How Do US Option Traders "Smirk" on China: Evidence from FXI Options

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Abstract

In this paper, we study the implied volatility smirk (IVS) of options written on the FXI, the FTSE/Xinhua China 50 Index exchange-traded fund (ETF), the largest and most active China-targeted ETF traded in the US. Using the methodology of Zhang and Xiang (2008), we document the empirical characteristics of the level, slope and curvature of IVS of the FXI options. We find that, on average, the IVS becomes steeper and more convex as the time to maturity increases. The level and curvature are usually positive, and the slope is negative. Our research will guide us to develop a more realistic FXI option-pricing model. Lastly, we provide evidence that the information in the quantified IV factors have some predictive power for the monthly FXI ETF returns, in and out of sample.

Keywords: FXI options; China equities; Implied volatility; FXI smirk.

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1 Introduction

This study quantifies and examines the shape and dynamics of the implied volatility (IV) of FXI exchange-traded fund (ETF) options, and tests the quantified IV factors as predictors of the underlying monthly FXI ETF returns. The FXI options market has become the largest and most liquid China-related options market. This is the first paper concentrating on the FXI options market and documents the empirical features of the IV smirk of FXI options. We adopt and expand the methodology developed by Zhang and Xiang (2008) to quantify the IV by fitting a quadratic function. This results in three IV factors: the level, slope and curvature. We further develop the constant maturity IV factors to study the term structure and time-series dynamics more accurately. On average, the FXI IV curve exhibits a smirk shape, similar to that of S&P 500 options. As the maturity of FXI options increases, the IV smirk becomes steeper and more convex. We also find that the first difference of the third cumulants, derived from the factors, has some predictability of the future FXI returns. The empirical features we present provide implications for the development of an FXI option pricing model and for traders to better understand this market.

FXI option contracts are traded in the US and have become the largest and most active options targeted on Chinese equities available to global traders. The underlying ETF, iShares China Large-Cap Exchange-Traded Fund, is an ETF seeking to replicate the performance of the Financial Times Stock Exchange (FTSE) China 50 Index. In 2001, when it was first launched, the index consisted of the 25 largest-capitalization Chinese equities that trade on the Hong Kong stock exchange. After a tremendous expansion in volume of the Chinese equity market, on 22 September 2014, the index expanded from 25 to 50 constituents. The FXI tracks the performance of the FTSE China 50 Index very closely, as can be observed in Figure 1. The FXI slightly underperforms the underlying index due to the fund fees. In Table 1, we can see that the FXI ETF has a larger market and is more liquid than other US-traded China-targeted ETFs, and therefore it is the most important fund providing exposure to Chinese equities. From reading the news on Chinese equities, it is obvious that the FXI is a reflection of the opportunities for investment in the economy of China. For example, the tariff war with America is among the factors depressing stocks in China recently and making some traders go bearish on FXI. "One options trader is betting on bigger losses for Beijing's big-cap stocks, targeting iShares China Large-Cap ETF (FXI) put options in today's trading," notes Schaeffers Investment Research (Venema (2018)). "Without a clear answer, a recent 6% run-up in the iShares China Large-Cap exchange-traded fund (ticker: FXI) looks like a one-off driven by an off-again turn in trade tensions and the June 1 inclusion of some Chinese A-shares in MSCI global indexes," Wall Street Journal (Mellow (2018)).

In this paper, we first study the shape and dynamics of the IV of FXI options. We find that the FXI IV usually exhibits a smirk shape. The overall level, which estimates the exact at-the-money IV (ATM IV), and slope, are usually positive and negative, respectively, while the curvature fluctuates around zero with a positive mean. The term structure of the level is upward sloping, while the term structures of the slope and curvature are downward sloping, on average. We also explore the time-series dynamics of the FXI IV curves and find that the level (ATM IV) and curvature mean-revert above zero while the slope is mostly negative. The level (ATM IV) factor mean-reverts with prolonged periods of high values (high ATM IV) during economic downturns, such as the global financial crisis (GFC). The spikes in the longer-maturity slope and curvature factors are larger in magnitude and more frequent than their short-maturity counterparts.

Next, inspired by Zhang and Xiang (2008), we believe that the factors of the IV curve are good proxies of the risk-neutral moments. Therefore, they are expected to have predictability of the future excess returns of the underlying FXI ETF, as is the case in other equity option markets (Ang, Hodrick, Xing, and Zhang (2006), Xing, Zhang, and Zhao (2010), Chang, Christoffersen, and Jacobs (2013a) and Chatrath, Miao, Ramchander, and Wang (2016)). We test the predictability of FXI monthly excess returns using the factors and the risk-neutral third and fourth cumulants (Chang, Zhang, and Zhao (2015) and Ruan and Zhang (2018)), as well as their first differences (Ang, Hodrick, Xing, and Zhang (2006)) for the in-sample and out-of-sample univariate regressions. We find that the first differences of the third cumulants can predict the future FXI monthly excess returns significantly in both in-sample and out-of-sample tests.

Theories on the IV smirk have made vast progress in recent decades. Under Black and Scholes (1973), options with the same time to maturity are supposed to have the same IV regardless of strike price. However, the IV calculated by the standard Black and Scholes (1973) method was found to be different across strikes with the same underlying asset and time to maturity (Rubinstein (1985)). Literature on the IV "smile" and "smirk" in the US market has been growing since the initial study by Rubinstein (1985). Many studies have found that the phenomenon of the implied volatility smile shape has become a smirk shape since the global market crash in 1987; that is, the implied volatility has become left-skewed since then (Corrado and Su (1997); Skiadopoulos, Hodges, and Clewlow (2000); Cont and Da Fonseca (2002); Carr and Wu (2003); Foresi and Wu (2005); Yan (2011); Fajardo (2017)).

To address the issue of different IVs at different strike prices, a number of stochastic volatility models have been created (such as Stein and Stein (1991); Heston (1993); Bates (1996); Barndorff-Nielsen and Shephard (2004)). IV is useful to measure the performance of a stochastic volatility option pricing model.

There is also a vast strand of literature trying to explain the causes of the shape of the IV curve (Garleanu, Pedersen, and Poteshman (2009); Xing, Zhang, and Zhao (2010); DeMiguel, Plyakha, Uppal, and Vilkov (2013); An, Ang, Bali, and Cakici (2014)). The errors of measurement and/or investor behaviour are among the proposed explanations for the volatility skewness (Pan (2002); Hentschel (2003); Bollen and Whaley (2004); Han (2007); Xing, Zhang, and Zhao (2010); DeMiguel, Plyakha, Uppal, and Vilkov (2013); An, Ang, Bali, and Cakici (2014)).

A growing literature is also focusing on the predictive power of the IV for the future returns of the underlying asset (Corrado and Su (1997); Dennis and Mayhew (2002); Jiang and Tian (2005); Dennis, Mayhew, and Stivers (2006); Xing, Zhang, and Zhao (2010); Doran and Krieger (2010); Yan (2011); Conrad, Dittmar, and Ghysels (2013); DeMiguel, Plyakha, Uppal, and Vilkov (2013); Cremers, Halling, and Weinbaum (2015); Vasquez (2017)).

There is a handful of studies exploring the IV shape in other popular stock markets and also trying to explain the phenomenon. Pena, Rubio, and Serna (1999) report the pattern of IVs of options written on the Spanish IBEX-35 index and try to explain the smile using transaction costs and time to expiration. Shiu, Pan, Lin, and Wu (2010) find that the shape of IVs of Taiwan TAIEX options changes from a smile before the sub-prime mortgage crisis to a smirk after the beginning of the crisis, and explain that the reason was the net buying pressure for index calls.

Studies on China-related options are rare and rather different from what we focus on. Chang, Luo, Shi, and Zhang (2013b) compare the warrants in China to typical options. Wu (2011) and Xiong and Yu (2011) study the warrant bubbles which are empirically related to the dramatic crash in 2007. Huang, Liu, Zhang, and Zhu (2018) construct China VIX with ETFs option data from SSE, HKEx and CBOE and find that China's volatility premiums exist in all three markets, which are significantly negative during market crash. There are a few studies focusing on modelling the IV of the Chinese stock market (Lee, Chen, and Rui (2001)), and the impact of IV on the market (Zhou, Zhang, and Zhang (2012)).

This work delivers three novel contributions. Our first contribution is that we provide the first comprehensive analysis of the IV shape and its dynamics in the world's largest emerging equity market, the Chinese market. The FXI options market is the largest and most liquid China-related equity options market and thus an ideal target to work on for investors and practitioners who are interested in the Chinese equity market. Our second contribution is that we calculate the term structures and their dynamics of the quantified FXI IV factors, the level, slope and curvature, which are useful for developing and calibrating an FXI option pricing model. Our empirical findings provide the starting point for the development of an FXI option pricing model. Lastly, we derive the first differences of the third cumulants from the factors and find they have some predictability of the future FXI returns. The empirical features we present provide implications for the development of an FXI option pricing model and for traders to better understand this market.

