Volatility Risks Implied From Short Term VIX Futures*

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Abstract

We use a dynamic term structure model to extract latent volatility risk factors from short term VIX futures. While the first factor, closely related to the level of volatility, does not contain predictive information about VIX futures returns, the second and third risk factors can significantly predict daily and weekly returns of VIX futures. The predictive power of the third volatility factor is particularly strong: It is robust to controlling for other known predictors, considering different VIX futures contracts and return calculation, and alternative methods for evaluating statistical significance. We find the third volatility factor captures both changes in risk and movements in open interest.

JEL Classification: G12

Keywords: short term VIX futures; term structure; return predictability; volatility risk

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1 Introduction

The development of volatility derivative markets over the last few decades has transformed volatility trading from a theoretical concept to daily practice.[1] A prominent example is VIX futures which allow market participants to gain exposure to the VIX index, a benchmark US equity volatility index closely watched by academics, practitioners, and policy makers alike. The Chicago Board Options Exchange (CBOE) introduced standard futures contracts with monthly expirations on the VIX index in March 2004 and the VIX futures market has soon become a key marketplace for trading volatility.[2] In July 2015, VIX futures contracts with weekly expirations also started trading. The introduction of weekly VIX futures improves market completeness and expands investment opportunities by significantly increasing the number of short term VIX futures available in the market. On a typical day, market participants can observe a sequence of short term VIX futures, expiring one week apart, for the six consecutive weekly expirations.

We argue those short term VIX futures contracts contain rich economic information about volatility risks and how they are priced. We apply a dynamic term structure model to extract three latent volatility risk factors from short term VIX futures and use the three volatility risk factors to forecast returns to holding VIX futures. We find the first volatility risk factor, which is closely related to the level of volatility, does not contain predictive information about subsequent VIX futures returns. In contract, the second and especially the third volatility risk factor have strong predictive power over future returns. The return predictability is highly significant at the daily and weekly horizons, but it does not persist to longer horizons.

[1] Brenner and Galai (1989) and Whaley (1993) demonstrate how futures and options on a volatility index can be used to manage volatility risks, long before those derivatives contracts became available in practice.

[2] Using unique regulatory data from the Commodity Futures Trading Commission (CFTC), Mixon and Onur (2015) show volatility trading primarily occurs in VIX futures for maturities less than one year.

We compare the predictive power of the second and third volatility risk factors we extract from short term VIX futures with that of a range of existing variables that may predict VIX futures returns. We first consider the underlying VIX index and the VVIX index as volatility and volatility of volatility are usually the key drivers of the volatility risk premium in many theoretical frameworks (e.g., Heston, 1993; Bollerslev, Tauchen, and Zhou, 2009). We also consider a few risk measures inferred from short term index options (e.g., Andersen, Fusari, and Todorov, 2017, 2020) and factors extracted from the term structure of the VIX index (Johnson, 2017). We find that the second volatility factor extracted from short term VIX futures is somewhat sensitive to controlling for other variables and becomes statistically insignificant in some specifications, suggesting that its predictive information overlaps with some of the existing variables. In contrast, the third volatility factor is not spanned by existing variables and remains a strong predictor in the presence of all the controls variables.

We then investigate which observable variables can explain the time varying third latent volatility risk factor we extract from short term VIX futures. We find the variation in the third volatility factor is related to not only the VIX and VVIX indexes but also open interest. Using data on traders positions, we further show that the comovement between open interest and volatility risk is due to the changes in trading positions from dealers and asset managers. These results are overall consistent with Hong and Yogo (2012) which emphasize the important role of open interest in futures markets and a growing literature that stresses the impact of supply and demand and the role of financial intermediaries (e.g., Gârleanu and Pedersen, 2009; Barras and Malkhozov, 2016; Chen, Joslin, and Ni, 2019). We also demonstrate that the use of weekly VIX futures in extracting volatility risks is critical for return predictability. When we repeat our empirical exercise using a sample that includes all VIX futures (i.e., both short term and long maturity contracts) and another sample that excludes weekly VIX futures, we find no predictability. These results suggest that the predictive information comes from short term VIX futures.

Our finding that the third volatility risk factor implied from short term VIX futures predicts daily and weekly returns of VIX futures is robust to different empirical implementation. Evaluating statistical significance for predictive regressions is difficult, especially when overlapping return observations are used. In our benchmark analysis, we report on the Hansen and Hodrick (1980) standard error, but we also show that the results are robust to different asymptotic standard errors and the scaled t-test of Hjalmarsson (2011). Moreover, while we demonstrate the substantial predictive power of the third volatility risk factor in the context of forecasting the returns of a VIX futures strategy with a constant maturity of two weeks, we also show that the results hold for other maturities and different return computations.

Related Literature

Our paper is closely related to two recent studies in the literature. Andersen, Fusari, and Todorov (2017) investigate short term market risks implied from weekly S&P 500 index options. Our paper also studies the information content of short term derivative securities, but we focus on weekly VIX futures and show that the predictive information embedded in short term VIX futures is incremental to that embedded in short term index options. Johnson (2017) extracts principal components from the VIX term structure and finds that the second principal component (*Slope*) can predict returns of a range of volatility assets. This paper is different from Johnson (2017) in that we study the term structure of short term VIX futures. We confirm the finding in Johnson (2017) that the level of volatility does not predict future volatility returns, but we also show that the term structure of short term VIX futures contains unique information about futures returns and our findings are robust to controlling for factors relating to the term structure of the VIX.

We also contribute to the growing literature on VIX futures. Mencia and Sentana (2013) compare a range of valuation models for VIX derivatives and find a model with central tendency and stochastic volatility can reliably price VIX derivatives.[3] Eraker and Wu (2017) propose an equilibrium model to explain the large negative average returns observed on VIX futures. Cheng (2018) show the volatility risk premium embedded in VIX futures tends to stay flat or fall when risks rise, a puzzling finding hard to reconcile with existing theories. The key difference between the above studies and this paper is that their focus is on standard monthly VIX futures while this paper aims to extract unique economic information embedded in short term contracts consisting of primarily weekly VIX futures.

The findings of this paper have implications on the extensive literature on volatility modeling. While the stochastic nature of volatility has long been recognized (see, among others, Bollerslev, 1986; Engle, 1982), it is somewhat surprising that multifactor models have not yet become more popular in the volatility literature.[4] Several existing studies consider a two-factor volatility specification (e.g., Christoffersen, Heston, and Jacobs, 2009; Engle, 1982; Bates, 2000; Adrian and Rosenberg, 2008; Lee and Engle, 1999), and our analysis suggests that it is beneficial to add a third factor in volatility modeling.

Lastly, this paper is related to a voluminous literature on return predictability. Most studies in this literature focus on the predictability of equity index returns, finding that a number of variables such as stock market valuation ratios and interest rates seem to have predictive power over future stock returns (see, among others, Fama and French, 1988; Campbell and Shiller, 1988; Ang and Bekaert, 2007).[5] Our paper is more closely related to the recent literature that investigates the predictability of volatility returns (e.g., Cheng, 2018, 2020; Hu and Jacobs, 2020).

[3]See also Zhang and Zhu (2006), Zhu and Lian (2012), and Park (2016).

[4]In the yield curve literature, it is well documented that at least three factors are needed to capture the movements in yields.

