Free (Almost) Variance Insurance *

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Abstract

The expected returns of short maturity options are large and negative, implying a negative variance risk premium. We find that the magnitude of this negative risk premium is monotonically decreasing with option maturity. The risk premium becomes insignificant for maturities beyond 6 months and the cost to insure the variance risk using long maturity options is 6 *bps* per month. In the context of a classical asset pricing model, this pattern suggests that variance betas should also be declining with maturity because the risk premium is proportional to the factor loading. However, variance betas are increasing with option maturity, challenging a one-factor model of the variance risk. A one-factor model of the short-term variance risk (*level*) fails to explain the cross-section of option returns and is forcefully rejected by asset pricing tests. We identify a *slope* factor in the term structure of risk neutral variances and find it crucial in explaining the cross section of option returns. The *slope* and *level* factors combined explain over 90% of the option return variations.

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1 Introduction

The volatility of stock returns is uncertain and options pay off when the volatility rises, offering a hedge against this volatility risk. Therefore, investors are willing to pay a premium to hold options and there is ample evidence documenting this negative volatility risk premium. The Black-Scholes implied volatilities of options are systematically higher than realized volatilities (Jackwerth and Rubinstein (1996)). The expected return of short-maturity index options is about -3% per week (Coval and Shumway (2001)), providing strong evidence of this negative volatility risk premium. Bakshi and Kapadia (2003) formalizes the intuition of using delta-hedged option gains to measure the volatility risk premium and also provides empirical support of a negative volatility risk premium. Carr and Wu (2009) compares the prices of synthetic variance swaps with realized variance to quantify the magnitude of the variance risk premium of both indices and individual stocks[1]. The stylized facts are expected option returns are large and negative, indicating a negative variance risk premium.

In a mainstream asset pricing model, the risk premium is determined by the factor risk premium and factor loading. Given a negative variance risk premium, options with higher variance beta should earn more negative returns. The variance beta is increasing with option maturity because long maturity options are more sensitive to the change of the variance. For instance, the first derivative of option price with respect to volatility (vega) is approximately proportional to the square root of maturity in both the Black-Scholes model and a stochastic volatility model (Hull and White (1987)). We focus on returns of delta hedged portfolios and this sensitivity is somewhat attenuated by the gains and losses from hedging. Overall, a long-maturity option still has a higher variance beta and empirically the variance beta is monotonically increasing with option maturity. As a result, the magnitude of the risk premium should be larger for options with longer maturity.

We test this prediction by examining index option returns across maturities and we find that the magnitude of option return is monotonically decreasing with option maturity. For the S&P 500 index (SPX), only the two shortest maturity options display a significantly negative average return. For SPX options of longer than 6 months till expiration, the expected returns are indistinguishable from 0 and the options of longer than 12-month maturity on average return -0.06% (6 *bps*) per month. The same holds true for other indices and in some occasions the long term option mean returns are even positive[2]. This is in sharp con-

[1]In principle, the variance risk premium is different from the volatility risk premium, although the two are very closely related. We are not making a particular distinction of the two in this study.

[2]A similar pattern is documented in currency options as in Low and Zhang (2005).

trast with the significantly negative expected returns found in short-maturity options. Jones (2006) finds that the negative returns of short maturity options are too large to be explained by the variance risk. While at the other end of the maturity spectrum, we document that the returns of long maturity options are too small to be consistent with the variance risk premium and long maturity contracts essentially provide investors with free insurance against the variance risk. More importantly, options with higher variance beta consistently earn less negative risk premium just as the growth portfolios have higher CAPM beta but earn lower returns (Fama and French (1993) and many others).

We find that the discrepancy comes from the one-factor structure of the variance risk premium. Following the VIX calculation methodology[3] and Carr and Wu (2009), we compute the risk neutral variances at 30-day and 365-day maturities. Besides the well documented 30-day short-term variance (level), we construct a slope factor as the difference between the 365-day and 30-day risk neutral variances. Using the delta-hedged options on 4 major indices as test assets, we estimate the risk premia of both the level and slope factors under the stochastic discount factor framework, as advocated by Cochrane (2005). The short-term level factor is important and negatively priced as documented in the existing literature (Ang, Hodrick, Xing, and Zhang (2006), Carr and Wu (2009)). However, the level factor by itself does not account for any cross-section variation of the expected option returns. Naturally, this one factor model is forcefully rejected by the over-identifying restriction in the GMM test (Hansen and Singleton (1982)). The slope factor is far more important than the level factor in explaining the return spreads between different options.

The two factors collectively explain majority of the cross-section variation and the GMM test fails to reject the model at all conventional levels. The level and slope factors are constructed using options on the proxy of the market portfolio at 2 maturities and yet explain the returns of options written on all assets across all maturities. We also assess the economic significance of both factors. The risk premium for the level factor is −1.4% per month and that of the slope factor is larger in magnitude, 1.5% per month. Long-term options load positively on the slope factor, whereas the loadings of short-term options on the slope factor are insignificant. This explains the upward sloping term structure of expected option returns. Overall, long-term options have high factor loadings on both the level and slope factors which approximately offset each other and thus earn close to 0 returns.

Our approach complements the existing literature on the variance risk premia. The variance risk premium in options has been estimated either as the difference between the

[3] http://www.cboe.com/micro/vix/vixwhite.pdf

risk neutral variance and the realized variance (Carr and Wu (2009), Bollerslev, Tauchen, and Zhou (2009)), or as a parameter in the parameter space that minimizes the option pricing errors (Bates (2000), Pan (2002)). Our asset pricing approach helps to identify common risk factors in option markets and facilitates comparison with other classical risk factors in the asset pricing literature. We can also directly asses the economic significance of the variance risk premia and test the importance of a factor with the presence of other factors. It is well known that the option payoff is skewed and leptokurtic, which favors our GMM approach because the GMM does not impose any distributional assumptions. Moreover, under the SDF framework, we can use a a straightforward metric to distinguish different models of the variance risk premium. A one-factor model of the volatility risk premium is rejected by the the GMM J-test while our two-factor model does pass the test.

The slope factor is related to several recent studies that show the advantage of a two-component model of volatility[4]. Bates (2000) and Xu and Taylor (1994) study the implications of two-factor stochastic volatility models for option pricing. Christoffersen, Jacobs, Ornthanalai, and Wang (2008) proposes a two-component model, one short-term and one long-term, and shows that the model better fits the option prices. Egloff, Leippold, and Wu (2010) also finds the two-component volatility model better explains the variance swap rates at different maturities. Our proposed slope factor proxies the difference between the long- and short-term variance in those models. And we further show that the slope factor is not only helping to reduce option pricing errors but indispensable in explaining expected option returns. We propose the two-factor model because it is unequivocally favored by traditional asset pricing measures. It is imperative to make the distinction because mis-specifying the two-factor model as a one-factor model leads to large welfare loss for investors (Zhou and Zhu (2012)).

We further investigate the economic content of the slope factor. Adrian and Rosenberg (2008) finds that the long-term volatility estimated using stock returns forecasts macroeconomic conditions. Consistent with their findings, the slope factor of the risk neutral variances also predicts the output of the industrial sector of the economy. This result is reminiscent of the slope of the yield curve forecasting macroeconomic activity (Harvey (1988), Estrella and Hardouvelis (1991)). As a result, the slope factor should be positively priced by the intertemporal capital asset pricing (ICAPM) intuition. Moreover, the dynamics of the slope factor is also examined by expectation hypothesis regressions. We first form portfolios of

[4] There is also a vast literature that shows two-factor volatility models better describe the dynamics of the stock return and foreign exchange rate volatilities, including but not limited to Alizadeh, Brandt, and Diebold (2002), Bollerslev and Zhou (2002), Chacko and Viceira (2003), Chernov, Gallant, Ghysels, and Tauchen (2003), and Brandt and Jones (2006).

buying long-maturity straddles and shorting short-maturity straddles, both delta-hedged and regress the returns of this portfolio on the lagged slope factor. This specification mimics the regression of long bond excess return on yield spreads in the fixed income literature.[5] Under the null hypothesis of a constant slope premium, the coefficient should be 0. This null hypothesis is strongly rejected for options on all 4 major indices across various long maturities. All point estimates are negative and the average monthly non-overlapping R^2 is above 10%.

Liu and Pan (2003) shows that in a one-factor stochastic volatility model an investor's optimal portfolio includes a short position in options. In the presence of a second volatility factors, the optimal portfolio is shown to contain a long position in the long-term variance contract and a short position in the short-term variance contract (Egloff, Leippold, and Wu (2010), Zhou and Zhu (2012)). The strategy is equivalent to buying (delta-hedged) long-maturity options and shorting (delta-hedged) short-maturity options, also know as the calendar spread. Our results provide empirical evidence for the optimal option portfolio allocation and hedging volatility risk. The calendar spread positively loads on the slope factor and offers investors an attractive risk and return trade off, generating an annualized Sharpe ratio of 1.2. More importantly, this strategy is not exposed to the sudden crashes because the strategy also loads positively on the short-term level factor. The largest monthly loss suffered was -3% and the overall realized skewness is positive.

Our paper relates to the burgeoning literature that examines expected option returns in the asset pricing framework. Goyal and Saretto (2009), and Cao and Han (2012) both document a large volatility premium in the cross-section of individual stock options. We focus on expected index option returns across maturities and stress the importance of a two-factor model for the volatility risk premium. Broadie, Chernov, and Johannes (2009) raises some concerns about option returns using only unhedged put options because of sampling problems and the impact of the underlying asset. We follow their suggestions by mainly examining delta-hedged option straddle returns, which alleviates the sampling problem. And our main results are robust to the choice of call, put, or straddle options.

