year swap rates and swaption. We use the Bloomberg Composite Rates (CMP) as the data source[1]. We examine one-month ahead future volatility; therefore, swaption with one-month maturity is used in this analysis.

IV of swaption from Bloomberg includes Black volatility (Black Vol) and normal volatility (normal Vol)[2]. Black Vol is the IV based on Black (1976), which assumes that the interest rate process is lognormal distribution. On the other hand, normal Vol is the IV assuming a normal

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[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 of the currently active, contributed, bank indications. We choose CMP depending on close time. We choose USD for New York time (CMPN), JPY for Tokyo time (CMPT), and EUR for London time (CMPL).

[2] Swaption is the option trade in OTC markets, and the source has to be determined. We 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.

distribution interest rate process. Particularly after negative interest rates are widespread in JPY and EUR, normal Vol becomes standard in the interest rate market (Bloomberg does not always provide Black Vol when the interest rate becomes negative); therefore, we use normal Vol for our analysis. As in previous studies (Fornari, 2005; Duyvesteyn and Zwart, (2015), we use IV from at the money (ATM) swaption.

2.2. Sampling procedure

When we 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, we check the robustness of our result by taking a non-overlapping sample on a monthly basis based on Christensen and Prabhala (1998) and Yu et al. (2010).

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

3. Methodology

3.1. Hypotheses

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

H1. IV is an unbiased estimator of future realized volatility (RV).
H2. IV has more explanatory power than HV (or the GARCH volatility forecast) for forecasting future RV.
H3. IV includes all information regarding future volatility; HV (or the GARCH volatility forecast) contains no information beyond the information already included in IV.

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

$$RV_t = \alpha + \beta IV_t + e_t \cdots (1)$$
$$RV_t = \alpha' + \beta' HV_t + e_t \cdots (2)$$
$$RV_t = \alpha + \beta IV_t + \beta' HV_t + e_t \cdots (3)$$

where RV_t is future RV, HV_t is HV, IV_t is normal volatility (IV), and e_t is the error term. We use one-month IV maturity and compute RV_t matching the remaining life of the IV. We repeat the same regressions, replacing HV (HV_t) by the GARCH volatility forecast.

3.2. Realized Volatility, Historical Volatility, GARCH

We have daily swap rate: $\{R_t, R_{t+1}, \ldots, R_{t+n}\}$, and we construct the difference of the swap rate: $r_t = R_t - R_{t-1}$. We estimate RV (RV_t) as the sum of their squares below.

$$RV_t = \sum_{i=1}^{T} r_{t+i}^2 \cdots (4)$$

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

We calculate HV (HV_t) as the annualized standard deviation of the daily change in the swap rate r_t. We use 20 trading days to compute HV on an annual basis to match the remaining option maturity.

We use GARCH forecast volatility using the GARCH(1,1) model as follows:

$$\varepsilon_t = \sigma_t z_t, \sigma_t > 0, z_t \sim N(0,1) \cdots (5)$$
$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha\varepsilon_{t-1}^2, \omega > 0, \beta, \alpha \geq 0 \cdots (6)$$

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

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

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

$$\hat{\sigma}_{t,T}^2 = \sum_{s=1}^{T} \hat{\sigma}_{t+s}^2 \quad \cdots (8)$$

T is the number of days ahead of the forecast, and $\hat{\sigma}^2_{t,T}$ is the forecast variance at time t over the next T days. We test the predictability of one-month ahead future volatility; we set T as 20. This forecast variance is multiplied by 250/T for annualizing. The parameters are estimated using the data from the last five years, and we compute forecast variance based on the estimates[3].

4. Empirical Results

4.1. Overlapping Data

Table 1 shows the results for the predictive power of IV, GARCH(1,1) and HV in forecasting the RV, which includes the estimates, t-statistics, and adjusted-R^2 in eqs.(1) to (3). We 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, we test H1 using eq.(1), In the first rows of each currency and tenor in Table 1, we report the coefficients, their t-statistics, and adjusted-R^2 in eq.(1). Regardless of the type of currency, the coefficients (β) for IV are statistically significant, which suggests IV contains the information on future RV. The predictability of the model is greater when the tenor is shorter according to adjusted-R^2.