[5]The statistical evidence for stock return predictability is not without controversy. See, for example, Stambaugh (1986, 1999), Kirby (1997), Goyal and Welch (2008), Boudoukh, Richardson, and Whitelaw (2008), Nelson and Kim (1993), Goetzmann and Jorion (1993), and Boudoukh, Israel, and Richardson (2020).

The rest of the paper is organized as follows. Section 2 discuses the data. Section 3 describes the model we use to extract volatility risk factors from short term VIX futures. Section 4 contains the predictability results and related discussion. Section 5 presents robustness analysis, and Section 6 concludes the paper.

2 Data

We obtain daily data on VIX futures from the Chicago Board Options Exchange (CBOE). The CBOE introduced standard futures on the VIX index on March 26, 2004. Those contracts expire monthly on the Wednesday that is exactly 30 days prior to the third Friday of the following month. VIX futures provide market participants with direct exposure to volatility and have experienced tremendous growth since their inception. On July 23, 2015, building on the huge success of monthly VIX futures, the CBOE launched weekly VIX futures that expire on other Wednesdays, filling the gap between monthly expirations. The addition of the so called 'Weeklys' significantly increases the number of short term VIX futures available in the marketplace.

In this paper, we focus on short term VIX futures, defined as those contracts that have a maturity within six weeks. Our final sample consists of both standard and weekly VIX futures, a total of 9885 observations, spanning from July 23 2015 to December 31 2021. Figure 1 plots the number of short term VIX futures on each day of our sample period. Most days we observe the prices for a sequence of short term VIX futures contracts, expiring one week apart, for the six consecutive weekly expirations. As an example, Figure 2 plots the term structure of short term VIX futures on two randomly selected days: November 6, 2015 and March 19, 2020. The blue circles denote weekly VIX futures and red diamonds denote standard monthly VIX futures. On November 6, 2015, the VIX stood at 14.33 and the term structure of VIX futures is upward sloping, although the relationship is not monotone. On March 19, 2020, the VIX was at 72 and the term structure is downward sloping. In subsequent sections, we demonstrate the changes in the shape of the term structure of short term VIX futures contain rich economic information about volatility risks and how they are priced.

Table 1 reports the summary statistics of short term VIX futures. The mean log price increases monotonically from 2.84 for futures contracts with a maturity less than a week to 2.92 for contracts with a maturity between five and six weeks. In other words, the term structure of short term VIX futures is in contango on average, consistent with the findings based on long maturity VIX futures. Short term VIX futures, especially those very close to maturity, exhibit large standard deviation, skewness, and kurtosis, suggesting that the term structure itself fluctuates considerably over time (see also Figure 2). Lastly, Table 1 shows that trading volume in short term VIX futures is similar across maturities, but contracts with a maturity between three to six weeks tend to have larger open interest.[6]

3 Model and Estimation Results

Section 3.1 describes the model we use to extract risk factors from the term structure of short term VIX futures. Section 3.2 summarizes the model estimation results.

3.1 The Model

We consider a parsimonious yet flexible term structure model to study the unbalanced panel of VIX futures (i.e., the number of available contracts and their maturities vary over time).

[6]We also find that standard monthly VIX futures contracts remain more popular than weekly futures with significantly higher trading volume and open interest.

The log price of the VIX denoted by s_t is assumed to follow an affine function of three risk factors:

$$s_t = \delta_0 + \ \delta_1 X_t, \tag{1}$$

where X_t represents the 3×1 vector of risk factors, δ_0 is a scalar, and δ_1 is a 1×3 vector. We assume X_t follows a first-order Gaussian vector autoregression (VAR) under the physical P and the risk-neutral Q measures:

$$X_t = K_0^P + K_1^P X_{t-1} + \Sigma\varepsilon_t, \tag{2}$$

$$X_t = K_0^Q + K_1^Q X_{t-1} + \Sigma\varepsilon_t, \tag{3}$$

where K_0^P, K_0^Q, and ε_t are 3×1 vectors, K_1^P and K_1^Q are 3×3 matrices, $\varepsilon_t \sim N(0,\, I_3)$, Σ is a 3×3 lower triangular matrix, and $\Sigma\Sigma'$ is the variance-covariance matrix.

Given the dynamics in equations (1)-(3), the model-implied log price of a futures contract with h-day maturity is given by (Duffie and Kan, 1996):

$$\widehat{f_t^h} = A_h(\Theta^Q) + B_h(\Theta^Q) X_t, \tag{4}$$

where the scalar A_h and the 1×3 vector B_h are functions of the parameters under the Q-dynamics, $\Theta^Q = \{K_0^Q,\, K_1^Q,\, \delta_0,\, \delta_1,\, \Sigma\}$, through a set of recursive equations (see Dai and Singleton (2000), Duffee (2002), and Joslin, Singleton, and Zhu (2011)).

We use the Kalman filter to filter the latent risk factors X_t.[7] The state propagation equation is specified in equation (2). The measurement equation is given by equation (4).

[7]Several estimation methodologies have been proposed in the literature to identify the latent variables, such as the efficient method of moments (Gallant and Tauchen, 1996), the exact inversion likelihood approach in Chen and Scott (1993) and Pearson and Sun (1994), and the Kalman filter method. Duffee and Stanton (2012) compare these methods and conclude that the Kalman filter has superior finite-sample properties.

We apply the Kalman filter to the state-space representation of our model and estimate the model parameters by minimizing the sum of the squared errors between model-implied and observed prices of VIX futures:

$$SSE(\Theta) = \sum_t \sum_h (\widehat{f_t^h}(\Theta) - f_t^h)^2, \tag{5}$$

where the full parameter set $\Theta = \{K_0^P, K_1^P, K_0^Q, K_1^Q, \delta_0, \delta_1, \Sigma\}$.[8]

3.2 Estimation Results

Table 2 reports estimated parameters using short term VIX futures. The first volatility risk factor is highly persistent. It has an AR(1) efficient of 0.9784 under the physical measure and 0.9881 under the risk neutral measure. This is not entirely surprising as the first volatility risk factor is closely related to the level of the volatility. In contrast, the second and especially third volatility risk factors are much less persistent. For example, the AR(1) coefficient under the physical measure is 0.8324 and 0.3176 for the second and third risk factors, respectively. Moreover, the estimated Σ suggests that shocks to the first volatility factor are much more volatile than those to the other two factors (0.0294 vs 0.0033 and 0.0002).

Figure 3 assesses the model fit by comparing model implied prices with the counterparts from the data. Our model with three latent volatility risk factors prices short term VIX futures very well and is capable of replicating the time series patterns in futures prices across different maturities. The root mean squared error based on the log VIX futures prices

[8] Estimation of term structure models usually maximizes the log likelihood. If the measurement errors are normally distributed and constant across maturities, the likelihood simply scales the mean-squared error. For other cases, optimizing the likelihood and the mean squared error leads to very similar parameter estimates. To facilitate the identification of model with latent factors, we follow Joslin, Singleton, and Zhu (2011) and Joslin, Le, and Singleton (2013) using the time-series information of the state variables as the initial values in our numerical implementation.

is about 0.06 on average across all contracts in our sample.