In the next section, we present the basic framework. In section 3, we introduce the data and present basic properties of the index options. In Section 4, we detail the calculations of delta-hedged option portfolio returns and the risk neutral variance. Section 5 presents the main results and Section 6 concludes.

[5]For example, Keim and Stambaugh (1986) and Fama and French (1989).

2 Framework

In this section, we present the theoretical framework under which we analyze the relation between the delta hedged option returns with the variance risk premium. The framework naturally generalizes the analysis in Bakshi and Kapadia (2003) to allow the stock return variance to be driven by a set of state variables.

2.1 Model Setup

Assume that the price dynamics in which the return volatility is stochastic,

$$\frac{dS_t}{S_t} = \mu_t^s(S_t, \sigma_t)dt + \sigma_t dW_t, \tag{1}$$

and the volatility is driven by a set of state variables under the physical measure,

$$\begin{aligned} dX_t &= \mu_t^X(X_t)dt + \Sigma_X(X)dB_t && (2)\\ \sigma_t &= b'X_t && (3)\\ d\sigma_t &= b'\mu_t^X(X_t)dt + b'\Sigma_X(X)dB_t && (4) \end{aligned}$$

where $\mu^X(X_t), b \in \mathbb{R}^k$, B_t denotes a k-dimensional Brownian motion with $\Sigma_X(X)\Sigma_X(X)'$ being positive definite and symmetric, and $\rho \in \mathbb{R}^k$ denotes the correlation between dW_t, and dB_t. Note that we can derive the dynamics of the variance by letting $v_t = \sigma_t^2$ and applying Ito's lemma,

$$dv_t = (2\sigma_t b'\mu_t^X(X_t) + b'\Sigma_X(X)\Sigma_X(X)'b)dt + 2\sigma_t b'\Sigma_X(X)dB_t. \tag{5}$$

It is clear that the volatility and variance are driven by the same set of state variables and therefore we will not particularly distinguish the volatility and variance risk premia.

2.2 Delta Hedging Gains

Following Bakshi and Kapadia (2003),

$$C_{t+\tau} = C_t + \int_t^{t+\tau} \frac{\partial C_u}{\partial S_u}du + \int_t^{t+\tau} \frac{\partial C_u}{\partial \sigma_u}d\sigma_u + \int_t^{t+\tau} b_u du, \tag{6}$$

where $b_u = \frac{\partial C_u}{\partial u} + \frac{1}{2}\sigma_u^2 S_u^2 \frac{\partial^2 C_u}{\partial S_u^2} + \frac{1}{2} b' \Sigma_X(X)\Sigma_X(X)' b \frac{\partial^2 C_u}{\partial \sigma_u^2} + b'\Sigma_X(X)\rho\sigma_u S_u \frac{\partial^2 C_u}{\partial S_u \partial \sigma_u}$.

The valuation equation for the call option is

$$\frac{1}{2}\sigma^2 S^2 \frac{\partial^2 C}{\partial S^2} + \frac{1}{2} b'\Sigma_X(X)\Sigma_X(X)' b \frac{\partial^2 C}{\partial \sigma^2} + b'\Sigma_X(X)\rho\sigma S \frac{\partial^2 C}{\partial S \partial \sigma} + rS\frac{\partial C}{\partial S} \\ + b'(\mu_t^X(X_t) - \gamma(X_t))\frac{\partial C}{\partial \sigma} + \frac{\partial C}{\partial t} - rC = 0, \tag{7}$$

where $\gamma(X_t) \equiv -\mathrm{Cov}(\frac{dm_t}{m_t}, dX_t)$ and measures the risk premium of the k-dimensional Brownian motion. Rearranging the above equation and we have

$$b_u = r(C_u - S_u \frac{\partial C_u}{\partial S_u}) - b'(\mu_u^X(X_u) - \gamma(X_u))\frac{\partial C_u}{\partial \sigma_u} \tag{8}$$

Substitute this into (6), we have

$$\begin{aligned} C_{t+\tau} &= C_t + \int_t^{t+\tau} \frac{\partial C_u}{\partial S_u} du + \int_t^{t+\tau} \frac{\partial C_u}{\partial \sigma_u} d\sigma_u \\ &+ \int_t^{t+\tau} (r(C_u - S_u \frac{\partial C_u}{\partial S_u}) - b'(\mu_u^X(X_u) - \gamma(X_u))\frac{\partial C_u}{\partial \sigma_u}) du, \end{aligned} \tag{9}$$

We further express the $d\sigma$ as in equation (4) and obtain

$$\begin{aligned} C_{t+\tau} &= C_t + \int_t^{t+\tau} \frac{\partial C_u}{\partial S_u} du + \int_t^{t+\tau} r(C_u - S_u \frac{\partial C_u}{\partial S_u}) du \\ &+ \int_t^{t+\tau} b'\gamma(X_u) \frac{\partial C_u}{\partial \sigma_u} du + \int_t^{t+\tau} b'\Sigma_X(X) \frac{\partial C_u}{\partial \sigma_u} dB_t, \end{aligned} \tag{10}$$

therefore the delta hedged gain $\Pi_{t,t+\tau}$ can be written as

$$\begin{aligned} \Pi_{t,t+\tau} &= C_{t+\tau} - C_t - \int_t^{t+\tau} \frac{\partial C_u}{\partial S_u} du - \int_t^{t+\tau} r(C_u - S_u \frac{\partial C_u}{\partial S_u}) du \\ &= \int_t^{t+\tau} b'\gamma(X_u) \frac{\partial C_u}{\partial \sigma_u} du + \int_t^{t+\tau} b'\Sigma_X(X) \frac{\partial C_u}{\partial \sigma_u} dB_t, \end{aligned} \tag{11}$$

The expected gain is

$$\mathbb{E}[\Pi_{t,t+\tau}] = \int_t^{t+\tau} E[b'\gamma(X_u)\frac{\partial C_u}{\partial \sigma_u}] du. \tag{12}$$

Similar to the findings in Bakshi and Kapadia (2003), the delta hedged gain is equal to the sum of the risk premia of all state variables that drive the volatility (variance). The general setup, however, does not directly identify the relevant factors. And our aim is not to estimate a parameterized version of the model but to establish that the delta-hedged option gains could relate to multiple factors. This allows for more complex structures in the variance risk premium and expected option returns.

3 Data

Our options data are from OptionMetrics, for the sample period between January 1996 and December 2011, a total of 192 months. We filter out the daily closing prices (by the average of best bid and offer) of options on 4 major indices, S&P 500 (SPX), NASDAQ Composite (NDX), Dow Jones Industrial Average (DJX), and S&P 100 (OEX), and drop the observations in which option prices violate the no-arbitrage bounds. The DJX options started trading in the final quarter of 1997 and the sample size for DJX options is therefore only 170 months. At the end of each month, we choose at-the-money (ATM) options of 5 different maturities, wherever available. Summary statistics of the 5 groups are presented in Table 1. There are four panels, each corresponding to a specific option index with different maturity, i.e, S&P 500, NASDAQ, DOW JONES, and S&P 100, in panel A, B, C and D individually. In each panel, we report the average characteristics across maturity groups.

The first maturity we choose is the options that mature in the 2nd calendar month since the month end. The average maturity is 50 days. Similarly, the second maturity represents options that mature in between the 4th and 6th month since the month end has an average of 141 days till maturity. The third group matures in between the 7th and 9th month after the month end and is on average about 230 days till maturity. The 4th group matures in between the 10th and 12th month after the month end and is on average about 320 days till expiration. Finally, the longest maturity group covers options with more than 650 days till expiration on average, and can be as long as 866 days for S&P 100 index.

Table 1 about here.

Within each maturity group, we further choose the option straddle, a call and a put with the same strike price, of which the strike price is closest to the index level and also require the moneyness (S/K) within 0.9 and 1.1. This filter eliminates some long term options and reduces the number of observations for some groups because the strike price is relatively coarse for certain long maturity options, especially for OEX options at the beginning of the sample period. The average moneyness of all option straddles, of all 4 indexes across all 5 maturities, is 1.00 as shown in Table 1. The absolute value of the deviation of moneyness from 1 is between 0 and 0.01 on average, confirming that we are picking ATM options. For those ATM option straddles, the deltas should be close to 0. For the shortest maturity group, deltas are between 0.04 and 0.07 for the 4 indexes. Option gammas are higher for short-term options as there is more convexity as time approaches expiration. The option time decay, measured by theta, becomes more and more negative as maturity date approaches. In the Black-Scholes model, the gains due to option gamma and theta offset each other on average. And option vegas, also shown in Table 1, are increasing with maturity approximately at the rate proportional to the square root of maturity.