Second, we test H2 using eq.(2). The results are displayed in the second row of each currency and tenor in Table 1. As we see in eq.(1), regardless of the type of currency, the coefficients (β') for the GARCH volatility forecast and HV are also statistically significant although IV is a better predictor according to adjusted-R^2 except for JPY. The predictability of the model is greater when the tenor is shorter according to adjusted-R^2, which is also the same as H1.

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

One of the reasons the GARCH volatility forecast and HV in the JPY market also have predictive power could be related to liquidity. The notional amount of JPY swaption is lower than that of USD and EUR swaption, as we see in section 1, suggesting that the liquidity of yen swaption could be lower. If the liquidity of the swaption market is lower, fewer investor opinions

[3] The parameters in the GARCH model are estimated applying ε_t as r_t because the swap rate does not seem to have autocorrelation, according to the Ljung-Box test.

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

		IV		GARCH			IV		HV			
	Year	α	β	α'	β'	Adjust-ed R^2	α	β	α'	β'	Adjust-ed R^2	Nobs of Obs
USD	5	8.625	0.874			0.645						2349
		(2.181)	(18.208)									
				8.007	0.890	0.576			25.879	0.737	0.522	2349
				(1.943)	(17.614)				(7.372)	(17.191)		
		8.151	0.837		0.042	0.645	8.207	0.985		-0.114	0.647	2349
		(2.059)	(8.360)		(0.446)		(2.036)	(7.904)		(-1.097)		
	10	13.540	0.830			0.520						2349
		(2.285)	(12.522)									
				14.101	0.823	0.427			34.009	0.666	0.421	2349
				(2.204)	(11.724)				(7.038)	(11.848)		
		14.811	0.896		-0.078	0.520	13.746	0.794		0.036	0.520	2349
		(2.468)	(6.977)		(-0.660)		(2.293)	(6.480)		(0.385)		
	20	24.631	0.691			0.496						2349
		(5.199)	(13.629)									
				14.441	0.822	0.393			34.514	0.648	0.399	2349
				(2.338)	(12.344)				(8.037)	(13.410)		
		26.055	0.723		-0.049	0.496	23.800	0.615		0.092	0.498	2349
		(4.930)	(6.700)		(-0.403)		(5.319)	(6.355)		(1.093)		
EUR	5	15.661	0.631			0.626						2349
		(6.097)	(15.979)									
				4.210	0.905	0.516			19.606	0.697	0.459	2349
				(1.326)	(16.808)				(7.987)	(15.433)		
		17.147	0.672		-0.071	0.626	16.387	0.678		-0.069	0.627	2349
		(6.188)	(8.359)		(-0.718)		(6.428)	(9.360)		(-0.875)		
	10	18.100	0.624			0.491						2349
		(6.086)	(15.087)									
				12.196	0.796	0.323			28.779	0.573	0.326	2349
				(2.905)	(12.292)				(9.860)	(12.155)		
		23.863	0.752		-0.231	0.498	18.668	0.689		-0.085	0.493	2349
		(6.030)	(10.496)		(-2.235)		(6.175)	(10.767)		(-1.338)		
	20	20.269	0.599			0.379						2347
		(3.865)	(8.058)									
				23.603	0.650	0.195			32.631	0.536	0.283	2347
				(2.878)	(5.109)				(5.865)	(5.794)		
		26.886	0.737		-0.257	0.389	20.268	0.591		0.009	0.379	2347
		(4.579)	(7.434)		(-2.211)		(3.861)	(6.625)		(0.084)		
JPY	5	3.058	0.757			0.573						2349
		(2.406)	(15.862)									
				0.839	0.881	0.587			6.019	0.778	0.582	2349
				(0.753)	(20.262)				(6.875)	(20.539)		
		0.886	0.328		0.531	0.602	3.440	0.373		0.437	0.609	2349
		(0.766)	(3.708)		(6.086)		(2.972)	(4.836)		(6.597)		
	10	8.089	0.653			0.347						2349
		(3.715)	(11.637)									
				1.240	0.901	0.420			12.137	0.666	0.421	2349
				(0.467)	(11.880)				(5.655)	(9.951)		
		1.161	0.124		0.766	0.423	8.981	0.203		0.513	0.433	2349
		(0.436)	(1.684)		(6.892)		(4.209)	(2.934)		(5.334)		
	20	11.599	0.579			0.225						2348
		(5.182)	(12.050)									
				6.945	0.776	0.285			17.022	0.576	0.320	2348
				(1.789)	(7.806)				(4.984)	(5.970)		
		5.721	0.156		0.626	0.290	14.210	0.121		0.499	0.324	2348
		(1.630)	(1.842)		(4.116)		(5.263)	(1.029)		(3.158)		