Figure 4 plots the time series of the three latent volatility risk factors filtered from short term VIX futures. All three factors exhibit considerable variation over time. A noticeable period is the beginning of the COVID-19 pandemic when all three volatility factors show very large movements.

4 Return Predictability

In this section, we examine if the three volatility risk factors extracted from the term structure of short term VIX futures can predict subsequent VIX futures returns. We begin by computing the returns on VIX futures in Section 4.1 and present our main results on predictability in Sections 4.2 and 4.3. Section 4.4 contains further discussions.

4.1 Measuring VIX Futures Returns

We construct daily returns of a long position in VIX futures with a constant maturity of 7 days, 14 days, 21 days and 28 days. While there is considerable evidence for the returns on 1-month and other longer maturity VIX futures (see, among others, Eraker and Wu, 2017; Cheng, 2018), our paper is the first comprehensive study to document the returns associated with short term VIX futures. To maintain the constant maturity, we follow the literature and use a linear combination of two VIX futures that are adjacent to the target maturity. For example, suppose at time t one observes a sequence of futures contracts $F_t(T_1)$, $F_t(T_2)$, $F_t(T_3)$, ..., $F_t(T_J)$ that mature at time T_1, T_2, T_3, ..., T_J. We keep a constant maturity T^*, with $T_1 < T^* < T_2$, by adjusting the weights on the two nearby VIX futures ($F_t(T_1)$ and

$F_t(T_2)$) on daily basis according to:

$$w_1(T_1 - t) + w_2(T_2 - t) = T^*$$
$$w_1 + w_2 = 1$$

where w_1 is the weight on the front contract $F_t(T_1)$ and w_2 is the weight on the second contract $F_t(T_2)$. As time goes by, this portfolio invests less in the front contract $F_t(T_1)$ and more in $F_t(T_2)$. When w_1 reaches zero, $F_t(T_2)$ then becomes the front futures, $F_t(T_3)$ becomes the second contract, and the next rolling cycle begins. The sample for VIX futures returns starts from 31 July 2015.

Table 3 reports the summary statistics of VIX futures returns. On average a long position in 1-week VIX futures loses about 18 basis points per day, and the average return tends to increase with the maturity (i.e., becomes less negative), although the relationship is not strictly monotone. On the other hand, the standard deviation of futures returns monotonically decreases with maturity from 0.072 for 1-week VIX futures to 0.051 for 4-week VIX futures. Lastly, all VIX futures returns exhibit large positive skewness and kurtosis.

Figure 5 plots daily returns of these constant maturity strategies to better understand their time series properties. Holding VIX futures yields a loss in majority of the sample, but occasionally generates large positive returns when there is a large unexpected increase in the underlying VIX index. The largest positive return occurs on February 5, 2018 when the VIX index jumped more than 100% in a single day after a prolonged period of low volatility.[9] These findings are consistent with the notion that VIX futures are volatility insurance. Figure 5 also shows that VIX futures returns are highly correlated. The correlations of 1-

[9]The sudden rise in the VIX on February 5, 2018 resulted in huge losses for short volatility funds and led to the collapse of a high profile exchange traded product XIV, an event dubbed as "Volmageddon".

week VIX futures returns with 2-, 3-, and 4-week VIX futures returns are 0.96, 0.94, and 0.93, respectively.

4.2 Main Results

In this section, we study if the three volatility risk factors extracted from short term VIX futures in Section 3 can forecast VIX futures returns we compute in Section 4.1. We focus on the predictability of the returns of the VIX futures portfolio that maintains a constant maturity of two weeks and report the results for other maturities in the robustness section.[10] Moreover, we consider not only predicting next day realized returns but also long horizon returns, which are compounded from daily returns over the relevant horizon. The predictive regressions we estimated are given by:

$$\sum_{i=1}^{h} r_{t+i} = \alpha_{t+h} + \beta_{t+h} v_t + \epsilon_{t+h} \tag{6}$$

where r is the daily (log) return of VIX futures, h is the index for the return horizon ranging from 1 day to 8 weeks, and v_t denotes the three latent volatility risk factors extracted from short term VIX futures. We estimate these predictive regressions at the daily level using overlapping returns. The use of overlapping return observations generates serial correlation in the residuals and therefore we compute t-stats based on the standard error of Hansen and Hodrick (1980).

Table 4 reports the results for these predictive regressions. Panel A shows that the first volatility risk factor f_1 extracted from short term VIX futures is negatively related to subsequent VIX futures returns, but this relationship is not statistically significant. The first risk

[10] Griffin and Shams (2018) document evidence for the VIX manipulation on the settlement dates of VIX futures. This issue is only relevant for the 1-week portfolio where we sometimes hold a contract to maturity.

factor is closely related to the level of the volatility, and the insignificant relationship between $f1$ and VIX futures returns is puzzling because many existing models (see, among others, Heston, 1993) would suggest that risk premium is in proportion to the level of volatility. This result, however, is consistent with the finding in Johnson (2017) that the level factor extracted the term structure of the VIX does not have predictive power over future returns.

Panel B shows that the second risk factor f_2 is positively related to subsequent VIX futures returns. The relationship is statistically significant at the daily and weekly horizons with a t-stat of 2.36 and 1.96, respectively. The predictability, however, drops substantially and becomes insignificant for longer horizons.

Panel C shows that the third volatility risk factor f_3 extracted from short term VIX futures is also positively related to VIX futures returns. Similar to the second factor, f_3 is a short term return predictor in that it has substantial predictive power over daily and weekly returns. Moreover, compared to f_2, the predictive power of f_3 appears to be much stronger with larger t-stats and R^2. For example, the third volatility factor forecasts next day VIX futures return with a t-stat of 4.48 and an adjusted R^2 of 1.16%, whereas the corresponding numbers for f_2 are 2.36 and 0.28%.

4.3 Controlling for Other Variables

The previous section documents that the second and third volatility risk factors extracted from the term structure of short term VIX futures predict daily and weekly returns of VIX futures. In this section, we investigate if the predictive power of the two risk factors persists when controlling for a range of other variables that may forecast VIX futures returns.

We first consider the VIX index and the VVIX index. The VVIX index is a volatility of volatility index calculated from VIX options using the same approach underlying the VIX index. The VIX and VVIX indexes are natural candidates because volatility or volatility of volatility is usually the key driver of the volatility risk premium in many theoretical frameworks (e.g., Heston, 1993; Bollerslev, Tauchen, and Zhou, 2009). We obtain the data on the VIX and VVIX indexes from the CBOE website. We also control for a few measures of volatility and jump risks inferred from short term options on the S&P 500 index. Specifically we consider Left Tail Volatility (LTV) which is an estimate of return volatility generated by the left tail of the one-week risk-neutral return distribution of the S&P 500 index, Left Tail Probability ($Jump$) which is the corresponding probability of a 10% left tail event in one week, and Sport Volatility Index (SV) which is the spot return volatility obtained from the cross-section of short-dated out-of-the-money option prices. Existing studies (e.g., Bollerslev and Todorov, 2011; Bollerslev, Todorov, and Xu, 2015; Andersen, Fusari, and Todorov, 2015b,a, 2020; Andersen, Todorov, and Ubukata, 2020) find these risk measures have important asset pricing implications. We download the data on these variables from tailindex.com and the sample ends on December 31, 2019. Lastly, Johnson (2017) finds that the second principal component of the VIX term structure ($Slope$) contains predictive information about future returns on a range of volatility assets including VIX futures, and therefore we also include $Slope$ as an additional control. The data is downloaded from Travis Johnson's website and the sample ends on June 28, 2019.