The rest of this study is organized as follows. In section 2, we provide a background of the FXI options, including its underlying, FXI ETF, and the FXI's target index. In section 3, we present our sample data. Then in section 4, we describe the methodology for data processing, for quantifying the IV of the FXI options and for predictive regressions. Section 5 presents and analyses the results, and lastly section 6 concludes.

2 Background of the FXI Options Market

The iShares China Large-Cap ETF, which is known as FXI, was created by BlackRock in 2004, seeking to track the investment results of the FTSE China 50 Index.

FXI option contracts have been traded at the CBOE from 2004 and are physically settled American-style options. Figure 2 reviews the volume and open interest growth on a daily basis during our sample period from 2004 to 2016. As we can see, the market has been growing in activity and size significantly over the past decade.

2.1 FTSE China 50 Index

The FTSE China 50 Index is composed of 50 large-capitalization Chinese equities that trade on the Hong Kong stock exchange.[1] It was designed by FTSE/Xinhua Index Ltd. and launched in 2001.

The index originally consisted only of H-shares and Red-chip stocks.[2] Along with the development of private enterprises in Mainland China and the ownership distribution of large companies in China shifting a lot, it became hard to ignore the importance of these companies on both the stock market and in the economy of China. As a result, P-chip stocks have been included in the index since 18 March 2013.[3] Only two P-chips were added into the index on that day, grabbing 9.5% of the total market capitalization of the index. At the end of April 2018, there were seven P-chip stocks (Table 2), which accounted for nearly 20% of the total market capitalization of the index. The largest P-chip added, the Internet Company Tencent, has been one of the top three holdings for many years.

The index was originally composed of 25 large-capitalization Chinese equities that trade on the Hong Kong stock exchange. Considering that the market had been through a tremendous growth phase, the index was approved to be enlarged from 25 holdings to 50 by the FTSE Russell advisory committee on 22 Sept. 2014. The newly included 25 stocks accounted for only 6.76% of the total weights on the transaction day.

[1] The 50 components of the index as of April 2018 are listed in Table 2, ranked by their weights. Table 3 reports the breakdown of the constituents by ICB (Industry Classification Benchmark).

[2] According to FTSE Russell, H-shares are securities of companies incorporated in the People's Republic of China (PRC) and nominated by the central government for listing and trading on the Hong Kong stock exchange. Like other securities trading on the Hong Kong stock exchange, there are no restrictions on who can trade H-shares. A Red-chip is a company incorporated outside the PRC that trades on the Hong Kong stock exchange and is a company that is substantially owned, directly or indirectly, by Mainland China state entities with the majority of its revenue or assets derived from Mainland China.

[3] A P-chip is a company controlled by mainland individuals, with the establishment and origin of the company in Mainland China. It must be incorporated outside of Mainland China and traded on the Hong Kong stock exchange with a majority of its revenue or assets derived from Mainland China.

2.2 FXI ETF

The FXI ETF is an exchange-traded fund designed to track the investment results of its underlying index, the FTSE China 50 Index. No less than 90% of the fund's assets shall be invested in the securities in the underlying index and depository receipts representing the securities of the underlying index, while the rest may be invested in derivatives, cash, cash equivalent, etc.[4] FXI delivers a fairly close but slight underperformance relative to the underlying index (benchmark), as shown in Figure 1. The cumulative underperformance relative to the index is mostly due to the cumulated fund fees.

Table 1 reports the four most liquid China-targeted US-traded ETFs.[5] Of these ETFs, FXI is the most mature, most liquid and largest fund. The total assets of the iShares MCSI China ETF (MCHI), the second largest of the ETFs, are less than one-fifth of those of FXI and are far larger than the other two ETFs, as of 30 April 2018. The FXI is by far the most traded of the China-targeted ETFs, as shown by the dollar trading volume over the whole sample and just for April 2018.

The FXI ETF's underlying index consists of stocks that are traded on the Hong Kong stock exchange, a crucial developed market in Asia. The Shanghai and Shenzhen stock exchanges in Mainland China are tricky for international investors because of restrictions. By contrast, the Hong Kong stock exchange is more developed and less restricted, and provides the access, transparency and liquidity required by global traders. For those who want to invest in or are interested in the emerging market of China, we believe that research on FXI would help provide the most reliable information compared with those on other China-related ETFs. In summary, FXI delivers a cheap, easy, transparent, liquid and reliable way for global traders to invest in the Chinese market.

[4]Table 2 lists securities that the FXI ETF invests in as of 30 April 2018.

[5]It should be noted that Direxion Daily China 3x Bull Shares (Ticker: YINN) delivers three times the return of FXI.

3 Data

We obtain the FXI options data, including the IVs, trading volumes, open interests and last prices and dividend distributions of the underlying from OptionMetrics Ivy DB for the sample period from 19 October 2004 to 29 April 2016. The underlying index data and the other ETF data are obtained from Bloomberg. The Treasury yield data, used to proxy the risk-free rate, is downloaded from the website of the United States Department of the Treasury.

As FXI options are American-style, the IV provided by OptionMetrics Ivy DB is calculated using an algorithm based on the industry-standard Cox-Ross-Rubinstein binomial tree model(Cox, Ross, and Rubinstein (1979)). To get the IV, first the model option price at time $t = 0$ is calculated using the binomial tree model, and then they extract the corresponding IV that results in the model price matching the market price.

Table 4 reports a summary of the options data before cleaning as described below. No obvious pattern can be observed across maturity groups for the number of observations or mean number of strikes and contracts. However, the trading volume and open interest seem to be decreasing as maturity increases. This indicates that the closer the expiration is, the more liquid the option is, and therefore the more reliable the IV data will be.

We clean the data by the following steps. First, we delete those options with a missing IV, zero IV, zero bid price or zero open interest for calculation. Second, options with less than six days to expiration are also removed because they may induce liquidity-related biases (Bakshi, Cao, and Chen (1997)) though there is some literature studying the small-time smile pattern (Forde and Jacquier (2009) and Forde, Jacquier, and Lee (2012)). Lastly, we delete those maturities with less than five non-zero volumes on each day for precision of the fittings.

4 Methodology

4.1 Risk-Free Rate

We proxy the risk-free rate by using US Treasury yields. In order to get the risk-free rate with the same maturities as the option contracts, we adopt the linear interpolation and extrapolation method. The approximate risk-free rate is given by

$$r_\tau = r_{\tau_1} + \frac{\tau - \tau_1}{\tau_2 - \tau_1}(r_{\tau_2} - r_{\tau_1}),$$

where r_τ is the target maturity risk-free rate, τ is the corresponding target time to maturity. r_{τ_1} and r_{τ_2} are the Treasury yield rates of maturity τ_1 and τ_2, respectively, that are closest to τ.[6]

4.2 Forward Price

According to the no-arbitrage rule, the forward price can be expressed as:

$$F_{t,T} = S_t e^{(r-q)(T-t)}, \tag{1}$$

where $F_{t,T}$ is the forward price at time t with expiration day T, S_t is the price of the underlying asset (i.e. the FXI ETF) and q is the continuously compounded dividend yield through time t to T.

Assuming that the dividend is reinvested, we approximate the dividend yield over the sample using the following equation:

$$\left(1 + \frac{D_1}{S_1}\right)\left(1 + \frac{D_2}{S_2}\right) \dots \left(1 + \frac{D_n}{S_n}\right) = e^{q(T-t)},$$

where D_i is the i-th time that dividend is paid in our sample and S_i is the price of FXI ETF on the payment date of D_i.The dividend schedule is reported in Table 5. Both

[6]For calculation, we transform the original risk-free rate data in 1, 3, 6 months, and 1, 2, 3 years to 30, 91, 182, 365, 730 and 1095 days, respectively.

sides of this equation are the cumulative growth of one share of the FXI ETF due to the reinvestment of the dividends. The left-hand side represents the actual growth of one share using discretely paid dividends, while the right-hand side is the equivalent growth represented by a continuously paid dividend. We solve the equation over our sample period to get the average continuously compounded dividend yield $q = 0.0193$, which we use in Eq. 1 to approximate the forward price $F_{t,T}$.

The market ATM strike price K_0 is the one closest to $F_{t,T}$ for each maturity and each day. Following Carr and Wu (2003), the methodology used by CBOE in the calculation of the VIX index and market practise, we select the IV of out-of-the-money options to represent the FXI options IV curve. An out-of-the-money option is normally more liquid and more model-sensitive than the in-the-money options, and therefore is widely used when examining IV curves by investigators, researchers and exchange holding companies, such as the CBOE. For put options we select those whose strike prices are smaller than the forward price, that is, $K < F_{t,T}$, and for calls we select those whose strike prices are larger than the forward price, that is, $K > F_{t,T}$.