NOTE: This table reports regression coefficients and t-statistics (in parentheses) for Eqs.(1) to (3) based on daily samples from January 2007 to December 2015. We use the Newey and West (1987) method to adjust the standard errors to compute the t statistics.

are reflected in the swaption premium, lowering the predictive power for future volatility.

4.2. Non-overlapping data

The result of Table 1 contains the overlapping data. Although the standard errors are adjusted by the Newey and West (1987) method, we use non-overlapping data to construct the monthly data to check the robustness of our results in eq.(3).

One problem with constructing the monthly data is lowering the frequency of data. We can extend the dataset from January 2005 for normal IV when we use weekly data. In this case, we can construct four datasets when we construct the monthly data from the weekly data; therefore, we use four datasets to check the robustness of our results in Table 1.

Table 2: Forecasting RV with IV, GARCH(1,1), and HV with non-overlapping data

				IV	GARCH			IV	HV		
	Year	week	α	β	β'	Adjust-ed R^2	α	β	β'	Adjust-ed R^2	Nobs of Obs
USD	5	first week	10.391	0.725	0.123	0.580	11.861	0.902	-0.072	0.579	144
			(1.707)	(4.587)	(0.832)		(1.895)	(3.673)	(-0.287)		
		second week	3.486	0.896	0.040	0.684	3.822	0.942	-0.010	0.684	143
			(0.646)	(6.218)	(0.340)		(0.657)	(6.133)	(-0.098)		
		third week	3.998	0.973	-0.044	0.681	3.066	1.017	-0.082	0.682	143
			(0.671)	(7.888)	(-0.417)		(0.492)	(7.648)	(-0.942)		
		fourth week	9.008	0.840	0.032	0.618	9.181	0.931	-0.064	0.619	143
			(1.884)	(5.746)	(0.261)		(1.747)	(5.470)	(-0.455)		
	10	first week	16.689	0.930	-0.134	0.506	14.317	0.789	0.029	0.504	144
			(2.310)	(4.263)	(-0.663)		(1.933)	(3.934)	(0.188)		
		second week	8.201	0.836	0.053	0.572	9.709	0.774	0.105	0.574	143
			(1.281)	(3.877)	(0.290)		(1.296)	(4.141)	(0.822)		
		third week	11.407	0.988	-0.129	0.566	9.804	0.792	0.084	0.566	143
			(1.543)	(4.793)	(-0.716)		(1.281)	(4.428)	(0.591)		
		fourth week	15.299	0.930	-0.115	0.496	13.980	0.756	0.074	0.496	143
			(2.441)	(3.384)	(-0.465)		(1.960)	(4.183)	(0.547)		
	20	first week	27.224	0.800	-0.148	0.506	21.929	0.635	0.080	0.504	144
			(3.419)	(4.855)	(-0.736)		(4.122)	(4.537)	(0.599)		
		second week	16.116	0.679	0.101	0.559	17.928	0.624	0.146	0.564	143
			(2.640)	(4.319)	(0.551)		(3.835)	(4.285)	(1.047)		
		third week	26.372	0.809	-0.139	0.522	21.415	0.609	0.123	0.523	143
			(3.237)	(3.939)	(-0.539)		(4.324)	(4.136)	(0.805)		
		fourth week	22.083	0.637	0.076	0.464	22.785	0.558	0.160	0.470	143
			(3.682)	(3.781)	(0.419)		(4.419)	(3.902)	(1.201)		