Tables 5 reports the results. We focus on forecasting daily and weekly returns of VIX futures because Table 4 indicates that the two volatility risk factors are short term return predictors. To facilitate the interpretation of slope estimates, we standardize all the variables so that the coefficients can be directly compared. Panel A of Tables 5 shows the predictive power of f_2 is somewhat sensitive to empirical implementation. While it remains statistically significant when forecasting next day VIX futures return, f_2 does not forecast weekly returns when control variables are included. In contrast, Panel B shows that the third volatility risk factor remains a strong predictor of VIX futures returns with larger coefficients in the presence of all the control variables, and it is statistically significant across all specifications.

4.4 Discussion

Section 4.3 demonstrates that the third latent volatility factor we extract from short term VIX futures is a strong predictor of daily and weekly VIX futures returns and its predictive power is robust to controlling for a range of variables. To better understand the economic interpretation of the third latent factor, we link its dynamics to observable variables by estimating the following time series regression:

$$v_t = a_t + b_t x_t + e_t \tag{7}$$

where v is the latent volatility factor and x is the explanatory variable including the VIX, the VVIX, trading volume, and open interest. Table 6 reports the results. Columns (1) and (2) indicate that the VIX and VVIX indexes are significantly correlated with the latent volatility factor (f_3) we estimated from short term VIX futures with an adjusted R^2 of 49.89% and 34.71%. Column (3) shows that only a tiny fraction of the variation in f_3 can be related to trading volume in short term VIX futures. In contrast, column (4) shows that open interest is able to explain a non-trivial portion of the variation in f_3 with a R^2 of 22.54%.

We also use data on trader positions to gain further insight about the strong correlation between open interest and the third volatility risk factor. The CFTC releases a weekly Traders in Financial Futures report, which breaks down open interest positions in VIX futures into different trader groups: dealers, asset managers, leverage funds, other reportable traders, and non-reportable traders.[11] Columns (5) to (9) in Table 6 report the results for

[11] For additional details, see https://www.cftc.gov/sites/default/files/idc/groups/public/

weekly regressions of f_3 onto net exposures (long minus short positions) of different trader groups. The strong comovement between open interest and f_3, documented in column (4), is primarily due to the changes in trading positions from dealers and asset managers, with a R^2 of 12.02% and 14.75%.

Moreover, we repeat the same empirical exercise by extracting three volatility risk factors from two different samples. The first alternative sample considers the full term structure of VIX futures including both short term and longer maturity VIX futures contracts. The second alternative sample excludes newly introduced weekly VIX futures and focuses on standard monthly contracts.

Table 7 reports the predictability results when the third volatility risk factor is extracted from the two alternative samples. In both samples, we find the third volatility risk factor does not predict futures returns. This finding suggests that the use of weekly VIX futures is critical and this predictive information is embedded in the shape of the term structure of short term VIX futures.

5 Robustness

This section presents robustness results. We first investigate if the predictive power of the third volatility risk factor extracted from the term structure of short term VIX futures is robust to considering alternative methods of evaluating statistical significance. We also assess whether our findings hold for different futures contracts and return calculations.

@commitmentsoftraders/documents/file/tfmexplanatorynotes.pdf. Cheng (2018) uses the same dataset to argue that the low premium response puzzle is potentially due to a fall in hedging demand when risk rises.

5.1 Statistical Significance

Statistical inference for predictive regressions with overlapping returns is difficult. Our benchmark analysis reports t-stats using the Hansen and Hodrick (1980) standard error. In this section, we discuss alternative computations of t-stats. First, we consider Newey and West (1987) standard errors with lag length equal to the number of overlapping observations. We also use the standard error proposed in Hodrick (1992). The Hodrick standard error exploits covariance stationarity to remove the overlapping structure of the error terms and is guaranteed to be positive. Lastly, we adopt the scaled t-test in Hjalmarsson (2011), which demonstrates that rather than using autocorrelation robust standard errors, the standard t-statistic can simply be divided by the square root of the forecasting horizon to correct for the effects of the overlap in the data.

Table 8 reports on these alternative measures of statistical significance. For comparison we also include the baseline Hansen and Hodrick t-stats from Table 4. While the magnitudes of t-stats are somewhat different for different methods, the overall conclusion is consistent with our benchmark results. The third volatility risk factor extracted from short term VIX futures strongly predicts daily and weekly returns of VIX futures and this relationship is highly statistically significant.

We also conduct a finite sample analysis to show our findings are not driven by small sample biases. It is well known from the literature that the finite sample biases in predictive regressions strongly depend on the persistence of the predictor. When a predictor is highly persistent, not only the slope coefficients are biased (Stambaugh, 1999), the t-stats and R^2 are also biased and these biases are further compounded in long horizon regressions with overlapping returns (e.g., Kirby, 1997; Boudoukh, Israel, and Richardson, 2020). As we show in Section 3.2, the third volatility factor has low persistence and therefore it is not surprising that statistical biases are very small in our set-up.

5.2 Different Contracts and Return Calculations

Our main analysis focuses on the predictability of the returns on a VIX futures portfolio that maintains a constant two-week maturity. In this section, we first report the results for other constant maturity strategies discussed in Section 4.1. Moreover, in addition to predicting VIX futures portfolio returns, we also use the third volatility risk factor to predict returns on individual VIX futures contracts. In particular, we construct daily returns of holding VIX futures that are nearest to maturity, second nearest to maturity, and third nearest to maturity and we compound these daily returns to relevant horizon as in our main analysis.

Table 9 reports the results. Panels A to C contain the results for forecasting the returns of VIX futures portfolios that maintain a constant maturity of one week, three weeks, and four weeks, and Panels D to F report the corresponding results for forecasting returns on individual contracts. Table 9 confirms our baseline finding that that the third volatility risk factor extracted from short term VIX futures robustly predicts daily and weekly returns of VIX futures.

6 Conclusion

We show short term VIX futures contracts contain rich economic information about volatility risks and their pricing. We use a dynamic term structure model to extract three latent volatility risk factors from short term VIX futures. We find the second and third volatility risk factors can predict daily and weekly returns of VIX futures. The predictive power of the third volatility factor is particularly strong. It remains statistically significant when controlling for risk measures implied from short term index options and factors relating to the VIX term structure, is robust to considering alternative methods for evaluating statistical significance, and holds for different VIX futures and return calculation.

This paper can be extended in several ways. First, it may prove interesting to combine the information from short term VIX futures and short term index options to produce more powerful predictors. Second, we have focused on the predictability of VIX futures returns, and extensions to investigating the asset pricing implications on other assets would be useful. We plan to address these in future research.