4.3 Moneyness

Following Zhang and Xiang (2008), the moneyness of an option, ξ, is defined as:

$$\xi = \frac{\ln(K/F_{t,T})}{\bar{\sigma}\sqrt{\tau}},$$

where K is the strike price, $F_{t,T}$ is the forward price, τ is the time to maturity of the option on an annual basis and $\bar{\sigma}$ denotes the average 30-day volatility of the underlying asset price. The $\bar{\sigma}$ in the denominator of moneyness is designed for comparisons across different underlying assets. We proxy $\bar{\sigma}$ each day by the 30-day ATM IV, which is calculated by interpolation between the ATM IVs with maturities closest to 30 days, from above and below.

4.4 Quantifying Implied Volatility

We then follow Zhang and Xiang (2008) in order to quantify the IV curve using the model given by

$$IV(\xi) = \gamma_0(1 + \gamma_1\xi + \gamma_2\xi^2), \tag{2}$$

where the factors γ_0, γ_1 and γ_2 capture the level, slope and curvature of the IV, respectively. The level is also referred to as an estimate of the exact ATM IV.

For the convenience of fitting and ANOVA test, we construct a simple second-order polynomial, that is,

$$IV(\xi) = \alpha_0 + \alpha_1\xi + \alpha_2\xi^2, \tag{3}$$

where the coefficients α_0, α_1 and α_2 can be easily converted to the quantified IV curve factors by:

$$\gamma_0 = \alpha_0,$$

$$\gamma_1 = \frac{\alpha_1}{\alpha_0},$$

$$\gamma_2 = \frac{\alpha_2}{\alpha_0}.$$

We fit the quadratic function, Eq.3, by a volume-weighted least square method (VWLS), that is, minimizing the volume-weighted mean square error given by

$$VWMSE = \frac{\sum_\xi \text{Volume} \times [IV_{market} - IV(\xi)]^2}{\sum_\xi \text{Volume}},$$

to obtain the coefficients (α_0,α_1,α_2) of Eq.3 which are converted to the dimensionless factors (γ_0,γ_1,γ_2) of Eq.2.

When the median volume of a particular maturity contract is less than 10, we adopt ordinary least squares (OLS) to fit the function instead of VWLS. Ideally, we would always use VWLS to emphasize information from more liquid contracts, but we also want to fit the market IVs well when trading is concentrated in a small number of contracts.

4.5 Predicting FXI Returns

Zhang and Xiang (2008) show that the factors used to quantify the IV curve are proportionately related to the risk-neutral moments, that is, the risk-neutral volatility, the skewness and the excess kurtosis. In line with Ang, Hodrick, Xing, and Zhang (2006), Xing, Zhang, and Zhao (2010), Chang, Christoffersen, and Jacobs (2013a) and Chatrath, Miao, Ramchander, and Wang (2016), we expect that those moments, and therefore the quantified IV factors, contain information on the future returns of the underlying FXI ETF. Then we test the predictability of the quantified IV factors and their first differences. Following Chang, Zhang, and Zhao (2015) and Ruan and Zhang (2018), we are also interested in the predictive power of the risk-neutral third and fourth cumulants and that of their first differences.

Following Conrad, Dittmar, and Ghysels (2013), An, Ang, Bali, and Cakici (2014) and Ruan and Zhang (2018), we test the predictability of FXI monthly excess returns using the IV factors. The FXI monthly excess returns are defined as

$$R_t = \ln \frac{S_t}{S_{t-1}} - r_t,$$

where S_t is the price of the FXI ETF in the end of month t and r_t is the one-month risk-free rate provided by the 30-day US Treasury yields.

We then calculate the factors at the end of each month using interpolation to match the days until the end of the predicted month. Following Bakshi, Kapadia, and Madan (2003) and Bali, Hu, and Murray (2017), the risk-neutral third and fourth cumulants are given by

$$TC = \gamma_1 \times \gamma_0^3, \quad FC = \gamma_2 \times \gamma_0^4, \tag{4}$$

where γ_0, γ_1 and γ_2 proxy the risk-neutral volatility, skewness and excess kurtosis, respectively.

We then run the following predictive regression for FXI monthly excess returns,

$$R_{t+1} = \alpha + \beta X_t + \epsilon_{t+1}, \tag{5}$$

where R_{t+1} is the FXI monthly excess return of month $t+1$ and ϵ_{t+1} is the residual. X_t is one of the predictors, that is, the level, slope, curvature, the third and fourth cumulants, or the first differences of these predictors, at the end of the month t.

In addition to the in-sample regressions, we also test the out-of-sample predictions for the FXI monthly excess returns. The evaluation sample is considered as an important parameter in terms of the power of the forecast evaluation tests (Welch and Goyal (2007), Rapach, Strauss, and Zhou (2010), Hansen and Timmermann (2012) and others). The out-of-sample r-squared (R^2_{OS}) is defined as:

$$R^2_{OS} = 1 - \frac{\sum_{t=n}^{N-1}(y_{t+1} - \hat{y}_{t+1|t})^2}{\sum_{t=n}^{N-1}(y_{t+1} - \bar{y}_{t+1|t})^2},$$

where $\bar{y}_{t+1|t} = \frac{1}{t}\sum_{i=1}^{t} y_i$. The null hypothesis is that the unconditional forecast is not inferior to the conditional forecast (Welch and Goyal (2007)). We also define the initial estimation ratio of the evaluation sample as ρ and set $\rho = 1/3$ and $1/2$ following Ruan and Zhang (2018).

5 Empirical Results

In this section, we report and discuss the results of quantifying the IV curves of FXI options. Following the method above, we plot the fitted IV curves for each available maturity every day to study the dynamics of the FXI option IV by examining the resulting level, slope and curvature factors. We then calculate the constant maturity IV factors in order to further study the FXI IV term structure and its time-series dynamics. Finally, we conduct an empirical test of FXI return predictability of the quantified IV factors.

5.1 Dynamics of the Quantified IV Curve

Figure 3 (a) shows the IV and trading volumes, provided by OptionMetrics Ivy DB, and the fitted IV curves using the methodology described in section 4 on 28 April 2018 for the time to maturity of 22 days. From this figure, a smirk can be observed. We will show that this kind of smirk is the typical shape of the FXI IV curve. Figure 3 (b) and (c) show the IVs of all the put and call option contracts for the same maturity and on the same day as Figure 3 (a). As we can see there is a slight jump at $\xi = 0$; that is, the IV of calls and puts are not equal at the ATM strike price. Cremers and Weinbaum (2010) and Doran, Fodor, and Jiang (2013) study this gap between put and call American option prices as a predictor of future returns of the underlying. This is not the focus in this paper. On this day for the 22 days to maturity options, our fitted IV curve matches the market data very closely.

We use the median volume filter mentioned in the methodology to get more precise fittings. This filter eliminates some of the strange fitted curves (Figure 4 (h)) that result from relative large volumes in a particular out-of-the-money option, forcing too much emphasis on fitting this IV. Using OLS in these cases results in a much better fit (Figure 5 (h)). The affected sample using OLS fittings accounts for 12% of the entire sample.

Figures 5, 6 and 7 show the market IV, fitted IV curves and the trading volumes for all available maturities on 28 April 2016, 15 May 2015 and 8 December 2014, respectively. As we can see, the smirk pattern can be observed in most of these graphs. The fitted curves seem to approximate the IV well, while there still exists a handful of abnormally shaped fitted curves which don't approximate the data well, even after the filter (Figure 5 (f) and (g)). This could be due to the relatively large trading volumes of a small number of deep out-of-the-money contracts forcing an unusual fitting by VWLS.

Table 6 summarizes the resulting parameters and factors as well as the forward prices, by maturity groups. The maturity groups are less than 30, 30 to 90, 90 to 180, 180 to 360 and more than 360 days, to provide initial analyses of the term structures of the factors. Overall, the exact ATM IV (level factor) is positive and the curves tend to be negatively sloped with some positive curvature (convexity), that is, a smirk shape as is found for S&P 500 options by Carr and Wu (2003), Foresi and Wu (2005) and Fajardo (2017), amongst others. The overall average level, slope and curvature are 0.3094, -0.1992 and 0.0771, respectively, with corresponding standard deviations of 0.1235, 0.1615 and 0.1482. Therefore, the level is mostly positive and the slope is mostly negative, while the curvature fluctuates between positive and negative values. The average term structures of $F_{t,T}$ and the level are upward sloping, and in contrast that of the slope are downward sloping. The term structure of the curvature is also downward sloping until the time to maturity is more than 360 days and then increases drastically. The standard deviations of $F_{t,T}$ and the factors increase with maturity except that of the level, which shows a downward trend across the maturity categories. This decrease in the standard deviation of the level with larger maturities may be a hint that the exact ATM IV mean-reverts, consistent with the common finding that the implied volatility of ATM US equity options mean-reverts (Dueker (1997); Fouque, Papanicolaou, and Sircar (2000); Higgs and Worthington (2008)). Table 6 also provides the proportion of fitted curves for which the coefficients are significant at the 5% level of significance. The proportion of significant coefficients of the ATM IV are always 100% while that of the slope decreases as the maturity increases, and for the curvature the decrease is very dramatic when the time to maturity is more than 360 days. The mean R^2 and R^2_{adj} are also shown in Table 6. Overall and for each maturity group, they are close to 100%, indicating that our quantification of the FXI IV is reliable. However, we can observe that the fit quality (R^2) decreases slightly as the maturity increases, which could be due to a decrease in trading activity and less consistent views by different option traders about longer-term volatility.