				IV	GARCH			IV	HV		
	Year	week	α	β	β'	Adjusted R^2	α	β	β'	Adjusted R^2	Nobs of Obs
EUR	5	first week	14.520	0.466	0.192	0.573	18.619	0.542	0.043	0.569	144
			(3.097)	(3.403)	(1.002)		(4.318)	(5.659)	(0.397)		
		second week	18.508	0.796	-0.228	0.607	15.125	0.748	-0.127	0.606	143
			(3.493)	(6.453)	(-1.418)		(3.289)	(7.046)	(-1.049)		
		third week	15.693	0.670	-0.036	0.607	15.637	0.704	-0.078	0.608	143
			(3.494)	(5.271)	(-0.229)		(3.712)	(6.835)	(-0.655)		
		fourth week	15.359	0.709	-0.082	0.655	14.047	0.700	-0.054	0.655	143
			(3.128)	(5.086)	(-0.429)		(3.548)	(7.409)	(-0.523)		
	10	first week	21.367	0.592	-0.033	0.475	21.972	0.685	-0.156	0.481	144
			(4.492)	(6.767)	(-0.238)		(6.338)	(7.435)	(-1.458)		
		second week	24.372	0.912	-0.422	0.509	16.032	0.808	-0.186	0.502	143
			(4.035)	(6.490)	(-2.067)		(3.782)	(7.848)	(-1.620)		
		third week	18.813	0.738	-0.133	0.506	15.800	0.669	-0.010	0.504	143
			(3.824)	(5.255)	(-0.694)		(4.283)	(4.728)	(-0.066)		
		fourth week	16.442	0.670	-0.028	0.522	15.338	0.593	0.079	0.524	143
			(3.482)	(4.774)	(-0.149)		(4.265)	(5.867)	(0.844)		
	20	first week	23.809	0.532	0.005	0.367	24.126	0.555	-0.027	0.367	144
			(5.127)	(5.166)	(0.046)		(5.339)	(3.560)	(-0.163)		
		second week	26.981	0.836	-0.372	0.405	18.633	0.704	-0.101	0.384	143
			(4.984)	(3.393)	(-1.402)		(2.819)	(4.415)	(-0.758)		
		third week	28.955	0.862	-0.423	0.418	18.403	0.617	0.016	0.397	143
			(4.580)	(4.202)	(-1.636)		(3.565)	(4.341)	(0.095)		
		fourth week	15.853	0.587	0.083	0.412	18.179	0.547	0.096	0.414	143
			(2.141)	(3.970)	(0.443)		(3.003)	(3.556)	(0.745)		
JPY	5	first week	-0.329	0.478	0.432	0.678	2.380	0.413	0.457	0.694	144
			(-0.183)	(2.939)	(2.741)		(1.413)	(5.044)	(5.919)		
		second week	0.628	0.405	0.489	0.654	2.911	0.420	0.435	0.658	143
			(0.359)	(3.682)	(4.322)		(1.914)	(4.153)	(4.296)		
		third week	0.681	0.283	0.621	0.619	3.484	0.369	0.480	0.621	143
			(0.354)	(2.295)	(4.792)		(1.999)	(3.051)	(4.357)		
		fourth week	3.172	0.475	0.326	0.553	4.531	0.451	0.337	0.563	143
			(1.479)	(3.339)	(2.178)		(2.321)	(3.951)	(3.193)		
	10	first week	-0.838	0.309	0.621	0.502	5.707	0.334	0.471	0.516	144
			(-0.269)	(2.799)	(5.189)		(2.211)	(3.202)	(4.318)		
		second week	1.974	0.077	0.803	0.457	9.619	0.128	0.602	0.467	143
			(0.576)	(0.717)	(6.317)		(3.385)	(1.199)	(5.915)		
		third week	3.289	0.160	0.686	0.363	10.621	0.179	0.516	0.386	143
			(0.812)	(1.205)	(4.270)		(2.822)	(1.338)	(4.246)		
		fourth week	5.446	0.273	0.502	0.332	10.566	0.337	0.327	0.331	143
			(1.389)	(2.545)	(3.625)		(3.021)	(3.606)	(3.231)		
	20	first week	2.278	0.181	0.675	0.368	9.960	0.225	0.487	0.369	144
			(0.657)	(1.932)	(5.172)		(3.080)	(2.346)	(4.685)		
		second week	6.299	0.133	0.632	0.334	13.262	0.143	0.501	0.340	143
			(1.402)	(0.905)	(3.609)		(3.307)	(0.844)	(3.116)		
		third week	5.668	0.231	0.549	0.244	14.579	0.164	0.443	0.279	143
			(1.099)	(1.519)	(2.834)		(2.498)	(0.868)	(2.916)		
		fourth week	11.270	0.170	0.476	0.177	18.765	0.114	0.393	0.208	143
			(1.972)	(1.616)	(3.096)		(2.977)	(0.547)	(2.169)		