4 Methodology

We focus on delta-hedged option returns so that the underlying index movement is not directly driving the option returns as cautioned by Broadie, Chernov, and Johannes (2009). Investing in a delta-hedged call option can be understood as a zero cost investment because the call option premium is financed by the short sale proceeds and the remaining proceeds is invested in risk free bonds. Following Cao and Han (2012), the dollar gain of buying a delta-hedged call option is computed by

$$\begin{aligned}\Pi_C &= C_{t+N} - C_t - \sum_{t_n=t}^{t+N-1} \Delta_{C,t_n}(S(t_{n+1}) - S(t_n)) + \sum_{t_n=t}^{t+N-1} \frac{a_n r_{t_n}}{365}(\Delta_{C,t_n} S(t_n) - C(t_n)) \\ &\quad - \sum_{t_n=t}^{t+N-1} \frac{a_n q_{t_n}}{365} \Delta_{C,t_n} S(t_n), \end{aligned} \tag{13}$$

where C_t is the price of a call option at day t, Δ_{C,t_n} is the delta of the option at t_n and positive, r_{t_n} is the risk free rate at t_n, q_{t_n} is the index dividend yield at t_n, and a_n is the number of calendar days between two consecutive trading days. For option contracts with missing closing prices or deltas, we use those of the previous trading day. The gain or loss of the call has 4 components, the gain from the change in the call option price, the cumulative gain from the dynamic delta hedging, the interest earned on the risk free bond, and the dividend paid out due to the short position in the underlying.

Note that the dollar gains (Π_C) represents the dollar return on a zero-cost portfolio. In order to calculate the excess rate of return, we normalize the dollar gain by the value of the initial lending amount $(\Delta_{C,t}S(t) - C(t))$,

$$r_C = \frac{\Pi_C}{\Delta_{C,t}S(t) - C(t)}. \tag{14}$$

The denominator is equal to the proceeds received from shorting the stock less the premium paid for the call option and always positive for at-the-money index options. This corresponds to the initial value of the long position in this zero cost call portfolio and we use it to deflate the dollar gain Π_C.

Similarly, the dollar gain for buying a delta-hedged put option is computed as follows,

$$\begin{aligned}\Pi_P &= P_{t+N} - P_t - \sum_{t_n=t}^{t+N-1} \Delta_{P,t_n}(S(t_{n+1}) - S(t_n)) + \sum_{t_n=t}^{t+N-1} \frac{a_n r_{t_n}}{365}(\Delta_{P,t_n}S(t_n) - P(t_n)) \\ &\quad - \sum_{t_n=t}^{t+N-1} \frac{a_n q_{t_n}}{365}\Delta_{P,t_n}S(t_n), \end{aligned} \tag{15}$$

where P_t is the price of a call option at day t, Δ_{P,t_n} is the delta of the option at t_n. Put is different from call in that Δ_{P,t_n} is negative while Δ_{C,t_n} is always positive. The delta-hedged put excess return is computed as

$$r_P = \frac{\Pi_P}{P(t) - \Delta_{P,t}S(t)}. \tag{16}$$

Delta-hedging a long put option requires longing the underlying and borrowing money to finance both the put and underlying. Δ_{P,t_n} is always negative and the denominator is equal to the put option premium plus the money needed to buy the underlying. This is the initial value of the long position in this zero cost put portfolio and thus used to deflate the dollar return Π_P.

In order to simultaneously examine both call and put option returns, we also compute the valued weighted average of the delta-hedged call returns and delta-hedged put returns. Both call and put returns are generated by zero cost portfolios. The weights are proportional to the long position values of each portfolio and equal to

$$\begin{aligned} w_C &= \frac{\Delta_{C,t}S(t) - C(t)}{\Delta_{C,t}S(t) - C(t) + P(t) - \Delta_{P,t}S(t)}, \\ w_P &= \frac{P(t) - \Delta_{P,t}S(t)}{\Delta_{C,t}S(t) - C(t) + P(t) - \Delta_{P,t}S(t)}. \end{aligned}$$

The value weighted call and put return corresponds to return of one call and one put option, both delta-hedged. Therefore, we define the straddle return as

$$\begin{aligned} r_S &= w_C r_C + w_P r_P \\ &= \frac{\Pi_C + \Pi_P}{\Delta_{C,t} S(t) - C(t) + P(t) - \Delta_{P,t} S(t)}. \end{aligned} \tag{17}$$

For at-the-money options, the amount of borrowing/lending is about the same for call and put options and this value weighted return is therefore approximately equal to the simple arithmetic average of the delta-hedged returns of a call and a put. This strategy corresponds to the conventional straddle because of the long position in a call and a put option.

We compute the risk neutral quadratic variation following the VIX calculation method. The calculation is based on the replication strategy of a variance swap using European options and futures contracts, as developed by Britten-Jones and Neuberger (2000), Jiang and Tian (2005), and Carr and Wu (2009). For each maturity T, the risk neutral variance

$$E_t^Q[RV_{t,T}] \approx \frac{2}{T-t} \int_0^\infty \frac{\Theta_t(K,T)}{B_t(T)K^2} dK - \frac{1}{T-t} (\frac{F}{K_0} - 1)^2$$

where $B_t(T)$ is the price of a risk free bond that pays 1 dollar at T, $\Theta_t(K,T)$ denotes the value of an out-of-the-money S&P 500 (SPX) European option with strike K and maturity T, F is the corresponding forward price, and K_0 is the first strike below the forward level. The integral is numerically computed with the trapezoidal method. The interest rate is linearly interpolated from two neighboring continuously compounded zero-coupon rates on the yield curve provided by OptionMetrics.[6] After we obtain the risk neutral variance of each option maturity, we compute the constant maturity risk-neutral variance by linearly interpolating the two closet observations and derive the risk-neutral variance of 30- and 365-day maturities. For robustness, we also calculate the risk neutral variance of the log price difference following Bakshi, Kapadia, and Madan (2003),

$$E_t^Q[(lnS(T) - lnS(t))^2] = \frac{2}{T-t} \int_0^\infty \frac{1 - ln[\frac{K}{S(t)}]}{B_t(T)K^2} \Theta_t(K,T) dK$$

where $B_t(T)$ is the price of a risk free bond that pays 1 dollar at T, $\Theta_t(K,T)$ denotes the value of an out-of-the-money European option with strike K and maturity T. The numerical integration and interpolations are implemented exactly the same as the first set of risk neutral variance computations.

[6]The yield curve is from the LIBOR rates.

5 Main Results

5.1 Delta-hedged returns across different maturity

We present our main results in this section. We begin with the returns of S&P500 index delta-hedged options, and report the call, put and the value-weighted average results in panel A, B and C of Table 2. Mean, median, min, and max monthly returns in the table are in percentages. The full sample period is from January 1996 to December 2011, a total of 192 months.

Table 2 about here.

For short term 2-month options, we confirm the general findings in the literature and document a large and negative returns for delta hedged calls, puts, and weighted average of call and put options. For instance, the average delta hedged straddle return is -0.39% per month (t=-4.19, using the 3 lags Newey-West standard error) and the mean returns of call and put option are very similar. The returns are smaller in magnitude than those in Coval and Shumway (2001) because they examine unhedged option returns and we present hedged option returns. We also examine unhedged option returns and find that the average returns of unhedged straddle is around -12% per month (unreported),[7] which is quantitatively very similar with the results in Coval and Shumway (2001).

When we extend the analysis to longer maturity options, there is a very strong pattern that for the delta-hedged calls, puts, and naturally, the weighted average, returns become monotonically less negative or even go positive with the maturity. We first examine call option returns in Panel A. The 2-month call options mean return is -0.34% per month (t=-3.34, using the 3 lags Newey-West standard error). The next maturity, 4-6 month group, call options return is -0.15% (t=-1.38), about half the size of that of the 2-month contract, and insignificantly different from 0 at all conventional levels. The average returns of the 7-9 month and 10-12 month options become even smaller in size and are both insignificant. For the longest maturity options, the mean return goes up to -0.07% (t=-0.49), or a mere -7 basis points, per month. Moreover, out of the 5 maturity groups, only the shortest maturity call option returns is statistically significant.

[7]The unhedged option return results are available upon request.

Put options show a very similar pattern. The 2-month put option returns -0.45% (t=-4.99) on average. As option maturity increases, the average return becomes less negative and smaller in magnitude, just as what we document for call options. Interestingly, the mean return of the longest maturity puts goes up to a stunning *positive* 0.03% (t=0.22). The weighted averages are constructed using one call and one put and the straddle returns resemble those observed in call and put options. The 2-month straddle average return is -0.39% (t=-4.19), and 4-6 month option straddle average return is -0.20%, about half the size of that of the 2-month contract, and also only significant at 10% level (t=-1.93). Again the other maturity straddle returns become smaller in magnitude and less significant. Overall, among the 15 option groups across all maturities, only 5 groups display a significantly negative mean return. The mean returns are indistinguishable from 0 for the vast majority. These evidence suggests the diminishing negative risk premium with time to maturity. It is also worth noting that the skewness is all positive because the losses from long option positions are always limited.

We observe a similar pattern in other three indices. In Table 3, for the interest of space, only the delta-hedged straddle returns are summarized in panel A, B, and C for NASDAQ, Dow Jones, and S&P 100 index.

Table 3 about here.

We note the less negative straddle returns with maturity for the NASDAQ and Dow Jones index. The S&P 100 index is a little different. It only has a very small sample for 7-9 months (75 months) and 10-12 months (26 months) due to the limited availability of long term contracts at the beginning of the sample period. As a result of the short sample period, the average return for 10-12 months happens to be very significantly negative (-0.42, t=-2.65). With this exception only, shorter maturity returns are more negative and statistically more significant for all the three indices. Among the 15 option groups of three indices across all maturities, less than half display a significantly negative mean return and majority of the mean returns is indistinguishable from 0. Another consistent finding is the positive skewness, although the magnitude varies with the index. Again, this is because options provide downside protections.