5.2 Constant Maturity Quantified IV Curve

Previously, we divided the IV curve factors into groups by maturity. However, this often groups many different maturities into one category on any given day. In order to examine the term structures of the level, slope and curvature factors and their time-series dynamics more accurately, we create the constant maturity factors. The constant maturity factors for the maturities of 30, 60, 90, 120, 150, 180 and 360 days are obtained by interpolation and extrapolation. Table 7 presents summary statistics for the constant maturity IV factors. The overall level, slope and curvature are as discussed above; that is, the level and slope are mostly positive and negative, respectively, while the curvature fluctuates around zero. The term structure of the level is now flat, different from the above result of being upward sloping, as shown in Table 6. Consistent with the results in Table 6, the term structure of the curvature is flat and that of the slope is downward sloping, and the standard deviations of the factors are increasing with maturity except the level, which decreases with maturity. In Figure 8, we present the predicted IV curves using the mean constant maturity factors to visualize the results presented in Table 7. We can see that the IV curve of the FXI options is usually in a smirk shape. As maturity increases, the smirk becomes more negatively sloped and more convex.

We plot the time-series of the 30-day and 180-day constant maturity factors in the left panel of Figure 9 in order to observe the time-series dynamics of the IV curve. In general the dynamics of 30- and 180-day constant maturities are consistent with the above results that the level time-series is always positive, the slope is usually negative and the curvature fluctuates around essentially zero. Specifically, in Figure 9 (a) the 30- and 180-day level factors mean revert with prolonged periods of high volatility during the GFC period (late 2007 to early 2009), the rapid recovery period (the second half of 2011) and the most recent depression period in China (early 2015 to 2016). In Figure 9 (c), we can see that the slope is usually negative, but the 180-day slope fluctuates a lot more. In Figure 9 (e), we can see that curvature tends to be slightly positive most of the time and the longer-maturity options IV curvature spikes are larger and more frequent. Turning to the difference in the 180- and 30-day factors in Figure 9 (b), (d) and (f), we can see that the short end term structures of the level (ATM IV), slope and curvature are usually downward sloping, downward sloping and flat, respectively. However, the level (ATM IV) experiences a period of extremely steep downward sloping term structure during the GFC.

To summarize, we find that overall the level is always positive and has a fairly flat term structure, the slope is negative and has a downward-sloping term structure and the curvature fluctuates around zero with a downward-sloping term structure for a maturity of less than 360 days. The level seems to mean-revert with prolonged periods of increased volatility during the GFC, recovery period and recent depression in China. The time-series of the level, slope and curvature are usually fluctuating around a positive, negative and slightly positive value, respectively, with times of spikes.

5.3 Predictability of FXI Returns

Table 8 shows the results of the in-sample and out-of-sample regressions. As we can see, in the in-sample tests, the first differences of the third cumulants appear to be useful to predict the future monthly excess returns of FXI, with a t statistic 2.40, which is significant at the 1% level of significance, and an r-squared statistic (R^2) of 5.00%. In the out-of-sample predictions, the first differences of the third cumulants show evidence of predictability with the out-of-sample r-squared statistic (R^2_{OS}) of 5.54% ($\rho = 1/3$) and 5.95% ($\rho = 1/2$). However, we find the other predictors have poor predictive performance both in in-sample and out-of-sample. Thus, we conclude that the first differences of the third cumulants can be used to predict the future FXI monthly excess returns. The first difference of the third cumulants is the difference of monthly jump frequencies in this case. The positive estimation of the first difference of the third cumulants to the FXI monthly returns means that when the option investors hold the opinion of less catastrophic events in the following month, they expect higher returns as compensation. These are initial results demonstrating the predictability using a simple method and may be vastly improved in future work.

6 Conclusion

In this paper, we study the IV smirk of FXI options and its dynamics, which further provide a modelling implication for option pricing for investors and practitioners. Following the methodology in Zhang and Xiang (2008), we fit a quadratic regression using VWLS each day and for each maturity over a sample period of 12 years to quantify the IV curve. The IV curve can be summarized by three factors: the level, slope and curvature every day and for each maturity. We then extend the methodology in Zhang and Xiang (2008) and calculate the constant maturity factors of the IV of FXI options to examine the term structure and dynamics of the factors. We can usually find a smirk shape in the fitted IV curves.

First, we divide the IV curve factors into groups by maturity to analyze the term structures of the factors. The IV usually has a positive level (exact ATM IV) with a negative slope and a curvature that fluctuates between positive and negative values. The term structure of the level and slope is upward and downward sloping, respectively, and that of the curvature is downward sloping until the maturity is more than 360 days, after which it increases drastically. The standard deviation of the level is decreasing across the maturity categories while others are increasing, which could imply that the ATM IV mean-reverts over the sample.

To examine the IV factor dynamics and term structures more accurately, we then calculate the constant maturity factors by interpolation and extrapolation, finding consistent results on average. However, the term structure of the level is flat, rather than upward sloping. From the fitted IV curves using the mean constant maturity factors, we can observe the IV smirk of the FXI options clearly. In order to investigate the time-series dynamics of the FXI IV curve, we plot the 30-day and 180-day dynamics and find that the 30- and 180-day levels have a similar shape with periods of high volatility related to the Chinese and global economy, indicating that the investors expect a similar volatility of the FXI returns. The slope and curvature are usually negative and slightly positive, but spikes of the 180-day ones are larger and more frequent. We can say that the slope and curvature are more volatile as the maturity increases. The term structures of the difference of the 180- and 30-day level (ATM IV) and slope are downward sloping while that of the curvature is flat. Further explanation of the fluctuation in the factors over time is necessary, and further work on finding the determinants of these time-series fluctuations would be of interest in our future work.

Lastly, we test the predictability of the FXI monthly excess returns using the factors, which proxy for the risk-neutral volatility, slope and curvature, and the risk-neutral third and fourth cumulants, their first differences. We test this with in-sample and out-of-sample regressions. We find that the first differences of the third cumulants can predict the future FXI monthly excess returns significantly both in the in-sample and out-of-sample regressions.

In this work, we show the overall IV smirk in FXI options, its term structures and dynamics. We quantify the IV curves through three factors: the level, slope and curvature. These could be used to calibrate the FXI option pricing model by converting them to risk-neutral moments, as in Zhang and Xiang (2008). Our empirical findings show that an FXI option pricing model must exhibit positive risk-neutral volatility, negative risk-neutral skewness and slightly positive risk-neutral excess kurtosis, on average, the magnitude of which changes with the maturity. These recommendations will help build a sound FXI option pricing model motivated by empirical characteristics.

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Table 1: Summary of relevant ETF's

This table reports summary information for the top 4 largest China-related ETFs as of 30 April 2018.

Symbol	ETF Name	Leverage	Issuer	Inception	Total Assets ($M)	Avg. Dollar Trading Volume since Inception	Avg. Dollar Trading Volume in Apr 2018
FXI	iShares China Large-Cap ETF	1	BlackRock	5-Oct-2004	4,481.12	586,319,037	1,122,664,445
MCHI	iShares MSCI China ETF	1	BlackRock	31-Mar-2011	3,508.17	43,678,452	205,829,647
ASHR	Deutsche X-trackers Harvest CSI 300 China A-Shares Fund	1	Deutsche Bank	6-Nov-2013	511.89	37,307,169	25,963,462
YINN	Direxion Daily China 3x Bull Shares	3	Direxion	3-Dec-2009	309.06	11,380,554	35,925,974

Table 2: Holdings of FXI ETF as of 30 April 2018

This table reports the 50 individual stocks and other investment of FXI ETF, and corresponding weights as of 30 April 2018.

