ABSTRACT

Title of Dissertation: ESSAYS ON EMPIRICAL ASSET PRICING

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This dissertation contains two essays empirically exploring the equity option markets. Chapter 1 studies the role played by institutional investors in determining equity option returns. In this chapter, I study whether institutional stock holdings predict equity option returns. I find that institutional concentration in the underlying stock negatively predicts the cross-section of corresponding option returns. Evidence is consistent with a hedging and demand pressure channel: For stocks with more concentrated ownership, some institutional holders are more likely to overweight them and demand more of their options to hedge. To absorb the order imbalances, dealers sell options and charge higher prices, leading to lower option returns. Using option holdings of U.S. equity mutual funds, I document a positive correlation between funds' stock concentration and their option share in the same firms. In Chapter 2 (joint with Steven Heston), we improve continuous-time variance swap approximation formulas to derive exact returns on benchmark VIX option portfolios. The new methodology preserves the variance swap interpretation that decomposes returns into realized variance and option implied-variance.

We apply this new methodology to explore return momentum on option portfolios across different $S\&P$ 500 stocks. We find that stock options with high historical returns continue to outperform options with low returns. This predictability has a quarterly pattern, resembling the pattern of stock momentum found by Heston and Sadka (2008). In contrast to stock momentum, option momentum lasts for up to five years, and does not reverse.

ESSAYS ON EMPIRICAL ASSET PRICING

by

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Chapter 1: Institutional Stock Holdings and the Cross-Section of Option Returns

1.1 Introduction

As a popular financial derivative, option is widely used for speculation and hedging purposes. There is a large literature studying whether option trading predicts stock returns through an information channel. This paper looks at the opposite direction: Could institutional investors' stock holdings predict option returns? I explore a hedging and demand pressure channel: Financial institutions are major holders of U.S. stock markets. Their stock holdings, viewed as endowments, should contain important information on their demands for options, which can be used by institutions to manage endowment risks. Since options cannot be perfectly hedged, option market makers will charge premiums for demand imbalances caused by institutions. If there are heterogeneous institutional hedging demands across firms, stock holdings may predict the cross-section of corresponding equity option returns.

In addition to directional risk, stock positions also expose their holders to stochastic variance risk, which is the focus of this paper. Survey evidence shows that variance risk is a major concern of institutional investors: 39% of them utilize variance derivatives to hedge against variance risk (The Economist Intelligence Unit 2012).[1] Since derivatives have embedded leverages, institutional investors use them as a low cost way to achieve desired risk exposures (Koski and Pontiff [1999]). Chen [2011] finds evidence that hedge funds use derivatives to reduce risk-taking; For mutual funds, derivative use is also negatively related with fund risk profile.[2] Due to limited evidence associating derivative use with increased institutional risk-taking[3], this paper focuses on institutional hedging demand for derivatives and abstracts away from speculating demand.

The effect of demand imbalance on option pricing has been documented by previous literature. Unlike in Black and Scholes [1973] model, option market makers cannot perfectly hedge their positions due to frictions in real market (Figlewski [1989]; Green and Figlewski [1999]). Muravyev [2016] finds that order imbalances attributable to inventory risk have greater predictive power than any other commonly used option return predictors. Garleanu, Pedersen, and Poteshman [2008] explicitly model demand pressure effects on option prices and empirically document that on average across firms, equity options are less used for hedging than index options are.[4] However, their model treats demand imbalance as exogenous and is agnostic

[1] For example, on 10/31/2000, an equity mutual fund called ClearBridge utilized a collar strategy to hedge against the potential variance risk originated from its largest equity holdings: it held a long position on Adobe Inc. stocks worth \$137 million and 4.75% of portfolio weight; the fund also long 1.8 million shares of Adobe puts, worth \$17.1 million, with a strike price of 140 and short 1.8 million shares of calls, worth \$9.1 million, with a strike price of 195. Option holdings of ClearBridge alone amount to 9.71% of Adobe's option market value.

[2] See Cao, Ghysels, and Hatheway [2011], Cici and Palacios [2015], and Koski and Pontiff [1999].

[3] The most commonly cited reason for derivative use by institutional investors is hedging (Levich, Hayt, and Ripston [1999]). In Koski and Pontiff [1999], only 8.5% of mutual funds use derivatives for speculative purposes.

[4] They find that end-users are net short equity options but are net long index options, especially for out-of-the-money index puts. Lakonishok, Lee, Pearson, and Poteshman [2007] find that demand for call is larger than that for put in equity option markets.

about the source of option end-users' demand. This paper specifically explores the hedging demand from institutional investors against variance risks originated from their stock positions. I also use institutional stock holdings to construct a proxy to measure heterogeneous option hedging demands across firms and show that it can predict cross-sectional option returns.

I measure the expensiveness of options using variance risk premium (VRP henceforth), calculated as the return of an option portfolio daily hedged by trading the underlying stock. I call it the VIX portfolio hereafter. The name comes from the CBOE VIX index, constructed from a portfolio of options whose held-to-maturity payoff equals the realized variance of the underlying stock return. I apply the CBOE methodology to individual firms and calculates returns of firms' VIX portfolios.