5.2 Variance risk factors

The delta hedged option returns is directly related to the variance risk premium (Bakshi and Kapadia (2003)). The negative returns of short term options is well documented as evidence of a large negative variance risk premium. From an asset pricing perspective, the expected return of a portfolio depends on the portfolio's factor loading with respect to the risk factor. Following the procedures outlined in the methodology part, we compute the 30-day risk neutral variance of the SPX options and use it as the risk factor. The risk neutral variance is very similar with the highly followed VIX index. This is the short-term risk neutral variance and we name it *level* as in the literature on the term structure of interest rate. Table 4 Panel A presents the summary statistics of the level factor as well as the classical Fama-French monthly factors from 1996 to 2011. The average level is 0.051 and it reaches 0.341 during the financial crisis in 2008. Panel B displays its Spearman correlation with other factors. The level has a strong and negative correlation with the market, confirming to the general finding in the literature. It also shows negative but insignificant correlations with the *hml* and *smb* factors.

Table 4 about here.

This level factor alone, however, has a hard time explaining why the expected returns of longer term options are close to 0. In a multi-factor asset pricing model, the expected excess return of an asset is equal to the product of its factor beta and the market price of risk of the factor. In a one-factor model of the variance risk, the variance risk premium being negative implies that the variance betas of longer term options should be close to 0 or very small. This is at heart of the problem.

Table 5 about here.

Long-term option prices are more sensitive to the underlying volatility. As we have shown in Table 1, the vegas (the first derivative of option price with respect to volatility) of options are approximately increasing at a rate equal to the square root of maturity. We mainly focus on delta-hedged option returns. The impact of the vega is attenuated by the gains (losses) from delta hedging and borrowing (lending) and the variance beta of options are not exactly increasing at the speed of square root of expiration time. Because the level factor is very persistent, we use the change in level as the risk factor and estimate the variance beta of each option portfolio by regressing monthly portfolio returns on the change of the level factor in a time-series regression. The level betas are shown in Table 5. For SPX options, the variance beta of the shortest maturity straddle is 0.255 and it goes up to 0.318 for the longest maturity option. Options on other indices show a similar pattern. Overall, the variance beta are mildly increasing, or at least non-decreasing, with maturity. In Figure 1, we plot mean returns of each portfolio that has more than 128 monthly observations (two thirds of the sample) against their estimated variance betas. For most portfolios, their variance level betas are concentrated in a narrow band while the expected returns are very different. If one were forced to draw a fitted line, the line would be upward sloping. This implies a positive variance risk premium, highlighting the inability of the short term variance (level) factor to explain longer term option returns.

Figure 1 about here.

To better understand the cross-section of option returns, we exploit the term structure of the risk neutral variances in the options market. This is motivated by several recent papers that show the importance of the long term volatility in option and variance swap pricing (Christoffersen, Jacobs, Ornthanalai, and Wang (2008) and Egloff, Leippold, and Wu (2010)). We compute the 365-day risk neutral variance, compute the difference between the 365- and 30-day (level) risk neutral variance, and name it *slope* as in the term structure of interest rate literature. The properties of the slope factor is presented in Table 4. The slope factor has a mean of 0 and median value of 0.004. More than half the time, the term structure of the risk neutral variances is upward sloping. It has a significant correlation of -0.324 with the level factor. This is to be expected because of the construction of the slope factor. It is also positively correlated with the market and *smb* factor. With the addition of the slope factor, we will investigate the asset pricing implications of the two factors.

5.3 Asset pricing tests

In this section we systematically examine whether the variance factors extracted from risk neutral variance can sufficiently explain index option returns across different maturities.

We consider the stochastic discount factor (SDF) because it provides us with a unifying framework for all possible systematic risk factors and it also directly asses the economic significance of each factor. Following the literature (Cochrane (2005)), the discount factor, m_t, can be written as a linear function of factors:

$$m_t = \left[1 - (\mathbf{f}_t - \mu)^\top \mathbf{b}\right]$$

where $\mathbf{f}_t$ is a $K \times 1$ vector of risk factors, $\mu = E(\mathbf{f}_t)$, and $\mathbf{b}$ is a $K \times 1$ vector of coefficients. In our baseline model, there are two variance factors, the changes in *level* and *slope* of risk-neutral variances, $\mathbf{f} = (\Delta l, \Delta s)'$. Then we use the GMM to test the Euler equation and check the goodness of fit of the model. The moment conditions become

$$E\left[\begin{array}{c} \mathbf{f_t} - \mu \\ r_t - r_t\left[(\mathbf{f}_t - \mu)^\top \mathbf{b}\right] \end{array}\right] = 0$$

We conduct two-step GMM and obtain almost identical results if we do iterative GMM. Following Yogo (2006) and Jagannathan and Wang (2009), our optimal weighting matrix is

$$W = \left[\begin{array}{cc} kI & 0 \\ 0 & \mathbf{\Sigma}_\mathbf{f}^{-1} \end{array}\right]$$

where k is a constant and $\Sigma_\mathbf{f}$ is the variance of the factors.

Ideally, we would use all the 20 delta-hedged straddle returns as test assets. But the sample period of some option portfolios are very short due to data availability issue, as shown in Table 3. We thus focus on those returns with sufficient observations, and specifically, those with at least above two thirds of the sample period.[8]

The two-step GMM is equivalent to a two-pass procedure which involves a set of time-series regressions in the first pass and a cross-sectional regression in the second pass. We first conduct the time series regression of each portfolio's excess return on the vector of risk factors.

$$R^e_{it} = a_i + \mathbf{f}_t^\top \beta_i + \varepsilon_{it}, t = 1, ..., T, \text{ for each } i = 1, ..., n$$

Here β_i represents the ith row in β. Then we conduct the cross-sectional regression of average portfolio returns on the estimated betas. Since our test asset is already the excess return, we do not add an intercept in the cross sectional regression.

$$\bar{R}^e_t = \hat{\beta}_i^\top \lambda + \alpha_i, \; i = 1, ..., n$$

where $\bar{R}^e_t = \frac{1}{T}\sum_{t=1}^T R^e_{it}$, $\hat{\beta}_i$ is the OLS estimate of β_i obtained in the first stage, and α_i is the pricing error $\hat{\alpha} = \bar{\mathbf{R}}^e - \hat{\beta}^\top \hat{\lambda}$.

It is known that the Euler equation implies the following relationship

[8]This criteria excludes NDX 10-12 and 13+ months, and OEX 7-9, 10-12, and 13+ months. We have tried different number of assets and repeat the GMM tests, the results are qualitatively very similar.

$$E(\mathbf{R}_t^e) = Cov\left(\mathbf{R}_t^e, \mathbf{f}_t^\top\right)\mathbf{b} = \underbrace{Cov\left(\mathbf{R}_t^e, \mathbf{f}_t^\top\right)Var\left(\mathbf{f}_t\right)^{-1}}_{\beta}\underbrace{Var\left(\mathbf{f}_t\right)\mathbf{b}}_{\lambda}$$

where β is a $N \times K$ matrix of factor betas, and λ is a $K \times 1$ vector of factor risk premia.

We measure the goodness of fit of the model by mean absolute pricing error (MAE) and root mean squared pricing error (RMSE) and

$$\begin{aligned} R^2 &= 1 - \frac{(\bar{\mathbf{R}}^e - \hat{\beta}^\top\hat{\lambda})^\top(\bar{\mathbf{R}}^e - \hat{\beta}^\top\hat{\lambda})}{(\bar{\mathbf{R}}^e - \ddot{R})^\top(\bar{\mathbf{R}}^e - \ddot{R}^e)} \\ \ddot{R}^e &= \sum\nolimits_{i=1}^{n} \bar{\mathbf{R}}^e/n \end{aligned}$$

In Table 6, panel A reports the GMM test results while panel B reports the two-pass Fama-MacBeth regressions results. In panel A, we report the estimates of bs, and implied factor risk premium λ, accompanied with the t-test through the Newey-West standard errors of 3 month lags.

Table 6 about here.

In the first two columns of panel A, we start from one-factor model, where the only factor is either the level or the slope. Our goal is first to examine whether the traditional one-factor structure is sufficient to account for the increasing option returns with maturity. Clearly, these two models do not perform well, as the J-stat for the level model is significant at 6% while that for the slope model is only marginally above 10%. Therefore we have to reject the level model and barely let the slope model pass. Besides, the estimates of coefficient b in each model are -7.21 and 15.93, both not significantly different from zero.

These results, especially that of the level factor model, may seem inconsistent from the literature. The reason is the test assets are the delta-hedged returns not only generated from short maturity, but span different maturity and can cover as long as more than 650 days. In contrast, when we turn to our baseline two-factor model, the estimates of two coefficients are both significantly positive, 26.51 and 69.57. The model is not rejected also, with a J-stat of 13.40 (p=0.27). The option returns are delta hedged and should be uncorrelated with market movement, at least locally. But the market return is correlated with both the level and slope factors. Therefore, we also augment the market excess return and expand the SDF as consisting three factors, which further improves the model performance. Compared to the two-factor model, the estimate of b_{level} changes to 71.61, while that of b_{slope} remains very similar. The estimate of coefficient to market excess return is 43.88, also significant at 1%.