Rank	Name	Asset Class	Weight%	Rank	Name	Asset Class	Weight%
1	China Construction Bank	Equity	9.19	29	China Vanke	Equity	0.92
2	Industrial and Commercial Bank of China	Equity	8.63	30	China Communications Construction	Equity	0.86
3	Tencent Holdings (P Chip)	Equity	8.21	31	China Minsheng Banking	Equity	0.84
4	Ping An Insurance	Equity	5.70	32	Fosun International (P Chip)	Equity	0.81
5	China Mobile (Red Chip)	Equity	5.64	33	BYD	Equity	0.81
6	Bank of China	Equity	4.59	34	Haitong Securities	Equity	0.79
7	CNOOC	Equity	4.25	35	Longfor Properties (P Chip)	Equity	0.74
8	China Petroleum & Chemical	Equity	4.19	36	New China Life Insurance	Equity	0.69
9	China Life Insurance	Equity	3.49	37	Guangzhou Automobile Group	Equity	0.69
10	China Merchants Bank	Equity	2.80	38	Postal Savings Bank of China	Equity	0.68
11	Petrochina	Equity	2.58	39	People's Insurance Company (Group)	Equity	0.68
12	Country Garden Holdings (P Chip)	Equity	2.56	40	CRRC	Equity	0.60
13	Agricultural Bank of China	Equity	2.44	41	Huatai Securities	Equity	0.59
14	China Overseas Land & Inv (Red Chip)	Equity	2.18	42	China Huarong Asset Management	Equity	0.56
15	Geely Automobile Holdings (P Chip)	Equity	2.16	43	China Railway Group	Equity	0.52
16	China Pacific Insurance (Group)	Equity	1.93	44	China Molybdenum	Equity	0.50
17	Sunny Optical Technology Group (P Chip)	Equity	1.81	45	GF Securities	Equity	0.46
18	China Resources Land (Red Chip)	Equity	1.70	46	Air China	Equity	0.41
19	China Evergrande Group (P Chip)	Equity	1.58	47	China Railway Construction	Equity	0.38
20	China Shenhua Energy	Equity	1.42	48	Guotai Junan Securities	Equity	0.33
21	China Unicom Hong Kong Ltd (Red Chip)	Equity	1.42	49	ZTE	Equity	0.29
22	PICC Property	Equity	1.36	50	China Everbright Bank	Equity	0.26
23	CITIC (Red Chip)	Equity	1.26	51	HKD Cash	Cash	0.07
24	Anhui Conch Cement	Equity	1.25	52	BLK CSH FND Treasury SL Agency	Money Market	0.06
25	China Telecom	Equity	1.14	53	Cash Collateral HKD UBFUT	Cash Collateral and Margins	0
26	Bank of Communications	Equity	1.08				
27	China Citic Bank	Equity	1.00	54	H-Shares Index May 18	Futures	0
28	CITIC Securities	Equity	0.94	55	USD Cash	Cash	-0.06
Totals							99.98

Table 3: Constituent breakdown as of 30 April 2018

This table reports the industry classification of 50 individual stocks and corresponding group weights of the FTSE China 50 Index as of 30 April 2018.

ICB Code	ICB Supersector	Number of Constituents	Weight%
8300	Banks	10	31.51
8500	Insurance	6	13.84
0500	Oil&Gas	3	11.01
8600	Real Estate	6	9.68
9500	Technology	2	8.62
6500	Telecommunications	3	8.19
8700	Financial Services	6	3.68
2700	Industrial Goods&Services	3	3.68
3300	Automobiles&Parts	3	3.65
2300	Construction&Materials	4	3.01
1700	Basic Resources	3	2.73
5700	Travel&Leisure	1	0.41
Totals		50	100

Table 4: Sample summary

This table reports the mean daily number of strikes, contracts, trading volume and open interest of the options data for the sample period 19 October 2004 to 29 April 2016 in each maturity category. The daily numbers of open interest or volume are calculated as the mean of the daily trading volume for overall and for each maturity category.

Maturity	Overall	< 30	$30 - 90$	$90 - 180$	$180 - 360$	> 360
Number of Observations	22,145	4,019	5,878	4,209	4,120	3,919
Mean Number of Strikes	39	42	44	47	38	20
Mean Number of Contracts	78	85	88	95	76	40
Mean Daily Trading Volume	55,919	22,709	23,642	8,538	4,750	1,563
Mean Daily Open Interest	1,511,243	434,264	520,272	322,366	253,253	102,963

Table 5: FXI dividend schedule

This table reports the dividend distributed in our sample period from 19 October 2004 to 29 April 2016.

Record Date	Payment Date	Dollar Amount Per Share
28-Dec-05	30-Dec-05	1.25
21-Dec-11	29-Dec-11	0.08
26-Dec-06	28-Dec-06	1.31
22-Jun-12	27-Jun-12	0.85
27-Dec-07	04-Jan-08	2.09
19-Dec-12	27-Dec-12	0.09
25-Jun-08	27-Jun-08	1.68
27-Jun-13	02-Jul-13	0.84
24-Dec-08	31-Dec-08	0.21
19-Dec-13	27-Dec-13	0.17
24-Jun-09	26-Jun-09	0.33
26-Jun-14	01-Jul-14	0.54
23-Dec-09	31-Dec-09	0.22
23-Dec-14	29-Dec-14	0.51
23-Jun-10	25-Jun-10	0.46
26-Jun-15	30-Jun-15	0.25
22-Dec-10	30-Dec-10	0.17
23-Dec-15	28-Dec-15	0.77
23-Jun-11	27-Jun-11	0.69

Table 6: Summary of quantified IV curve coefficients and factors

This table reports summary results for the estimated IV function:

$$\mathrm{IV}(\xi)=\alpha_0+\alpha_1\xi+\alpha_2\xi^2,$$

where IV is the implied volatility and ξ is the moneyness of the option. We include a filter of those maturities with contracts whose median volume is smaller than ten. We fit those particular regressions using OLS, which account for 12% of all regressors. The estimated coefficients $\hat{\alpha}_0$, $\hat{\alpha}_1$, $\hat{\alpha}_2$ can be converted to the quantified IV factors $\hat{\gamma}_0$, $\hat{\gamma}_1$, $\hat{\gamma}_2$. We fit the regression for each day and each maturity over the entire sample, as described in Section 4. The percentage of the significant coefficients is the percentage of parameter estimates that are significant at the 5% level of significance.

Maturity	Overall	< 30	$30-90$	$90-180$	$180-360$	> 360
			Mean			
$F_{t,T}$	52.8957	49.2058	52.2675	52.4790	53.0587	61.4866
$\hat{\alpha}_0$	0.3094	0.3037	0.3098	0.3085	0.3060	0.3249
$\hat{\alpha}_1$	-0.0640	-0.0374	-0.0513	-0.0704	-0.0812	-0.1063
$\hat{\alpha}_2$	0.0209	0.0229	0.0185	0.0180	0.0178	0.0346
γ_0	0.3094	0.3037	0.3098	0.3085	0.3060	0.3249
γ_1	-0.1992	-0.1147	-0.1624	-0.2216	-0.2565	-0.3181
γ_2	0.0766	0.0892	0.0716	0.0665	0.0659	0.1074
			Standard Deviation			
$F_{t,T}$	38.2849	32.2338	36.5272	37.8987	38.2603	50.0689
$\hat{\alpha}_0$	0.1232	0.1342	0.1373	0.1171	0.1038	0.0996
$\hat{\alpha}_1$	0.0592	0.0373	0.0475	0.0566	0.0644	0.0769
$\hat{\alpha}_2$	0.0429	0.0266	0.0241	0.0354	0.0539	0.0800
γ_0	0.1232	0.1342	0.1373	0.1171	0.1038	0.0996
γ_1	0.1621	0.1009	0.1295	0.1505	0.1727	0.2058
γ_2	0.1469	0.1145	0.0977	0.1194	0.1845	0.2510
			%Significant Coefficients at 5% level of significance			
$\hat{\alpha}_0$	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
$\hat{\alpha}_1$	98.24%	94.45%	98.95%	99.22%	99.40%	99.48%
$\hat{\alpha}_2$	81.31%	89.49%	84.84%	81.16%	76.22%	65.76%
			R^2			
Mean R^2	98.25%	98.54%	98.49%	98.33%	98.08%	97.19%
Mean R^2_{adj}	98.00%	98.23%	98.31%	98.19%	97.85%	96.62%
			Daily Trading Volume			
Mean Daily Volume	49,238	19,840	21,382	8,414	4,956	1,815

Table 7: Summary of constant maturity quantified IV factors

This table reports summary statistics of the fitting results overall and for constant maturities of 30, 60, 90, 120, 150, 180 and 360 days, which are calculated interpolating and extrapolating the estimated coefficients and factors.