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Table 1: Summary Statistics of Short Term VIX Futures

Maturity	Log Futures Prices				Avg Volume	Avg Open Interest	No. of Obs.
	Mean	St.Dev	Skewness	Kurtosis			
Within 7 days	2.8437	0.3371	0.8727	4.0807	23982	15778	1621
7-14 days	2.8638	0.3183	0.8417	4.0129	25994	30319	1625
14-21 days	2.8808	0.3063	0.8605	4.0277	26043	38369	1625
21-28 days	2.8960	0.2984	0.8567	3.9892	26592	45764	1957
28-35 days	2.9103	0.2901	0.8459	3.8535	27261	48530	1601
35-42 days	2.9202	0.2849	0.8419	3.7224	27371	45857	1456

Notes: This table presents the summary statistics for the log VIX futures prices from July 23 2015 to December 31 2021. We use the closing prices of VIX futures on each trading day for maturities within 42 days. We present sample mean, standard deviation, skewness, kurtosis, average trading volume, average open interest, and number of observations for six different maturity groups.

Table 2: Parameter Estimates

K_0^P	K_1^P			δ_0		δ_1
0.1049	0.9784	-0.1439	0.9853	-0.0001		0.6062
0.0492	-0.0070	0.8324	1.8480			1.5237
-0.0013	-0.0023	0.0349	0.3176			0.4943
K_0^Q	K_1^Q			Σ		
0.0528	0.9881	-0.0454	-0.0357	0.0294		
0.0216	-0.0047	0.9183	0.3407	-0.0007	0.0033	
0.0000	-0.0066	0.0973	0.0858	-0.0008	-0.0044	0.0002

Notes: This table presents the estimated parameters for the no-arbitrage term structure model with three latent risk factors using short term VIX futures. The sample period is from July 23 2015 to December 31 2021.

Table 3: Descriptive Statistics of VIX Futures Returns

Maturity (days)	Obs	Mean	Std	Skew	Kurt
7	1619	-0.00185	0.0723	3.7823	41.1322
14	1619	-0.00153	0.0632	3.9951	48.7259
21	1619	-0.00179	0.0551	2.9303	27.3409
28	1619	-0.00118	0.0510	2.7772	23.9573

Notes: This table reports mean, standard deviation (Std), skewness (Skew) and kurtosis (Kurt) of daily returns of a long position in VIX futures with a constant maturity of 7, 14, 21, and 28 days.

Table 4: Predicting VIX Futures Returns

Panel A: f_1							
Horizon	1d	1w	2w	3w	4w	6w	8w
Slope	-0.00	-0.01	-0.02	-0.04	-0.05	-0.07	-0.08
t	(-1.76)	(-1.67)	(-1.62)	(-1.64)	(-1.66)	(-1.67)	(-1.64)
R^2	0.15%	0.72%	1.48%	2.35%	3.12%	4.55%	5.71%
Panel B: f_2							
Horizon	1d	1w	2w	3w	4w	6w	8w
Slope	0.02	0.08	0.14	0.21	0.28	0.38	0.48
t	(2.36)	(1.96)	(1.76)	(1.80)	(1.81)	(1.73)	(1.68)
R^2	0.28%	0.99%	1.69%	2.72%	3.54%	4.64%	5.71%
Panel C: f_3							
Horizon	1d	1w	2w	3w	4w	6w	8w
Slope	0.49	1.15	1.78	2.56	3.40	4.60	5.65
t	(4.48)	(2.48)	(1.90)	(1.83)	(1.87)	(1.77)	(1.68)
R^2	1.16%	1.41%	1.68%	2.34%	3.17%	4.04%	4.73%

Notes: This table reports the results for the predictive regressions of VIX futures returns against the three volatility risk factors extracted from short term VIX futures (f_1, f_2, and f_3). The t-stats are based on Hansen and Hodrick (1980) standard error.

Table 5: Predicting VIX Futures Returns: Controlling for Other Variables

Panel A: f_2

	Daily						Weekly					
f_2	0.08	0.06	0.08	0.09	0.08	0.10	0.12	0.08	0.10	0.05	0.09	0.10
	(2.37)	(2.05)	(2.62)	(2.28)	(2.54)	(2.59)	(1.71)	(1.28)	(1.52)	(0.65)	(1.41)	(1.31)
VIX	0.04						0.03					
	(1.00)						(0.43)					
$VVIX$		0.01						-0.04				
		(0.23)						(-0.59)				
LTV			-0.01						-0.04			
			(-0.27)						(-0.64)			
$Jump$				0.02						-0.06		
				(0.55)						(-0.71)		
SV					-0.00						-0.02	
					(-0.01)						(-0.34)	
$Slope$						0.04						0.02
						(0.92)						(0.28)
R^2	0.28%	0.22%	0.44%	0.46%	0.44%	0.52%	0.97%	1.01%	0.89%	0.94%	0.80%	0.66%

Panel B: f_3

	Daily						Weekly					
f_3	0.19	0.14	0.15	0.19	0.16	0.18	0.16	0.11	0.14	0.13	0.14	0.16
	(5.41)	(4.69)	(5.11)	(5.27)	(5.10)	(5.18)	(2.55)	(1.90)	(2.63)	(2.27)	(2.62)	(2.74)
VIX	0.11						0.06					
	(3.17)						(0.85)					
$VVIX$		0.06						-0.02				
		(1.83)						(-0.29)				
LTV			0.01						-0.02			
			(0.34)						(-0.36)			
$Jump$				0.07						-0.02		
				(1.90)						(-0.31)		
SV					0.02						-0.01	
					(0.62)						(-0.15)	
$Slope$						0.05						0.02
						(1.35)						(0.36)
R^2	1.71%	1.31%	2.12%	2.43%	2.15%	2.49%	1.52%	1.37%	1.94%	1.93%	1.90%	2.11%

Notes: This table reports the results for VIX futures return predictive regressions with the second and third volatility risk factors extracted from short term VIX futures, controlling for a range of existing variables. For control variables, we consider the VIX index (VIX), the VVIX index ($VVIX$), several risk measures implied from short term index options (LTV, $Jump$, and SV), and the slope factor of Johnson (2017). The t-stats based on Hansen and Hodrick (1980) standard error are reported in brackets.

Table 6: Explaining the Third Latent Volatility Factor

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VIX	-0.71								
	(-40.21)								
$VVIX$		-0.59							
		(-29.39)							
$Volume$			0.20						
			(8.38)						
$OpenInterest$				0.48					
				(21.75)					
$Dealers$					0.35				
					(6.84)				
$AssetMgrs$						-0.38			
						(-7.68)			
Lev_{Money}							-0.16		
							(-2.91)		
$Other_{Rept}$								0.29	
								(5.57)	
$NonRept$									0.08
									(-1.44)
VIX	49.89%	34.71%	4.09%	22.54%	12.02%	14.75%	2.17%	8.23%	0.32%

Notes: This table reports results for regressions of the third volatility risk factor onto explanatory variables including the VIX, the VVIX, trading volume and open interest in short term VIX futures, and net positions of different trader groups. Columns (1) to (4) are based on daily regressions and columns (5) to (9) are based on weekly regressions.