Panel B reports the two-pass procedure results. As well known the OLS standard error is not reliable due to the error-in-variable problem when the second pass βs are estimated, so we only report the t-test by standard errors with Shanken correction (Shanken (1992)). When we examine the statistical significance of risk factor premium λs again, we find that the Shanken correction generates numerically different test statistics from those in panel A but none material effects. The bad performance of the single-factor models are again reflected by the almost zero R^2. It is -0.18 for level model and 0.16 for slope model. The differences in these two R^2s indicate that level model does not explain any of the cross sectional differences in the monotonically increasing options with maturity, while slope model can, but not to a sufficient degree. These two models also generate large pricing errors, monthly MAE of 0.12% and 0.10%, and monthly RMSE of 0.15% and 0.12% separately. The slope factor still is more important than level factor.

Figure 2 about here.

Again, two-factor model entails a much better explanatory power, improving R^2 substantially to 0.67, and also reducing the monthly MAE to 0.06% and RMSE to 0.08% by about a half from one factor models. The greatly improved performance can be attributable to the complementary roles played by each separate factor in the model. Finally, inclusion of market excess return further bring explanatory power up, as R^2 grows to 84%, and reduces MAE and RMSE considerably to 0.04% and 0.05% monthly. The goodness of fit of each model is also illustrated in Figure 2. Panel A and B plot the average return of each test portfolio against its fitted return in the two one-factor models. In both panels, there is not nearly enough spread in the fitted returns and this highlights the problem of the one-factor models. Panel C plots the mean returns against fitted returns in the two-factor model. Most of the portfolios line up very closely to the 45 degree line and shows a good fit. Finally, Panel D plots that pattern in the model, in which the two variance factors are augmented by the market excess return. It shows a further improvement on the graph in Panel C.

Then we turn back to the asset return factor loadings βs in the first pass regression. For asset returns to display a spread, there must be non zero *beta*s across assets along with the non zero factor risk premium. We document a very general pattern such that the βs grow with the maturity, for both the level and slope. For example, on average, the level βs change from 0.3 for short-maturity straddle returns to more than 0.6 for longest-maturity straddle returns. The slope βs change from 0.04 for short-maturity straddle returns to average 0.6 for longest-maturity straddle returns. It is noteworthy that for the short-maturity, level β is much larger than slope β. Moreover, short-maturity level βs is the only group with statistically insignificant estimates (we again use 3 lags Newey-West standard errors to conduct t-test). Given the magnitudes of two factor risk premiums, the dominance of the former β determines the negative variance risk premium of short-maturity options. In contrast, close size of both βs for longer maturity returns indicates that their return will be much less negative with the maturity.

Table 7 about here.

5.4 Classical risk factors

We further investigate the explanatory power of classical risk factors, like the Fama-French factors, momentum, and market wide liquidity (Pástor and Stambaugh (2003)) to the option returns. We run time series regression of each portfolio's excess return on any set of the above factors:

$$R_{it}^e = \alpha_i + \mathbf{f}_t^\top \beta_i + \varepsilon_{it}, t = 1, ..., T, \text{ for each } i = 1, ..., n$$

Here β_i represents the ith row in β. The conventional factor models are CAPM, Fama-French three factor, and Fama-French three factor augmented with liquidity model. In order to conduct time series bases tests, we choose the traded liquidity factor from Pástor and Stambaugh (2003) as a measure of the market wide liquidity. And our two variance risk factors are not excess returns, therefore we construct factor mimicking portfolios and use the factor mimicking portfolio returns as proxies for the variance factors in the time-series regression tests.

For each set of factors as the explanatory variables, we have a specific regression intercept α. Given the multiple asset returns we test at the same time, we conduct a test of the significance whether all these αs are jointly different from zero. This is achieved through the GRS test in the finite sample, and for robustness, we also conduct the large-sample χ^2 tests, assuming i.i.d. residuals then alternatively the HAC residuals with 3 mont lags. (For a textbook treatment, see Cochrane (2005).)

The time series test results are presented in Table 8. We first examine the classical Fama-French 3 factors that are very successful in explaining the cross section of stock returns. Both the finite sample GRS test and two versions of large sample χ^2 tests strongly reject the Fama-French 3-factor model. All p-values are 0. Pricing errors are relatively big. The RMSE is about 0.2% per month or 2.4% per year and the R^2 is less than 20%. This confirms the general finding in Carr and Wu (2009). Then we augment the 3-factor model using the momentum factor and the market wide liquidity factor respectively. The momentum and liquidity factors barely improve the model performance. In both cases, we still find strong rejections from the GRS test and both versions of the χ^2 tests. And the pricing errors are also similar with the Fama-French 3-factor model.

Our two variance factors explain the option straddle returns much better. The GRS test still rejects the null. But both large sample χ^2 tests fail to reject the model at all conventional levels. The p-values are 0.26 and 0.46 respectively. The pricing error shrinks from 20 basis points (bps) to less than 4 bps per month. And the R^2 jumps to 91.5%. Finally, we augment the two variance factors by the market excess return. The results are quantitatively very similar with the two variance factor model. Overall, the the time series results corroborate our main finding in the GMM and Fama-MacBeth tests.

Table 8 about here.

5.5 Predictive regressions

The slope factor commands a significant risk premium. Following the ICAPM intuition, it implies that the slope factor should positively forecast future investment opportunities. We investigate whether the slope factor forecasts macroeconomic conditions. More specifically, we examine the aggregate output and test whether the slope factor predicts the growth rate of the seasonally adjusted industrial production.

Table 9 presents the time series regression results of the growth rate of industrial production on lagged slope factor. Because of the serial correlation in the industrial production growth rate, we control for lagged growth rate to isolate the information in the term structure of variances and all standard errors are Newey-West adjusted with 6 lags. The slope factor strongly forecasts the industrial production growth of the next 3 months. The point estimates 0.048 ($t = 1.99$), 0.080 ($t = 2.11$), and 0.074 ($t = 2.29$) and all are statistically significant at 5% level. The coefficient is highest for the 2nd month at 0.080. A one standard deviation shock to the slope factor indicates a 0.19%[9] increase in the output growth rate 2 month later. In order to gauge the economic significance of the predictive power, we compare it with the average output growth rate. During the sample period, the average output growth rate is 1.8% per year or 0.15% per month. The slope predicts the aggregate output growth and therefore innovations of the slope factor should be priced by the ICAPM intuition. This explains the positive risk premium of the slope factor. The results also relate to the finding that the long term variance forecasts macroeconomic variables as in Adrian and Rosenberg (2008).

Table 9 about here.

5.6 Calendar spread returns

To better understand the importance of the slope factor, In this section we examine the return characteristics of the calendar spread strategy, to long the longer-maturity options (4-6, 7-9, 10-12, and >12 months) and short the short-maturity options (2 months). We examine this strategy with both calls and puts, and again to save the space, we only report the straddle results. The mean return, the t-statistics with Newey-West standard errors, and the Sharpe ratio in panel A of Table 10.

Table 10 about here.

Given the pattern from delta-hedged straddle returns in section 5.1, it is perhaps no surprise that most of these returns are all positively significant (except calendar spread longing the 10-12 months S&P 100 index, which has only 26 months period). And there is an increasing trend of the mean returns with the maturity generally.

The calendar spread is very profitable – the Sharpe ratios are usually about 0.3 at a monthly basis, translating to as high as between 1.1 and 1.2 annually. Again this is true for all the portfolios except S&P 100 index 10-12 months calendar spread. Although there is a reservation whether Sharpe ratio is a very telling statistics on option returns as in stock returns, it reveals important information in terms of how we should restrict the pricing

[9]The standard deviation of the slope is 0.024 as shown in Table 4.

kernel as in Cochrane and Saa-Requejo (2000). We also consider that perhaps one way to lift such reservation is that, also inheriting from the delta-hedged return results, the calendar spread returns are not subject to crash events in sample and display a positive skewness. Moreover, the margin requirement of writing naked options is prohibitively high for investors (Santa-Clara and Saretto (2009)). The calendar spread strategy essentially eliminates the high margin because of the offsetting long and short option positions.

We further investigate whether the slope premium is constant by expectation hypothesis type predictive regressions. In panel B, we examine the time series regression results of the calendar spread on lagged level and slope of the risk neutral variance.

$$cs_{j,t+1} = c_0 + c_{slope}s_t + c_{level}l_t + \varepsilon_{t+1}$$

where $cs_{j,t+1}$, the calendar spread return, is defined as $r_{j,t+1} - r_{2,t+1}$, and $r_{j,t+1}$ denotes the returns of the j-month index option straddle return. This specification is motivated by those studies on the expectation hypothesis in the term structure of interest rate literature. The calendar spread return has a very high

The results in Panel B of Table 10 shows strong rejection of the null of no predictability. The point estimates of the slope are statistically significant for all 20 portfolios at 10% level. 19 out of the 20 estimates are significant at 5% level. The average adjusted R^2 is above 10% for monthly non-overlapping regressions. The results complements the findings in the existing literature on the level premium. Carr and Wu (2009) conducts a similar regression and rejects that null that the risk premium of the level is constant.

Table 10 about here.

5.7 Robustness

Recent studies (Christoffersen, Goyenko, Jacobs, and Karoui (2011) and Muravyev (2011)) both find liquidity is priced in the cross-section of option returns. While we have shown that the aggregate market liquidity as a systematic risk factor does not explain the expected option returns, it is possible that long maturity options earn higher returns because of they are more illiquid. We examine a host of common liquidity measures for options across all maturities, including the relative bid-ask spread, dollar trading volume, and open interest. The results are shown in Table 11.

Table 11 about here.