Maturity	Overall	30	60	90	120	150	180	360
				Mean				
$\hat{\alpha}_0$	0.3174	0.3221	0.3225	0.3203	0.3195	0.3190	0.3193	0.3267
$\hat{\alpha}_1$	-0.0678	-0.0528	-0.0586	-0.0656	-0.0714	-0.0766	-0.0813	-0.0950
$\hat{\alpha}_2$	0.0197	0.0194	0.0168	0.0167	0.0163	0.0167	0.0177	0.0255
γ_0	0.3174	0.3221	0.3225	0.3203	0.3195	0.3190	0.3193	0.3267
γ_1	-0.2080	-0.1588	-0.1790	-0.2016	-0.2191	-0.2343	-0.2477	-0.2809
γ_2	0.0705	0.0745	0.0636	0.0621	0.0597	0.0602	0.0630	0.0843
				Standard Deviation				
$\hat{\alpha}_0$	0.1247	0.1502	0.1414	0.1323	0.1265	0.1223	0.1193	0.1080
$\hat{\alpha}_1$	0.0530	0.0370	0.0477	0.0516	0.0551	0.0592	0.0616	0.0676
$\hat{\alpha}_2$	0.0229	0.0184	0.0216	0.0258	0.0274	0.0325	0.0415	0.0512
γ_0	0.1247	0.1502	0.1414	0.1323	0.1265	0.1223	0.1193	0.1080
γ_1	0.1336	0.0864	0.1234	0.1357	0.1435	0.1524	0.1561	0.1697
γ_2	0.0814	0.0811	0.0838	0.0961	0.0965	0.1072	0.1322	0.1591

Table 8: Predictability of FXI returns

This table reports the estimated slope coefficients $\hat{\beta}$, their t-statistics, the in-sample r-squared (R^2) statistics and out-of-sample r-squared (R^2_{OS}) statistics for the predictive regression described in Eq. 5. TC and FC are the third and fourth cumulants obtained through Eq. 4. DLevel, DSlope, DCurv, DTC and DFC are the first differences of the corresponding predictors. $\rho = 1/3$ and $\rho = 1/2$ are the initial estimation ratios of the evaluation samples that we choose.

	$\hat{\beta}$	t	$R^2(\%)$	$R^2_{OS}(\%)$	
				$\rho = 1/3$	$\rho = 1/2$
Full sample (2004.10-2016.04)					
Level	-0.04	(-0.49)	0.22	-16.93	-2.50
Slope	-0.12	(-0.84)	0.64	-339.55	-41.38
Curv	0.09	(0.48)	0.21	-25.87	-0.43
DLevel	0.17	(-1.07)	1.05	-8.40	-6.76
DSlope	0.00	(0.01)	0.00	-8.74	-2.08
DCurv	-0.05	(-0.29)	0.08	-7.36	-3.07
TC	-0.14	(-0.33)	0.10	-28.32	-4.28
FC	2.49	(0.63)	0.36	-0.92	-11.46
DTC	41.00	(2.40)	5.00	5.54	5.95
DFC	141.41	(1.79)	2.84	-2.91	-6.70

Figure 1: Performance of the FXI ETF and its benchmark index

This figure reflects the hypothetical growth of a $10,000 investment in the FXI ETF and the benchmark index (Ticker: XIN0I) from 08 October 2004 to 30 April 2018. Dividends are assumed to be reinvested. Fund expenses are deducted for the FXI ETF.

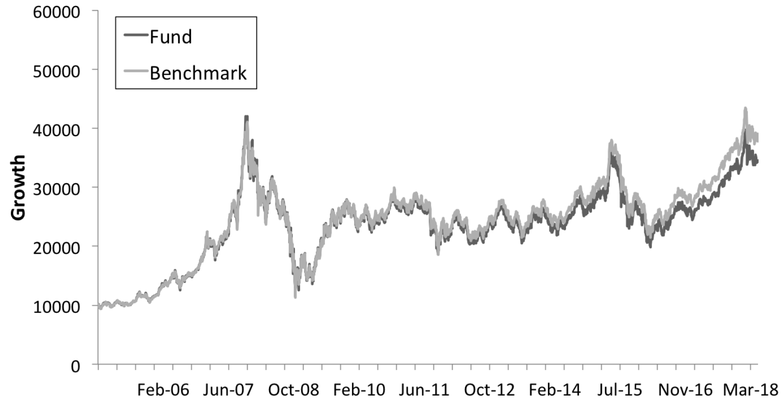


Figure 2: The FXI options market growth

This figure illustrates the daily total volume and open interest of the FXI options market from 19 October, 2004 to 29 April, 2016.

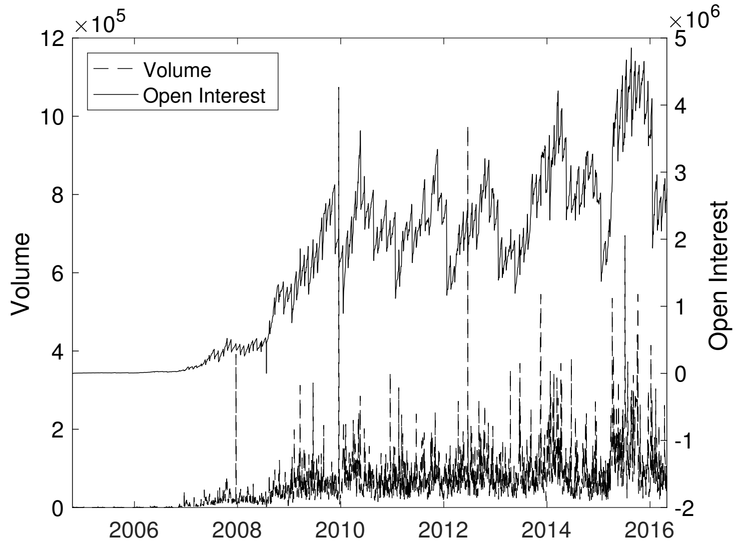
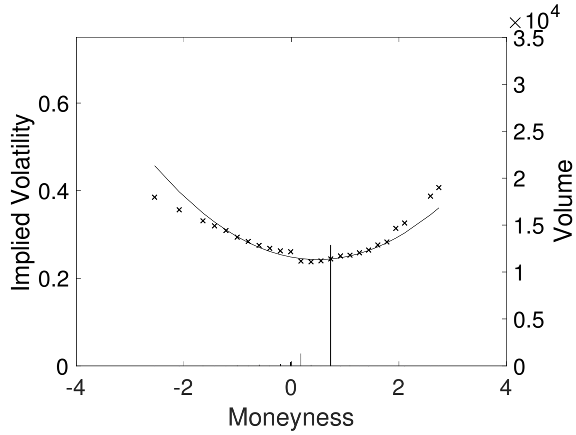
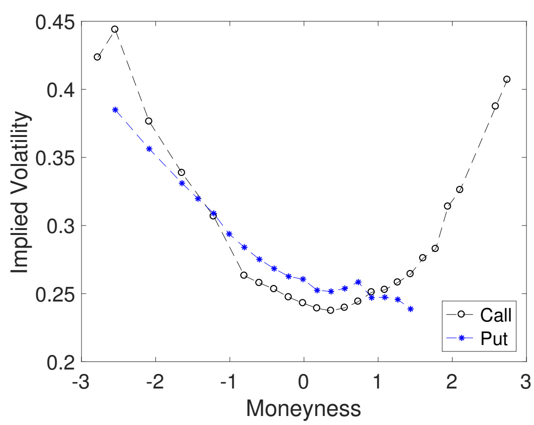


Figure 3: The IV smile on 28 April 2016 for options expiring on 20 May 2016

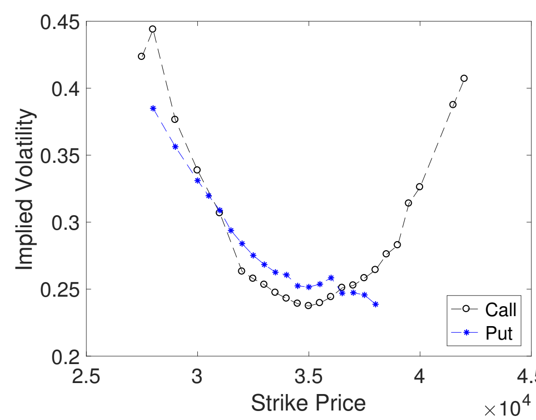
Graph 3 (a) illustrates the market IV (crosses) and the fitted IV curve on 28 April 2016. The time to maturity is 22 days and the options will expire on 20 May 2016. Bars in the figure represent the volume. Graph (b) and (c) show the market put and call option IV against moneyness and strike price, respectively.