Table 7: Predicting VIX Futures Returns: Extracting Volatility Factors From Alternative Samples

Panel A: Using All VIX Futures							
Horizon	1d	1w	2w	3w	4w	6w	8w
Slope	-0.00	-0.06	-0.14	-0.20	-0.28	-0.43	-0.55
t	(-0.41)	(-1.66)	(-1.97)	(-1.97)	(-2.07)	(-2.24)	(-2.25)
R^2	-0.05%	0.67%	2.04%	3.03%	4.22%	6.97%	8.85%
Panel B: Using Standard Monthly VIX Futures							
Horizon	1d	1w	2w	3w	4w	6w	8w
Slope	0.00	-0.01	-0.03	-0.03	-0.06	-0.11	-0.15
t	(0.87)	(-0.44)	(-0.60)	(-0.47)	(-0.78)	(-1.12)	(-1.19)
R^2	-0.02%	-0.02%	0.09%	0.06%	0.33%	0.96%	1.30%

Notes: This table reports the results for predictive regressions where the three latent volatility risk factors are estimated from two alternative samples. Panel A reports on the sample that includes all VIX futures (both short term and long maturity contracts) and Panel B reports on the sample that excludes all weekly VIX futures.

Table 8: Robustness: Statistical Significance

Horizon	1d	1w	2w	3w	4w	6w	8w
Slope	0.49	1.15	1.78	2.56	3.40	4.60	5.65
HH	(4.48)	(2.48)	(1.90)	(1.83)	(1.87)	(1.77)	(1.68)
NW	(3.49)	(2.69)	(2.92)	(2.93)	(2.91)	(2.76)	(2.65)
Hodrick	(3.31)	(2.29)	(1.77)	(1.68)	(1.70)	(1.53)	(1.40)
Scaled t	(4.48)	(2.45)	(1.78)	(1.68)	(1.68)	(1.53)	(1.43)
R^2	1.16%	1.41%	1.68%	2.34%	3.17%	4.04%	4.73%

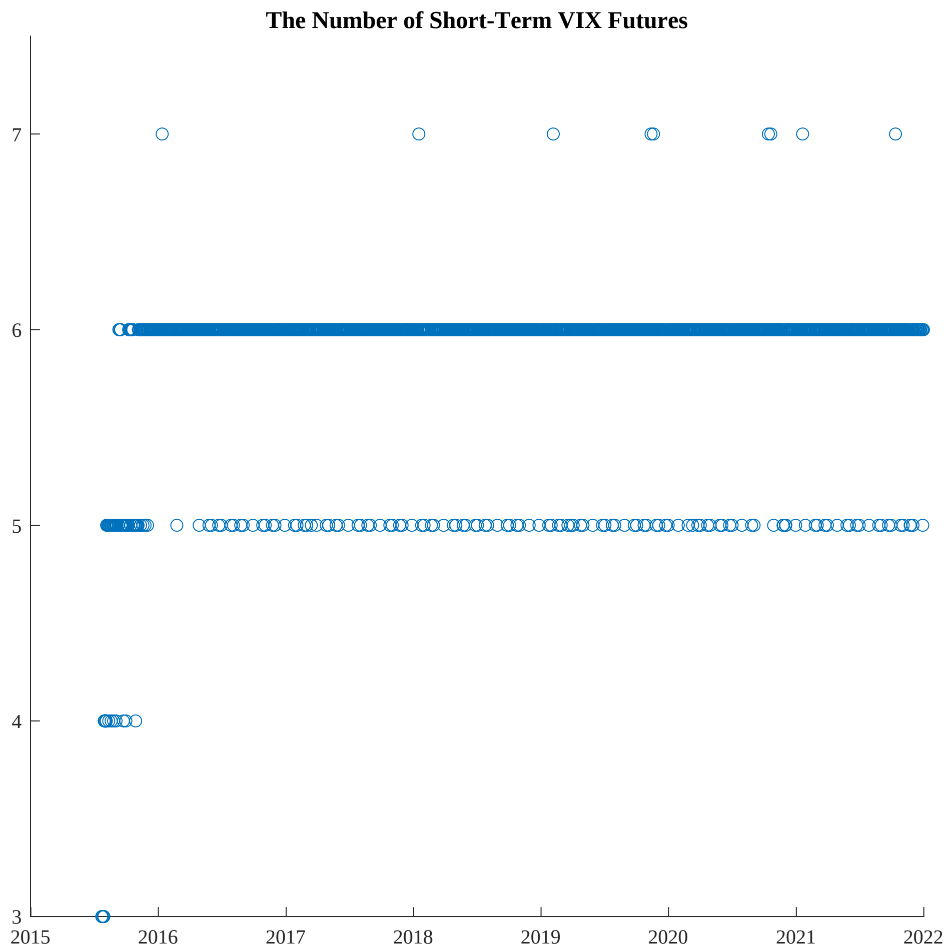
Notes: This table reports on the statistical significance of VIX futures return predictability regression with the third volatility risk factor implied from short term VIX futures. We consider Hansen and Hodrick (1980) (HH), Newey and West (1987) (NW), Hodrick (1992) standard errors and the scaled t-stat in Hjalmarsson (2011).

Table 9: Robustness: Alternative Returns

Panel A: Constant Maturity Strategy One Week							
Horizon	1d	1w	2w	3w	4w	6w	8w
Slope	0.44	1.16	1.92	2.94	4.00	5.71	7.30
t	(3.47)	(2.10)	(1.71)	(1.72)	(1.79)	(1.76)	(1.72)
R^2	0.68%	1.01%	1.38%	2.14%	3.01%	4.12%	5.18%
Panel B: Constant Maturity Strategy Three Weeks							
Horizon	1d	1w	2w	3w	4w	6w	8w
Slope	0.43	1.05	1.65	2.38	3.11	4.15	5.05
t	(4.32)	(2.55)	(1.97)	(1.89)	(1.89)	(1.76)	(1.68)
R^2	1.08%	1.50%	1.85%	2.55%	3.31%	4.06%	4.69%
Panel C: Constant Maturity Strategy Four Weeks							
Horizon	1d	1w	2w	3w	4w	6w	8w
Slope	0.38	0.98	1.55	2.23	2.96	3.99	4.90
t	(4.16)	(2.59)	(1.99)	(1.89)	(1.93)	(1.81)	(1.74)
R^2	1.00%	1.55%	1.91%	2.60%	3.45%	4.32%	5.07%
Panel D: Nearest to Maturity Contract							
Horizon	1d	1w	2w	3w	4w	6w	8w
Slope	0.45	1.13	1.85	2.78	3.82	5.52	7.18
t	(3.49)	(1.99)	(1.56)	(1.53)	(1.59)	(1.60)	(1.61)
R^2	0.68%	0.89%	1.14%	1.69%	2.36%	3.32%	4.36%
Panel E: Second Nearest to Maturity Contract							
Horizon	1d	1w	2w	3w	4w	6w	8w
Slope	0.45	1.08	1.74	2.55	3.47	4.85	5.89
t	(3.96)	(2.29)	(1.84)	(1.82)	(1.88)	(1.85)	(1.76)
R^2	0.89%	1.16%	1.51%	2.21%	3.12%	4.26%	4.96%
Panel F: Third Nearest to Maturity Contract							
Horizon	1d	1w	2w	3w	4w	6w	8w
Slope	0.52	1.13	1.72	2.41	3.17	4.29	5.06
t	(5.03)	(2.74)	(2.07)	(1.95)	(1.95)	(1.86)	(1.72)
R^2	1.48%	1.68%	1.94%	2.59%	3.40%	4.32%	4.74%