Contrary to conjecture that long-maturity options are illiquid, the relative bid-ask spread (half of the difference between the bid and ask divided by the average of bid and ask) is actually decreasing with option maturity. For the SPX options, the bid-ask spread is about 13% of the option price for the 2-month maturity contracts and the spread drops to 5% for the longest maturity contracts. The relative spread as a fraction of the option premium is actually lower for long dated options. This pattern is consistent across all 4 indices and confirms the finding in Christoffersen, Goyenko, Jacobs, and Karoui (2011). The dollar volume is generally decreasing with option maturity. The pattern for the open interest is mixed. For the SPX options, the open interest actually first increases with maturity for the first 3 maturity groups before it decreases. In summary, the shortest maturity contract are the most expensive to trade because of the highest bid-ask spread and are as actively traded as the next 2 maturities. Overall, there is no consistent evidence that option liquidity is monotonically decreasing with maturity.

Table 12 about here.

We finally examine the robustness of the main results in two subsample periods. Table 12 presents the mean returns of all delta-hedged option straddle returns of the two halves. Panel A presents the first half of the sample which runs from 1996 to 2003 and includes the dot-com bubble period. The options returns show a similar pattern in that mean returns are generally increasing with maturity and the long maturity options in general have insignificant returns. The only exception is the longest maturity OEX option which has only 11 observations in the sample period. In fact, there are 3 other groups in the first half of the sample that does not have any qualifying observations and therefore are left blank in this panel. Panel B shows the second half which covers from 2004 to 2011and thus the financial crisis. We find the same upward sloping term structure of expected option returns. Long maturity options earn close to 0 returns and mean returns of the longest maturity option of both the SPX and DJX are even positive.

6 Conclusion

In this paper, we study the variance risk premium in a classical asset pricing framework. Comparing with the large and negative risk premium in short-maturity options, we find that long maturity options have both higher exposure to the variance risk and less negative risk premium. For the S&P 500 index, both call and put options of longer than 6-month maturity have variance risk premium indistinguishable from 0. The results suggest that it is essentially free to insure against the variance risk using long maturity option contracts and cast doubts on the one-factor variance risk model. Indeed, we examine index options on all major stock market indexes and find no relationship between the options' variance betas and their expected returns. In another word, there is no risk return relationship for the commonly used variance risk factor. A one-factor model is strongly rejected under a stochastic discount factor framework.

The mismatch stems from the one-factor assumption of the variance risk and more factors are needed just as term structure of interest rates models. In addition to the variance level factor, a second slope factor in the term structure of the risk neutral variances is necessary to explain the expected returns of index options. The variance level factor commands a large and negative risk premium, as documented in the extant literature. The slope factor, on the other hand, commands a positive risk premium. Short-maturity options only load on the variance level factor and earn large and negative risk premium. Long-maturity options have large exposure to both the level and slope factors and the risk premia of the two sources by and large cancel out. This is why long maturity options have high variance beta and earn low risk premium.

The slope factor is predicting future economic activities and therefore provides a forward looking measure of the macroeconomic conditions. Such a variable ought to command a positive risk premium according to the ICAPM model. Moreover, we find that the risk premium of the slope factor is also time varying. The properties of the slope factor provide economic interpretations of the risk neutral variances and provide the economic underpinning of the risk premium in long maturity options.

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Table 1: Summary Statistics

This table presents the average number of calendar days to maturity, moneyness, absolute deviation, delta, and vega of the option straddles on the 4 major indexes. For each index, we present the average characteristics of each maturity group. Moneyness is defined as the spot price S divided by the option strike price K. Absolute moneyness deviation is defined as $|\frac{S}{K} - 1|$. Delta, Gamma, and Vega are the corresponding straddle greeks of the Black-Scholes model. Panels A through D present the results of the S&P500, NASDAQ Composite, Dow Jones Industrial Average, and S&P 100 respectively. The sample period is 1996 to 2011.

Panel A: S&P 500 Index

Maturity (months)	2	$4-6$	$7-9$	$10-12$	>12
Number of Days to Maturity	50.09	141.83	233.87	324.71	656.84
Moneyness	1.00	1.00	1.00	1.00	1.00
Absolute Moneyness Deviation	0.00	0.00	0.01	0.01	0.01
Delta	0.06	0.10	0.13	0.15	0.21
Gamma ($\times$ 100)	1.10	0.62	0.46	0.38	0.26
Theta	-248.04	-149.17	-114.77	-96.61	-67.03
Vega	326.90	549.04	701.39	819.06	1115.21

Panel B: NASDAQ Composite Index

Maturity (months)	2	$4-6$	$7-9$	$10-12$	>12
Number of Days to Maturity	49.92	141.27	231.98	323.45	679.99
Moneyness	1.00	1.00	1.00	1.00	1.00
Absolute Moneyness Deviation	0.00	0.01	0.01	0.00	0.01
Delta	0.07	0.12	0.13	0.12	0.24
Gamma ($\times$ 100)	0.58	0.33	0.25	0.17	0.13
Theta	-574.95	-329.98	-239.55	-199.05	-124.58
Vega	483.55	802.75	1001.41	1356.87	1772.35

Panel C: Dow Jones Industrial Average Index

Maturity (months)	2	$4-6$	$7-9$	$10-12$	>12
Number of Days to Maturity	49.94	141.02	232.33	323.39	661.18
Moneyness	1.00	1.00	1.00	1.00	1.00
Absolute Moneyness Deviation	0.00	0.01	0.01	0.01	0.01
Delta	0.04	0.08	0.10	0.12	0.18
Gamma ($\times$ 100)	11.79	6.51	4.83	3.98	2.65
Theta	-22.14	-13.38	-10.34	-8.68	-5.93
Vega	29.86	50.05	63.93	74.77	101.84

Panel D: S&P 100 Index

Maturity (months)	2	$4-6$	$7-9$	$10-12$	>12
Number of Days to Maturity	49.92	135.03	215.52	320.73	866.65
Moneyness	1.00	1.00	1.00	1.00	1.00
Absolute Moneyness Deviation	0.00	0.01	0.01	0.01	0.01
Delta	0.06	0.08	0.09	0.10	0.17
Gamma ($\times$ 100)	2.06	1.19	0.96	0.88	0.49
Theta	-131.92	-83.01	-61.98	-44.38	-28.76
Vega	171.89	279.64	341.19	404.28	625.17

Table 2: S&P 500 Index Option Returns

This table presents the properties of delta-hedged option returns of different maturities. Mean, min, median, and max returns are monthly returns in percentage. Monthly Sharpe ratios are also computed. Panels A, B, and C present the results of call, put, and straddle options respectively. The sample period is 1996 to 2011. The t-stats in the parentheses are computed using Newey and West adjusted standard errors with 3 lags (6).

Panel A: Call Options

Maturity (months)	2	$4-6$	$7-9$	$10-12$	>12
Mean	-0.337	-0.148	-0.092	-0.082	-0.067
	(-3.34)	(-1.38)	(-0.85)	(-0.73)	(-0.49)
Min	-4.596	-4.164	-4.025	-3.907	-5.302
Median	-0.382	-0.233	-0.127	-0.086	-0.034
Max	7.552	6.890	6.977	7.649	9.294
Skewness	1.255	1.498	1.190	1.073	0.883
Kurtosis	11.249	9.275	8.162	7.603	8.080
SR	-0.268	-0.113	-0.067	-0.057	-0.038
Obs	192	192	191	192	192

Panel B: Put Options

Maturity (months)	2	$4-6$	$7-9$	$10-12$	>12
Mean	-0.447	-0.253	-0.160	-0.106	0.028
	(-4.99)	(-2.59)	(-1.47)	(-0.95)	(0.22)
Min	-3.829	-3.380	-2.985	-3.105	-4.165
Median	-0.561	-0.312	-0.186	-0.159	-0.090
Max	5.333	6.385	6.944	7.709	10.066
Skewness	1.125	1.319	1.461	1.305	1.272
Kurtosis	6.644	7.981	8.834	8.526	8.612
SR	-0.388	-0.208	-0.121	-0.078	0.017
Obs	192	192	191	192	192

Panel C: Straddle Returns

Maturity (months)	2	$4-6$	$7-9$	$10-12$	>12
Mean	-0.389	-0.195	-0.119	-0.086	-0.003
	(-4.19)	(-1.93)	(-1.12)	(-0.79)	(-0.02)
Min	-4.077	-3.730	-3.322	-3.088	-3.723
Median	-0.480	-0.280	-0.158	-0.102	-0.056
Max	6.400	6.189	6.959	7.682	9.730
Skewness	1.346	1.462	1.463	1.346	1.386
Kurtosis	9.108	8.526	9.124	8.809	9.493
SR	-0.337	-0.159	-0.091	-0.064	-0.002
Obs	192	192	191	192	192

Table 3: Returns of Options on Major Indices

This table presents the returns of delta-hedged option straddles on major indices (weighted average of call and put options). Mean, min, median, and max returns are monthly returns in percentage. Monthly Sharpe ratios are also computed. Panels A, B, and C present the results of the NASDAQ Composite (NDX), Dow Jones Industrial Average (DJX), and S&P 100 (OEX) respectively. The sample period is 1996 to 2011. The t-stats in the parentheses are computed using Newey and West adjusted standard errors with 3 lags.