(a)



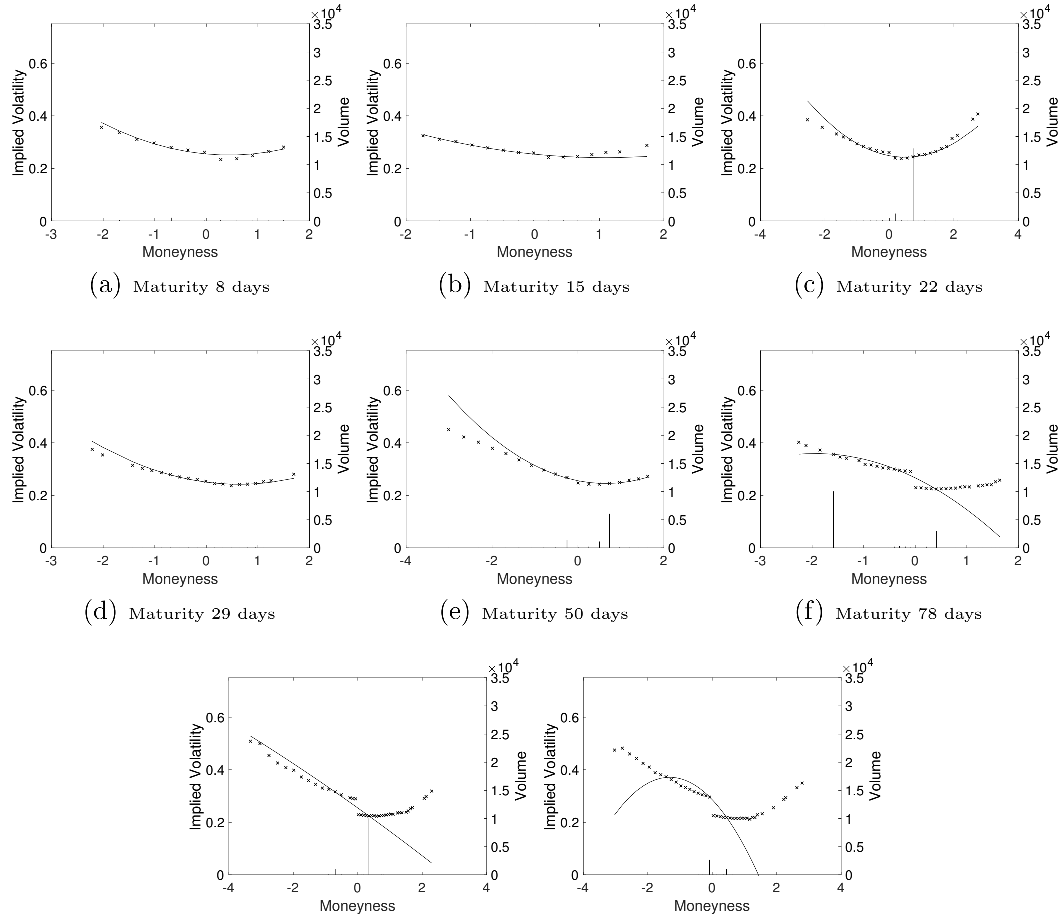
(b)



(c)

Figure 4: The IV curves without the volume filter on 28 April 2016

This figure illustrates the market and fitted IV curves for each available time to maturity on 28 April 2016, without the median volume filter, described in section 4. Crosses in each graph are the market IVs. The solid lines are fitted IV and the bars are the trading volumes.



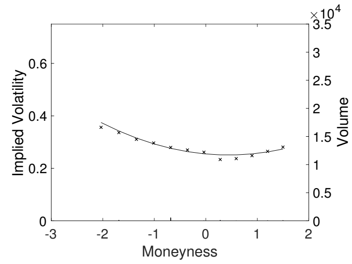
(a) Maturity 8 days (b) Maturity 15 days (c) Maturity 22 days

(d) Maturity 29 days (e) Maturity 50 days (f) Maturity 78 days

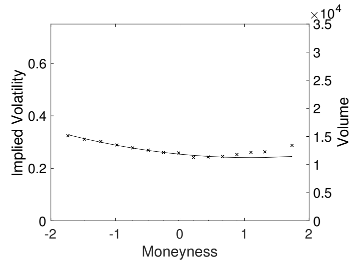
(g) Maturity 113 days (h) Maturity 267 days

Figure 5: The IV curves on 28 April, 2016

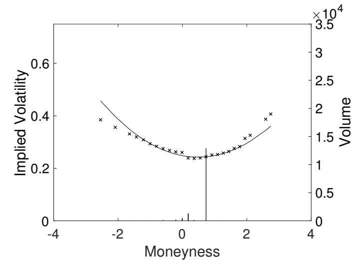
This figure illustrates market and fitted IV curves for each available time to maturity 8, 15, 22, 29, 50, 78, 113 and 267 days, with the median volume filter. Crosses in each graph are the market IVs. The solid lines are fitted IV curves and the bars are the trading volumes.



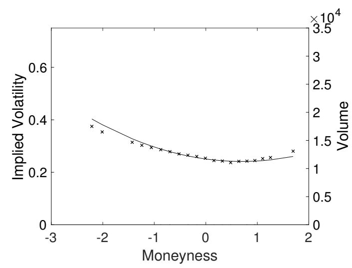
(a) Maturity 8 days



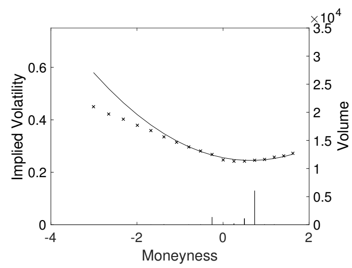
(b) Maturity 15 days



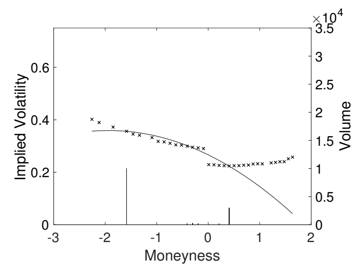
(c) Maturity 22 days



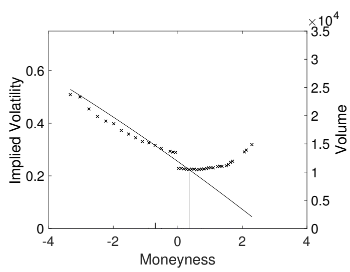
(d) Maturity 29 days



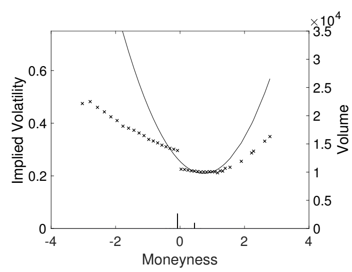
(e) Maturity 50 days



(f) Maturity 78 days



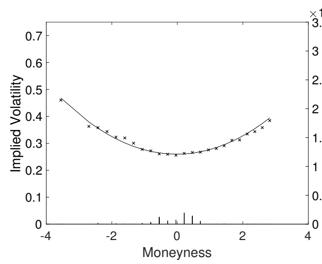
(g) Maturity 113 days



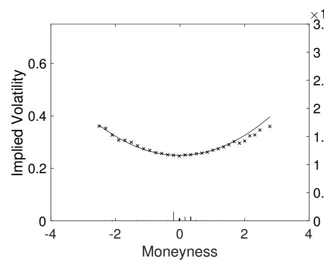
(h) Maturity 267 days

Figure 6: The IV curves on 15 May, 2015

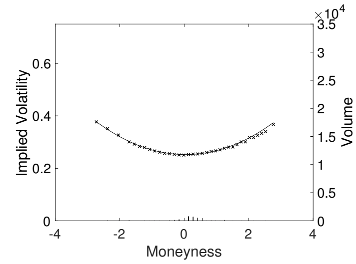
This figure illustrates market and fitted IV curves for each available time to maturity 7, 14, 21, 28, 35, 42, 63, 98, 189, 245 and 616 days, with the median volume filter. Crosses in each graph are the market IVs. The solid lines are fitted IV curves and the bars are the trading volumes.