NOTE: This table reports regression coefficients and t-statistics (in parentheses) for eq.(3) based on monthly samples from January 2005 to December 2015. We use the Newey and West (1987) method to adjust the standard errors to compute the t statistics.

In Table 2, we report the coefficients, their t-statistics, and adjusted-R^2 in eq.(3) using weekly data from January 2005 to December 2015. In this case, the estimates depend on the datasets (first week, second week, third week, fourth week), displayed in each row. We confirm the same result as in Table 1, which shows that IV is the only predictor for future volatility for USD and EUR, but the GARCH forecast and HV have greater predictive power for the RV in terms of JPY. The predictability of the model is also greater when the tenor is shorter according to adjusted-R^2, which is consistent with the result in Table 1.

4.3. During and after the financial crisis

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

We estimate eq.(3) using the dataset for January 2008 to December 2009 for the financial crisis period and show the result in Table 3. During the financial crisis, the predictive power of USD, EUR, and JPY markets was lower in terms of adjusted-R^2, and the coefficient of IV in the JPY market is statistically insignificant or negative although the GARCH forecast and HV remain significant. We explain these results by the lack of liquidity during the financial crisis.

We 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 result in Table 1. IV has predictive power, although the GARCH forecast or HV can also predict future RV except for 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 less compared with adjusted-R^2 during the financial crisis. This is consistent with previous studies, such as Trebbi and Xiao (2015), which finds no systematic evidence of deterioration in liquidity levels or structural breaks in the US fixed income market during periods of post-crisis regulatory interventions.

Table 3: Forecasting RV with IV, GARCH(1,1) and HV during/after the financial crisis

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

Year		IV	GARCH			IV	HV		
	α	β	β'	Adjusted R^2	α	β	β'	Adjusted R^2	Nobs of Obs
USD 5	72.977	0.698	-0.209	0.180	59.865	0.781	-0.215	0.188	523
	(2.813)	(4.585)	(-0.875)		(3.594)	(4.823)	(-1.338)		
10	76.864	0.653	-0.201	0.133	72.985	0.486	0.004	0.128	523
	(3.959)	(3.576)	(-1.011)		(4.056)	(2.987)	(0.027)		
20	78.145	0.545	-0.186	0.193	71.011	0.430	0.002	0.187	523
	(4.581)	(4.469)	(-1.119)		(4.598)	(3.975)	(0.013)		
EUR 5	39.175	0.463	-0.049	0.292	42.407	0.537	-0.182	0.306	523
	(3.199)	(4.282)	(-0.261)		(4.724)	(4.662)	(-1.298)		
10	24.835	0.628	-0.083	0.430	22.209	0.514	0.092	0.431	523
	(3.385)	(4.920)	(-0.447)		(3.379)	(5.705)	(0.813)		
20	31.215	0.688	-0.248	0.282	29.250	0.333	0.243	0.289	522
	(3.457)	(4.725)	(-1.325)		(3.257)	(3.146)	(1.334)		
JPY 5	3.801	0.238	0.592	0.372	11.507	0.185	0.513	0.393	523
	(0.968)	(1.830)	(5.115)		(2.882)	(1.465)	(5.868)		
10	23.079	-0.269	0.861	0.136	39.813	-0.333	0.608	0.202	523
	(2.486)	(-1.437)	(4.030)		(4.487)	(-1.868)	(3.966)		
20	52.271	-0.529	0.706	0.098	63.715	-0.672	0.631	0.210	523
	(6.212)	(-2.443)	(3.539)		(6.079)	(-2.617)	(3.071)		