Panel A: NASDAQ Composite Index

Maturity (months)	2	$4-6$	$7-9$	$10-12$	>12
Mean	-0.284	-0.042	-0.037	-0.015	-0.062
	(-2.44)	(-0.33)	(-0.27)	(-0.06)	(-0.29)
Min	-4.537	-4.092	-5.333	-3.314	-4.281
Median	-0.381	-0.313	-0.205	-0.224	-0.231
Max	4.999	6.268	6.431	6.509	7.068
Skewness	0.423	0.781	0.676	0.866	0.937
Kurtosis	4.383	4.749	4.938	4.598	5.037
SR	-0.199	-0.027	-0.023	-0.008	-0.034
Obs	192	190	175	57	85

Panel B: Dow Jones Industrial Average Index

Maturity (months)	2	$4-6$	$7-9$	$10-12$	>12
Mean	-0.485	-0.280	-0.214	-0.167	-0.086
	(-4.51)	(-2.27)	(-1.75)	(-1.34)	(-0.63)
Min	-4.682	-4.650	-4.181	-4.098	-3.847
Median	-0.535	-0.330	-0.253	-0.230	-0.156
Max	5.919	7.994	7.924	8.647	9.833
Skewness	1.102	1.914	1.527	1.609	1.425
Kurtosis	8.403	12.562	10.170	11.108	10.605
SR	-0.402	-0.204	-0.153	-0.116	-0.054
Obs	170	170	170	170	170

Panel C: S&P 100 Index

Maturity (months)	2	$4-6$	$7-9$	$10-12$	>12
Mean	-0.403	-0.223	-0.249	-0.419	-0.120
	(-4.45)	(-2.11)	(-1.97)	(-2.65)	(-0.59)
Min	-4.228	-4.134	-3.627	-1.772	-4.605
Median	-0.504	-0.414	-0.322	-0.347	-0.288
Max	5.679	7.454	5.452	1.996	11.524
Skewness	1.122	1.650	1.097	0.453	2.322
Kurtosis	7.537	10.384	7.904	3.376	15.744
SR	-0.354	-0.172	-0.199	-0.473	-0.064
Obs	192	191	75	26	106

Table 4: Variance Factors

This table presents properties of our level and slope factors. Pane A shows the summary statistics of the level and slope factors, as well as the monthly Fama-French factors. Panel B presents the pairwise Spearman correlations among factors. Corresponding p-values are in the parentheses.

Panel A: Summary Statistics

	Mean	**Std**	**Median**	**Min**	**Max**
level	0.051	0.045	0.041	0.009	0.341
slope	0.000	0.024	0.004	-0.159	0.046
mkt	0.004	0.049	0.010	-0.185	0.115
smb	0.003	0.038	0.000	-0.166	0.221
hml	0.003	0.036	0.002	-0.129	0.139

Panel B: Correlations

	level	*slope*	*mkt*	*smb*	*hml*
level		-0.324	-0.233	-0.080	-0.091
		(0.00)	(0.00)	(0.27)	(0.21)
slope			0.257	0.147	-0.007
			(0.00)	(0.04)	(0.92)
mkt				0.304	-0.227
				(0.00)	(0.00)
smb					-0.149
					(0.04)

Table 5: Portfolio Variance Betas

This table reports factor loadings of the 20 delta-hedged index option straddles with respect to the level factor in the Fama-MacBeth regressions. The t-stats in the parentheses are computed using Newey and West adjusted standard errors with 3 lags.

Maturity (months)	**SPX**	**DJX**	**NDX**	**OEX**
2	0.255	0.250	0.241	0.255
	(8.81)	(9.30)	(9.96)	(10.56)
$4-6$	0.286	0.317	0.296	0.312
	(9.47)	(7.64)	(12.44)	(10.12)
$7-9$	0.294	0.304	0.295	0.303
	(8.26)	(8.37)	(8.81)	(7.34)
$10-12$	0.293	0.301	0.278	-0.235
	(7.55)	(7.27)	(6.75)	(-2.01)
> 12	0.318	0.297	0.304	0.372
	(7.08)	(5.92)	(6.29)	(5.80)

Table 6: Asset Pricing Tests

This table presents results of GMM and Fama-MacBeth (FMB) procedures using 20 delta-hedged index option straddles as test assets (weighted average of call and put options). Market prices of the level and slope factors are presented. We also present the adjusted R^2, J-stats of the GMM tests, the square root of mean squared errors ($RMSE$) and the mean absolute pricing errors (MAE). The $RMSE$ and MAE are expressed in monthly percentages. Panels A reports the GMM results. The t-stats in the parentheses are computed using Newey and West adjusted standard errors with 3 lags. P-values associated with the J-stats are in square brackets. Panel B reports the Fama-MacBeth results. The second stage of the FMB does not include a constant. The t-stats are adjusted with the Shanken's correction.

Panel A: GMM Tests

b_{level}	-7.206		26.509	71.613
	(-1.19)		(1.95)	(2.62)
λ_{level}	-0.006		-0.015	-0.017
	(-1.81)		(-3.95)	(-4.83)
b_{slope}		15.934	69.566	69.179
		(1.17)	(3.03)	(2.28)
λ_{slope}		0.007	0.017	0.015
		(1.85)	(4.88)	(4.25)
b_{mkt}				43.883
				(3.72)
λ_{mkt}				0.073
				(3.72)
J-stat	21.956	19.589	13.400	6.553
	[0.06]	[0.11]	[0.27]	[0.68]
R^2	-0.178	0.157	0.671	0.844
MAE	0.118	0.099	0.058	0.041
$RMSE$	0.145	0.123	0.077	0.053

Panel B: Fama-MacBeth Regressions

λ_{level}	-0.006		-0.015	-0.017
	(-2.08)		(-3.93)	(-3.23)
λ_{slope}		0.007	0.017	0.015
		(2.22)	(4.61)	(2.71)
λ_{mkt}				0.073
				(2.52)
R^2	-0.178	0.157	0.671	0.844
MAE	0.118	0.099	0.058	0.041
$RMSE$	0.145	0.123	0.077	0.053

Table 7: Portfolio Betas

This table reports factor loadings of the 20 delta-hedged index option straddles in the Fama-MacBeth regressions. Panel A reports the β loadings with respect to the level factor. Panel B reports the β loadings with respect to the slope factor. The t-stats in the parentheses are computed using Newey and West adjusted standard errors with 3 lags.

Panel A: Level βs

Maturity (months)	**SPX**	**DJX**	**NDX**	**OEX**
2	0.282	0.272	0.320	0.304
	(6.23)	(8.26)	(5.78)	(8.86)
$4-6$	0.470	0.497	0.475	0.500
	(10.24)	(7.88)	(6.50)	(8.94)
$7-9$	0.520	0.547	0.667	0.336
	(8.76)	(8.52)	(9.20)	(6.18)
$10-12$	0.559	0.571	0.694	0.591
	(7.72)	(6.58)	(12.05)	(2.51)
> 12	0.689	0.708	0.826	1.004
	(6.46)	(7.58)	(10.11)	(10.33)

Panel B: Slope βs

Maturity (months)	**SPX**	**DJX**	**NDX**	**OEX**
2	0.043	0.035	0.126	0.078
	(0.58)	(0.54)	(1.58)	(1.30)
$4-6$	0.293	0.290	0.286	0.302
	(3.92)	(3.52)	(2.61)	(3.68)
$7-9$	0.361	0.392	0.602	0.055
	(3.71)	(4.15)	(5.30)	(0.73)
$10-12$	0.427	0.435	0.736	1.063
	(3.87)	(3.60)	(7.57)	(5.16)
> 12	0.593	0.664	0.926	1.117
	(3.65)	(5.23)	(6.74)	(8.16)

Table 8: Time Series Tests

This table presents time series tests of the variance risk factors as well as alternative models. The liquidity factor is the traded liquidity factor from Pástor and Stambaugh (2003). Our variance factors are factor mimicking portfolios of the level and slope factors. We present the GRS test, the large-sample χ^2 tests, assuming both i.i.d. residuals (χ_1^2) and HAC residuals (χ_2^2). Associated p-values are in the parentheses. We also compute the MAE, $RMSE$ and $\hat{R}^2$ to demonstrate the goodness of fit. Both the MAE and $RMSE$ are in percentage per month.

	GRS	χ_1^2	χ_2^2	MAE	$RMSE$	$\hat{R}^2$
Fama-French 3-Factor Model	17.803	57.706	42.439	0.162	0.204	0.192
	(0.00)	(0.00)	(0.00)			
Carhart 4-Factor Model	7.787	33.670	59.274	0.245	0.271	0.191
	(0.00)	(0.00)	(0.00)			
Fama-French 3-Factor + Liquidity Model	12.850	55.558	44.953	0.140	0.180	0.227
	(0.00)	(0.00)	(0.00)			
Variance Risk 2-Factor Model	8.365	18.068	14.821	0.031	0.039	0.915
	(0.00)	(0.26)	(0.46)			
Variance Risk 2-Factor + Market Model	5.696	18.459	16.598	0.032	0.039	0.915
	(0.00)	(0.24)	(0.34)			

Table 9: Predicting Industrial Production Growth

This table reports the predictive regression of the monthly growth rate of seasonally adjusted industrial production on the slope factor. The sample period is from 1996 to 2011. The Newey-West adjusted t-statistics are in the parentheses.

con	0.002	0.001	0.001	0.001	0.001	0.001
	(1.81)	(1.55)	(1.79)	(1.68)	(1.78)	(1.40)
ΔIP_t		0.242				
		(2.26)				
$slope_t$	0.057	0.048				
	(1.97)	(1.99)				
ΔIP_{t-1}				0.310		
				(5.14)		
$slope_{t-1}$			0.091	0.080		
			(2.04)	(2.11)		
ΔIP_{t-2}						0.348
						(3.93)
$slope_{t-2}$					0.087	0.074
					(2.73)	(3.29)
R^2	0.032	0.084	0.090	0.182	0.080	0.197

Table 10: Returns of Calendar Spread

This table reports the properties of calendar spread returns. The calendar spread is defined as longing the long maturity delta-hedged option portfolio and shorting the 2-month delta-hedged option portfolio. The time-to-expiration of the long maturity option is shown in the column labeled maturity. Panel A presents the mean returns and Sharpe ratios of the calendar spreads. Panel B presents the predictive regression of the calendar spread returns on the slope and level factors. The Newey-West adjusted t-statistics are in the parentheses.