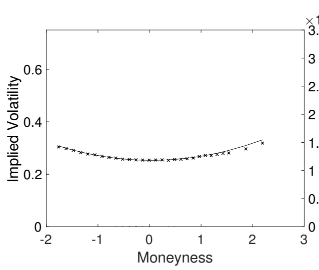
(a) Maturity 7 days



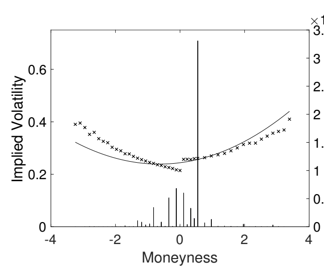
(b) Maturity 14 days



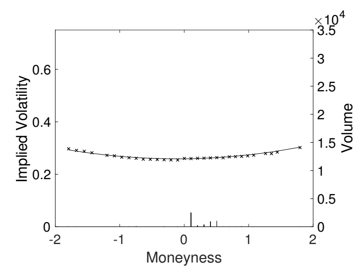
(c) Maturity 21 days



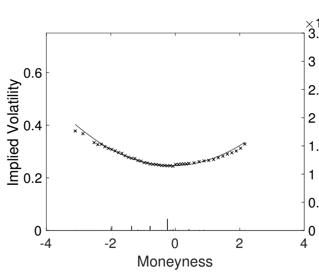
(d) Maturity 28 days



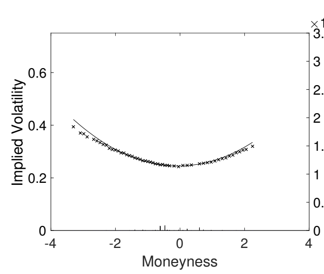
(e) Maturity 35 days



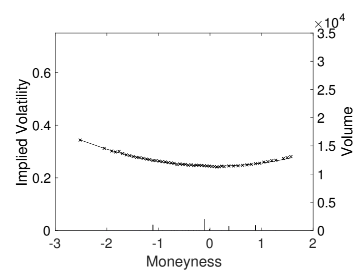
(f) Maturity 42 days



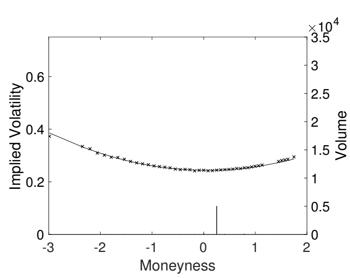
(g) Maturity 63 days



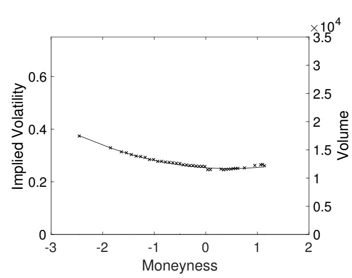
(h) Maturity 98 days



(i) Maturity 189 days



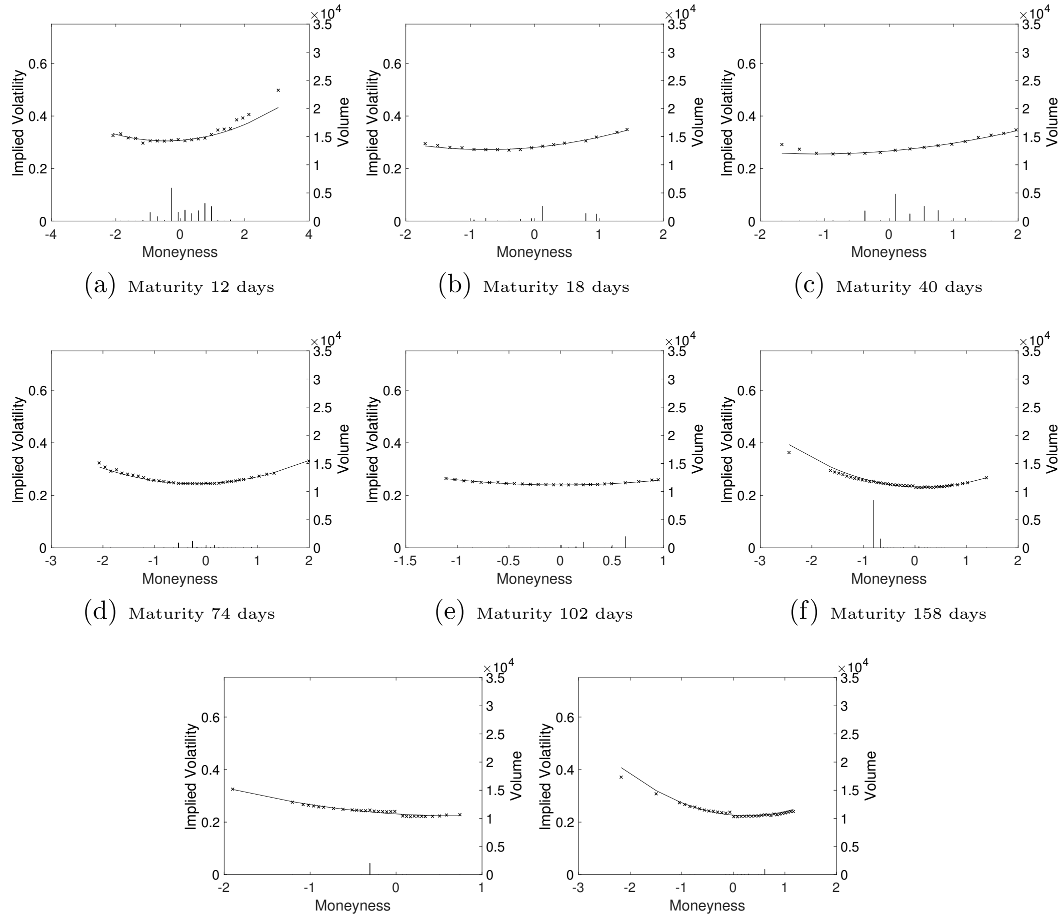
(j) Maturity 245 days



(k) Maturity 616 days

Figure 7: The IV curves on 08 December, 2014

This figure illustrates market and fitted IV curves for each available time to maturity 12, 18, 25, 40, 74, 102, 158, 256 and 403 days, with the median volume filter. Crosses in each graph are the market IVs. The solid lines are fitted IV curves and the bars are the trading volumes.



(a) Maturity 12 days

(b) Maturity 18 days

(c) Maturity 40 days

(d) Maturity 74 days

(e) Maturity 102 days

(f) Maturity 158 days

(g) Maturity 256 days

(h) Maturity 403 days

Figure 8: The fitted IV curves using the constant maturity IV factors

This figure shows the fitted IV curves resulting from the mean constant maturity IV factors.

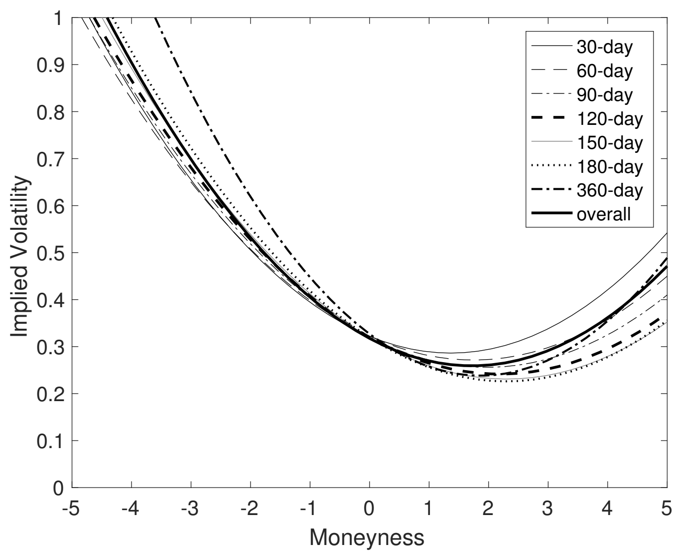
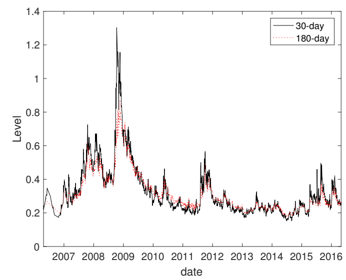
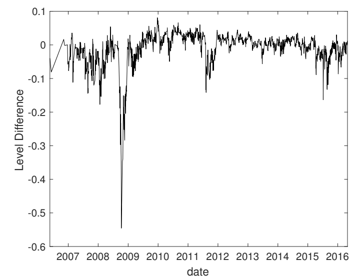


Figure 9: Constant maturity implied volatility dynamics

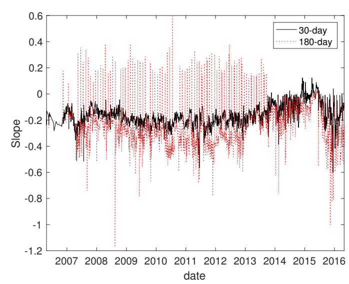
This figure shows the 30-day and 180-day constant maturity dynamics of the exact ATM IV, γ_0, the slope, γ_1, and the curvature, γ_2, factors that quantify the IV curves. The left column graphs represent the time-series of the constant maturity IV factors, while the right column shows the difference of the 180- less 30-day factors.



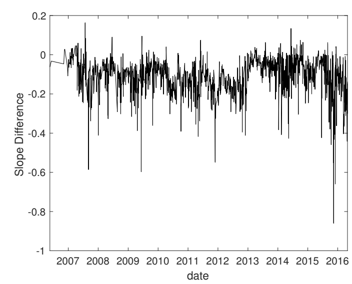
(a) ATM IV



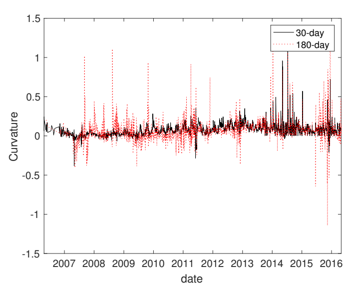
(b) Level Difference



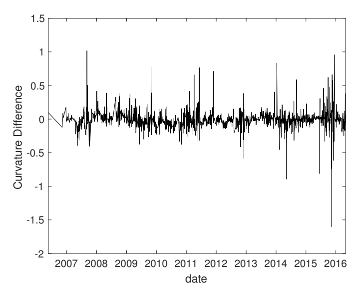
(c) Slope



(d) Slope Difference



(e) Curvature



(f) Curvature Difference