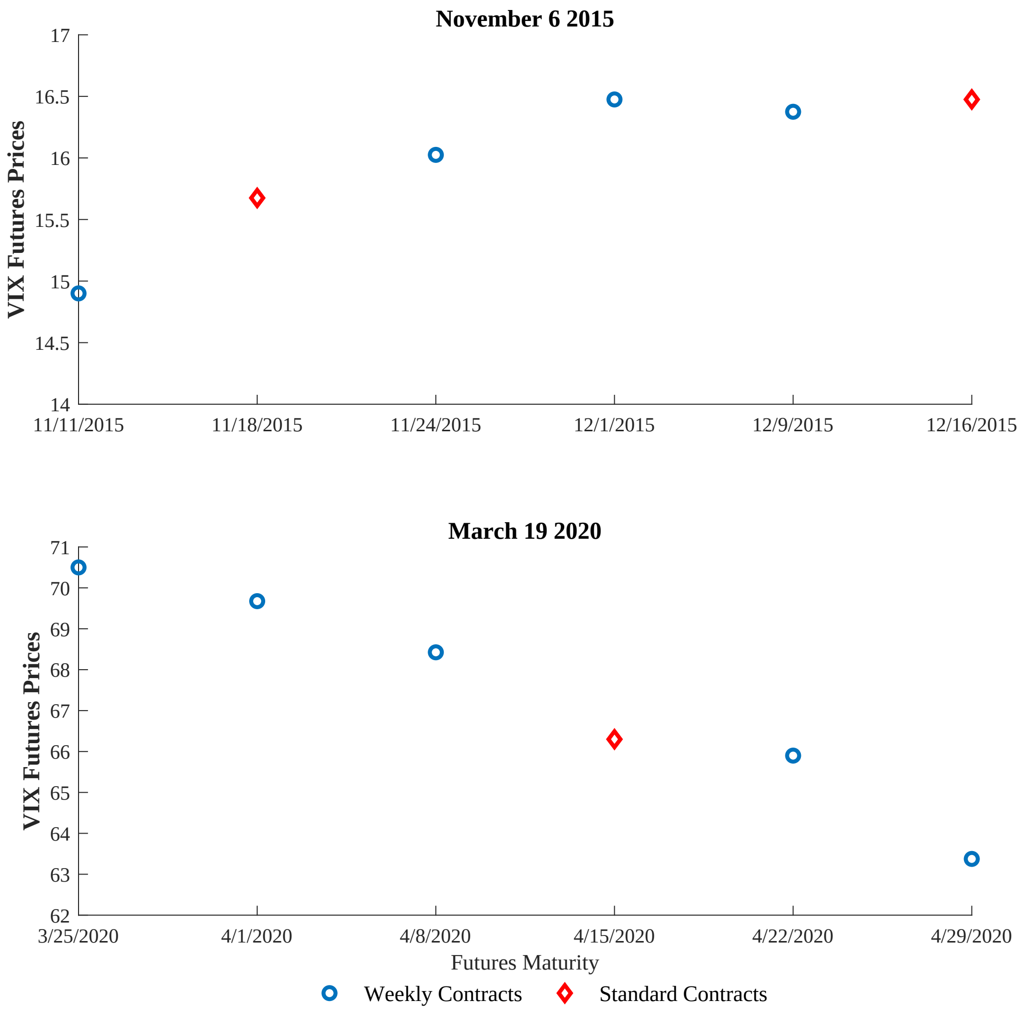
Notes: This table reports the results for predictive regressions of different VIX futures returns on the third volatility risk factor extracted from short term VIX futures. We consider forecasting the returns of VIX futures portfolios that maintain a constant maturity of one week, three weeks, and four weeks (Panels A to C) as well as forecasting returns on individual contracts (Panels D to F).

Figure 1: Daily Number of Short Term VIX Futures



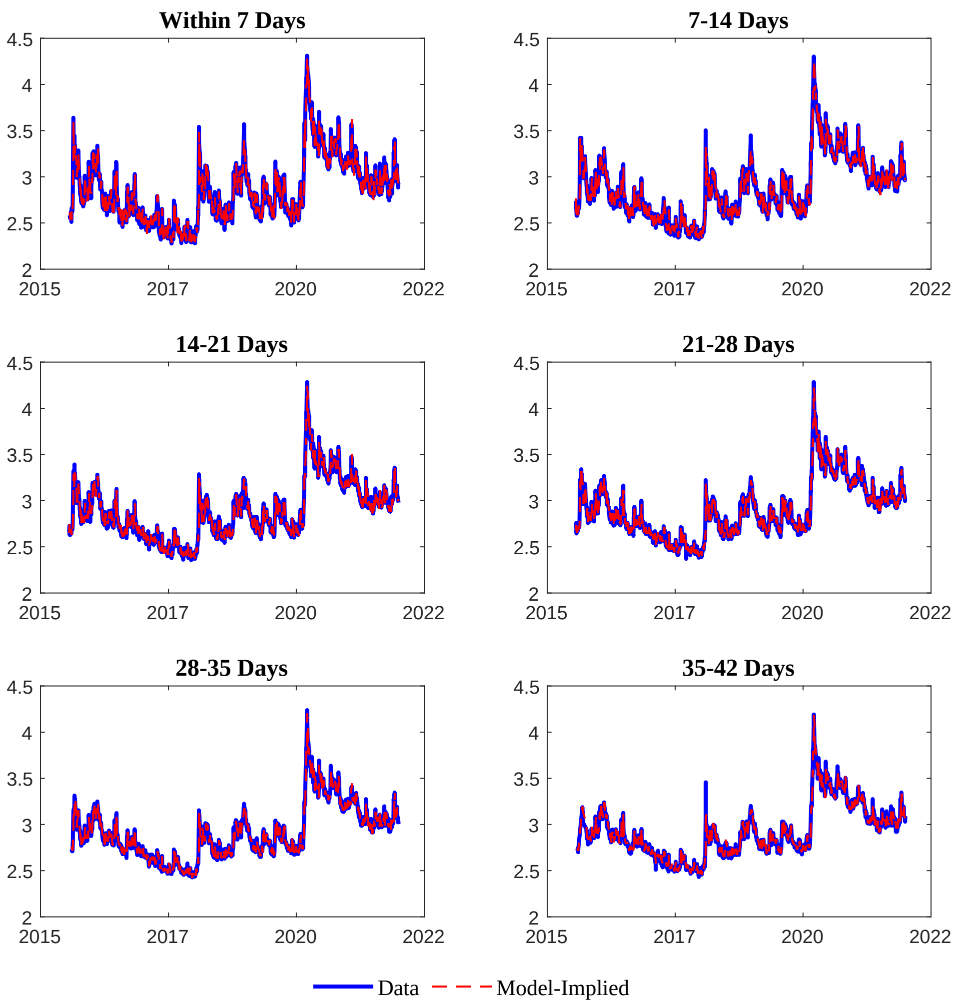
Notes: This figure plots the daily number of short term VIX futures with a maturity less than six weeks. Sample period: July 23, 2015 to 31 December 2021.