Panel A: Expected Calendar Spread Returns

Maturity (months)	**SPX**	**DJX**	**NDX**	**OEX**
$4-6$	0.194	0.206	0.234	0.185
	(3.95)	(3.33)	(3.71)	(3.83)
SR	0.31	0.30	0.29	0.29
$7-9$	0.266	0.272	0.284	0.218
	(4.43)	(4.06)	(3.63)	(2.87)
SR	0.34	0.33	0.28	0.34
$10-12$	0.303	0.319	0.289	-0.034
	(4.58)	(4.17)	(2.83)	(-0.35)
SR	0.34	0.33	0.30	-0.05
> 12	0.387	0.400	0.247	0.253
	(4.11)	(4.10)	(1.90)	(2.55)
SR	0.31	0.32	0.20	0.18

Panel B: Forecasting Calendar Spread Returns

	Maturity (months)	c_{slope}		c_{level}		R^2
SPX	$4-6$	-0.131	(-3.90)	-0.026	(-1.45)	0.152
	$7-9$	-0.132	(-2.99)	-0.021	(-0.98)	0.105
	$10-12$	-0.158	(-3.19)	-0.026	(-1.10)	0.113
	> 12	-0.213	(-3.15)	-0.037	(-1.22)	0.102
DJX	$4-6$	-0.122	(-2.58)	-0.018	(-0.74)	0.127
	$7-9$	-0.133	(-2.47)	-0.018	(-0.67)	0.107
	$10-12$	-0.136	(-2.28)	-0.014	(-0.48)	0.084
	> 12	-0.184	(-2.54)	-0.024	(-0.63)	0.088
NDX	$4-6$	-0.073	(-1.75)	-0.019	(-1.11)	0.016
	$7-9$	-0.125	(-3.20)	-0.021	(-1.08)	0.046
	$10-12$	-0.180	(-2.78)	-0.052	(-1.60)	0.129
	> 12	-0.161	(-2.33)	-0.024	(-0.70)	0.059
OEX	$4-6$	-0.133	(-3.87)	-0.026	(-1.71)	0.151
	$7-9$	-0.125	(-2.66)	-0.005	(-0.17)	0.160
	$10-12$	-0.295	(-4.13)	-0.054	(-2.25)	0.159
	> 12	-0.257	(-2.14)	-0.060	(-1.44)	0.092

Table 11: Liquidity of Index Options

This table presents the daily average bid-ask spread, dollar volume (in thousands), and open interest (in thousands) of both call and put options across all maturities. The spread is computed as relative spread, normalized by the average of bid and ask prices. The sample period is 1996 to 2011.

Panel A: S&P 500 Index

Maturity (months)	2	4 – 6	7 – 9	10 – 12	> 12
Bid-ask Spread	0.13	0.11	0.07	0.06	0.05
Dollar Volume	8353.34	6579.35	5021.63	4060.11	3675.22
Open Interest	4756.44	7289.83	5156.96	3653.45	3598.40

Panel B: NASDAQ Composite Index

Maturity (months)	2	4 – 6	7 – 9	10 – 12	> 12
Bid-ask Spread	0.17	0.10	0.06	0.05	0.03
Dollar Volume	364.00	309.73	156.51	116.86	149.04
Open Interest	1228.59	924.49	1085.81	250.86	403.02

Panel C: Dow Jones Industrial Average Index

Maturity (months)	2	4 – 6	7 – 9	10 – 12	> 12
Bid-ask Spread	0.23	0.17	0.12	0.10	0.08
Dollar Volume	938.05	1009.12	628.80	461.33	593.12
Open Interest	133.77	62.26	34.76	28.94	40.24

Panel D: S&P 100 Index

Maturity (months)	2	4 – 6	7 – 9	10 – 12	> 12
Bid-ask Spread	0.12	0.09	0.09	0.08	0.04
Dollar Volume	541.77	402.32	496.75	410.38	138.61
Open Interest	483.71	290.17	211.63	168.97	108.35

Table 12: Subsample Results

This table reports the mean returns of all delta-hedged option portfolios for the two subsample period. Mean monthly returns are in percentages. The Newey-West adjusted t-statistics are in the parentheses. Panel A presents the first half of the sample period and Panel B presents the second half. Missing observations are left in blank.

Panel A: 1996 to 2003

Maturity (months)	SPX	NDX	DJX	OEX
2	-0.469	-0.227	-0.699	-0.488
	(-3.90)	(-1.14)	(-4.47)	(-3.96)
$4-6$	-0.157	-0.210	-0.345	-0.191
	(-1.33)	(-1.07)	(-2.31)	(-1.53)
$7-9$	-0.092	-0.159	-0.300	-0.027
	(-0.76)	(-0.72)	(-2.01)	(-0.19)
$10-12$	-0.080		-0.282	
	(-0.63)		(-1.83)	
> 12	-0.031		-0.209	-0.942
	(-0.19)		(-1.21)	(-3.21)

Panel B: 2004 to 2011

Maturity (months)	SPX	NDX	DJX	OEX
2	-0.310	-0.342	-0.321	-0.317
	(-2.20)	(-2.82)	(-2.26)	(-2.25)
$4-6$	-0.234	-0.289	-0.230	-0.254
	(-1.41)	(-1.92)	(-1.23)	(-1.46)
$7-9$	-0.146	-0.197	-0.147	-0.348
	(-0.83)	(-1.26)	(-0.80)	(-2.06)
$10-12$	-0.093	-0.015	-0.077	-0.419
	(-0.52)	(-0.06)	(-0.42)	(-2.65)
> 12	0.025	-0.062	0.009	-0.034
	(0.12)	(-0.29)	(0.05)	(-0.15)

Figure 1: Mean Returns and Level β

This figure plots the mean realized returns ($\hat{rx} = E_T[R_t^e]$) of delta-hedged option portfolios (weighted average of call and put options) against their variance level betas. The betas are computed by running time series regression of each option straddle return against the 30-day risk neutral variance factor (level).

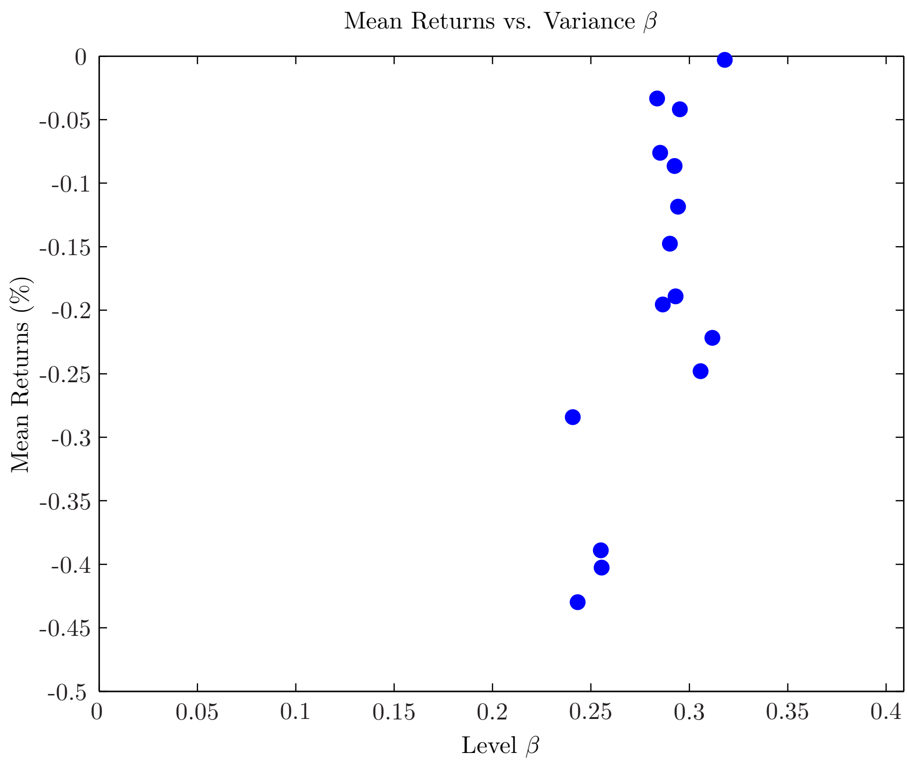

Figure 2: Mean Returns and Fitted Returns

This figure compares the fitted returns ($\bar{rx} = \hat{\beta}^{\top}\hat{\lambda}$) and the mean realized returns ($\hat{rx} = E_T[R_t^e]$) of delta-hedged option portfolios (weighted average of call and put options) measured by different models. Panel A, B, C, and D report results from one factor model with level only, one factor model with slope only, two factor model, and two factor augmented with market excess return, individually. All the returns are at monthly frequency, and in percentage points.