After financial crisis(2010/1～2015/1)

Year		IV	GARCH			IV	HV		
	α	β	β'	Adjusted R^2	α	β	β'	Adjusted R^2	Nobs of Obs
USD 5	9.323	0.809	0.014	0.445	9.546	0.813	0.009	0.445	1565
	(1.972)	(9.930)	(0.189)		(2.146)	(10.218)	(0.122)		
10	9.263	0.748	0.090	0.343	12.233	0.692	0.124	0.346	1565
	(1.389)	(5.818)	(0.765)		(1.866)	(5.531)	(1.431)		
20	18.076	0.634	0.096	0.316	20.773	0.573	0.139	0.321	1565
	(2.733)	(5.470)	(0.802)		(3.502)	(5.107)	(1.649)		
EUR 5	17.986	0.929	-0.361	0.594	12.164	0.816	-0.152	0.587	1565
	(5.899)	(8.928)	(-2.722)		(5.047)	(11.707)	(-2.198)		
10	31.858	0.861	-0.461	0.422	18.784	0.764	-0.170	0.408	1565
	(5.647)	(9.529)	(-3.174)		(5.377)	(9.692)	(-2.217)		
20	(28.499)	(0.809)	(-0.346)	0.377	17.449	0.829	-0.231	0.374	1565
	4.515	10.924	-2.775		(4.506)	(8.651)	(-2.292)		
JPY 5	2.761	0.197	0.537	0.354	5.601	0.160	0.509	0.394	1565
	(1.985)	(2.090)	(4.493)		(4.712)	(1.851)	(5.800)		
10	2.908	0.129	0.663	0.333	9.097	0.156	0.502	0.365	1565
	(1.202)	(1.293)	(4.713)		(4.729)	(1.768)	(5.415)		
20	3.889	0.270	0.471	0.326	8.513	0.333	0.312	0.329	1565
	(1.644)	(2.553)	(3.947)		(3.553)	(3.909)	(4.413)		

NOTE: This table reports regression coefficients and t-statistics (in parentheses) for eq.(3). We use the Newey and West (1987) method to adjust the standard errors to compute the t statistics.

5. Conclusion

This is the first paper to estimate the predictability of IV for the fixed income market using swaption data. The result of IV based on equity or foreign exchange shows stronger predictive power of future RV based on USD and EUR swaption. We also show that liquidity could also be an important factor in predicting future volatility. According to JPY swaption, the predictability of IV is lower, and GARCH forecast and HV have stronger predictive power for future volatility.

The implications for risk managers from our conclusions are clear and important. With exposure to the interest risk of 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 JPY, GARCH forecast volatility or HV should also be checked. If there is some suspicion that the market has a liquidity-related problem, these checks are even more important.

Further analysis is required to investigate the liquidity problem to predict future RV. The swaption is traded in the OTC market; therefore, it is difficult to capture the degree of liquidity in a direct way. However, for the data of listed options, such as US Treasury Futures Options or JGB Futures Options, we can obtain some data related to liquidity, such as trading volume. At the same time, if we use the listed option, we can use the intraday data; thus, we can obtain more accurate estimates of RV. We intend to extend our analysis using the listed option to check whether our conclusion is robust.

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