Figure 2: The Term Structure of Short Term VIX Futures



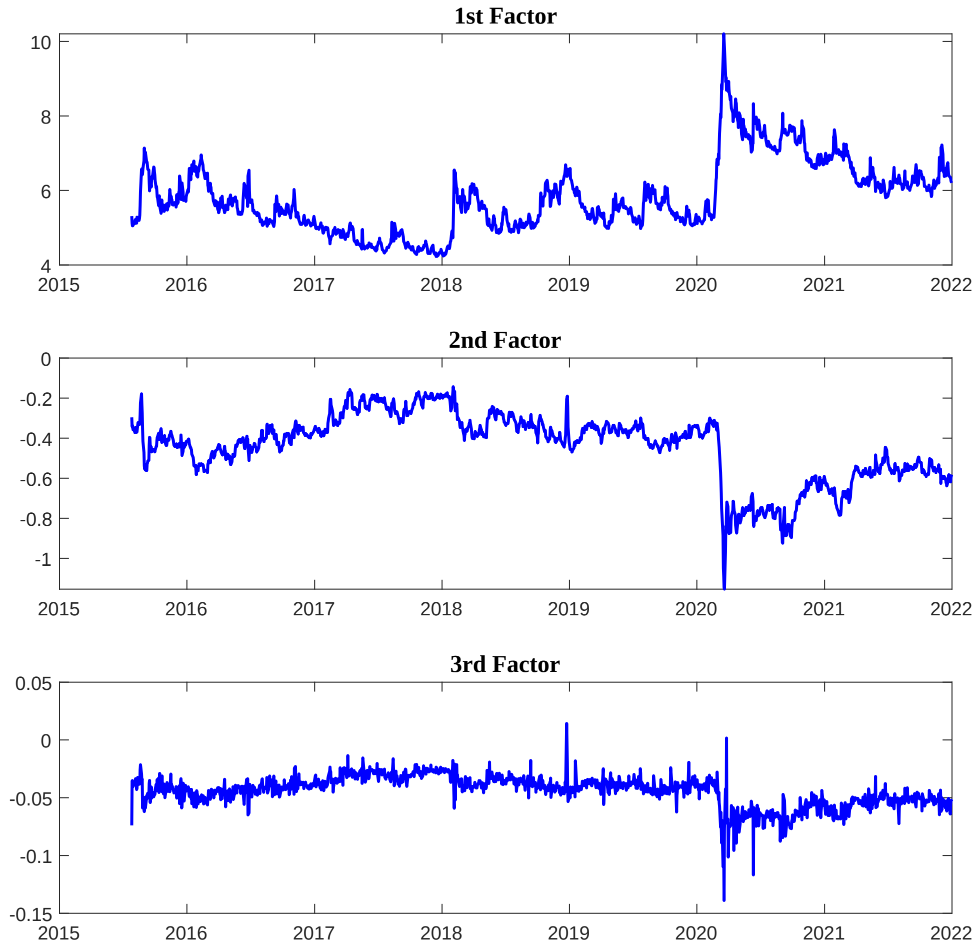
Notes: This figure plots the term structure of short term VIX futures observed on November 6 2015 and March 19 2020.

Figure 3: Model Fit



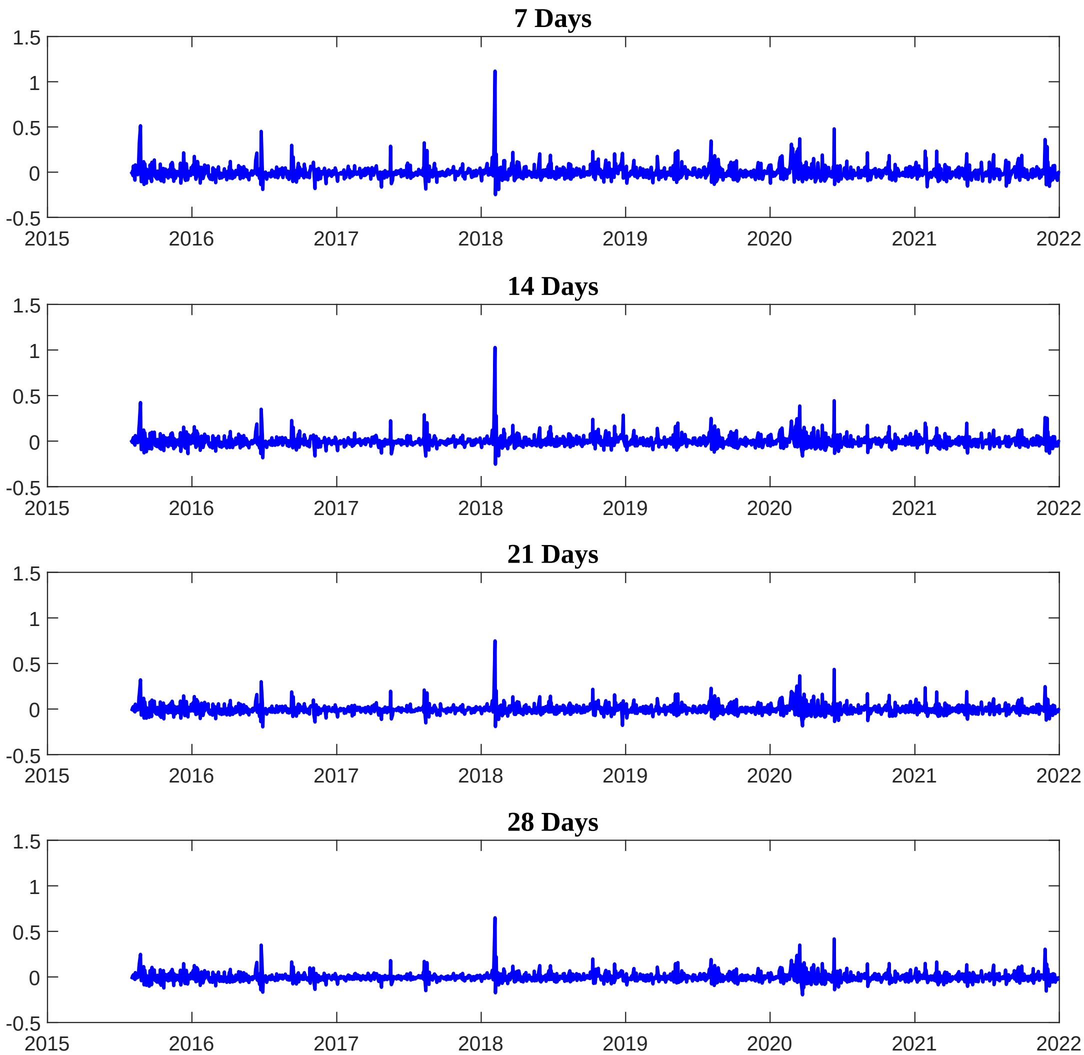
Notes: This figure plots the model-implied log VIX futures prices and the counterparts from the data. The solid line (blue) represents the data. The dashed line (red) represents the model-implied log VIX futures prices. We plot the results for six different maturity groups. The sample period is from July 23 2015 to December 31 2021.

Figure 4: Volatility Risk Factors



Notes: This figure plots the three latent volatility risk factors filtered from short term VIX futures. The sample period is from July 23 2015 to December 31 2021.

Figure 5: Daily Returns of Constant Maturity VIX Futures Strategies



Notes: This figure plots daily returns of a long position in VIX portfolios that maintain a constant maturity of 1, 2, 3, and 4 weeks.