I use the Herfindahl-Hirschman Index (HHI henceforth) of institutional ownership of a firm's stocks as a firm-level proxy for institutional investors' hedging demands against stochastic variance risk originated from their stock positions. This measure is motivated from a model in Smith [2019]: In a stochastic variance setting, investors' stock positions expose them to variance risk and they hedge the risk by long VIX portfolio whose payoff equals future realized variance. In equilibrium, HHI is proportional to investors' aggregate hedging demand for VIX portfolio.[5] Intuitively, for stocks with more concentrated ownership, some institutional holders are more likely to overweight them and demand more of their options to hedge.

Empirically, I find that HHI negatively predicts the cross-section of option

[5]Each investor's hedging demand for the variance derivative is a quadratic function of her stock holding. Summing across investors, the aggregate hedging demand is proportional to HHI.

returns. Using Morningstar dataset on holdings of U.S. equity mutual funds, I identify funds that use equity options and show that the predictability of HHI comes from funds that actually use options, especially from those long puts. I also find the predictability driven by funds that overweight the firm relative to their benchmark indexes. After matching option holdings with underlying firms, I find that when a firm's HHI increases, its option market becomes more active and mutual funds take a larger share in this market. Robustness checks show that HHI does not predict future stock return or variance. Its option return predictability does not work through an information channel. Also, its predictability cannot be explained by firm size or number of firm's institutional holders.

I construct HHI using individual mutual fund level stock holdings in S12 database and more aggregate level holdings of 13f institution in S34, respectively. Both measures negatively predict cross-sectional option returns. In a horse race, individual fund level HHI can subsume the information contained in the institution level HHI. A possible reason is that due to managerial compensation incentives, fund managers make hedging decisions based on their own fund holdings and not on the fund family holdings aggregated into S34. In this case, fund level HHI constructed from S12 is a better proxy for hedging demand. This paper focuses on the fund level measure.

For the hedging and demand pressure channel to work, there are two necessary components: order imbalance and price impact. I check the two parts, respectively, by testing related theories in the literature. I find that the predictability is stronger among stocks held by mutual fund holders who suffer recent lower performance[6] and have higher flow volatilities and portfolio concentrations. This is expected because those stocks' fund holders are more likely to use options to hedge and cause order imbalances. The predictability is stronger during periods in which intermediaries suffer tighter funding liquidity constraint, because intermediaries as option market makers charge higher compensation for bearing order imbalances when they are more constrained. The predictability is also stronger among stocks with higher stochastic volatility risk, jump risk and stock market illiquidity. This is because options written on those stocks are more difficult to hedge and have higher price impact (Garleanu et al. (2008)). A given level of order imbalance can cause a larger cross-sectional dispersion in those stocks' option returns.

I further examine how HHI is related with the systematic and idiosyncratic components of VRP. Assuming stock returns follow the market model, I write firm's VRP as a weighted average of systematic and idiosyncratic components. Then I use a cross-sectional regression to estimate the two components jointly and find that HHI is negatively related with both components. If some institutional investors hold concentrated positions in firms with higher HHI, they are supposed to be more sensitive to both systematic and idiosyncratic variances and pay higher premiums to hedge those risks. This will lead to more negative systematic and idiosyncratic VRP.

The systematic VRP embedded in equity options is estimated to be 12.3%,

[6] I find a reversed pattern at year-end, consistent with the managerial gaming story in Brown, Harlow, and Starks [1996] and Chevalier and Ellison [1997]: For window dressing purpose at the end of year, loser funds increase risk-taking and winners tend to hedge to preserve good results.

statistically different from that measured by S&P 500 Index options (-23.2%). A trading strategy that long firms with high exposure to systematic variance risk and short those with low exposure generates a monthly return of 17.5% and an annual Sharpe Ratio of 1.76. The profits cannot be explained by the volatility mispricing in Goyal and Saretto [2009] and the idiosyncratic volatility effect in Cao and Han [2013]. The underpricing of systematic variance risk in equity options can partially explain the puzzle that equity options appear cheaper than index options.[7]

I offer a partial explanation for the differential pricing from the perspective of different demand patterns and compositions of traders in index and equity option markets. It has been well documented that equity options are less used for hedging than index options are[8] and that individual investors have a larger impact in equity option markets than in index option market[9]. I hypothesize that in equity option markets, compared with less sophisticated individual investors who are more likely to chase a firm's idiosyncratic variance for lottery-like payoffs,[10] institutional investors who hold concentrated positions in the firm would pay more attention to systematic variance, which will be priced more consistently with that embedded in index options. After sorting firms by HHI, I find that systematic VRP estimated from equity options of higher HHI subgroup becomes less positive and gets closer to that estimated from index options. This is consistent with the hypothesis.

[7] See Bakshi and Kapadia [2003b], Bakshi, Kapadia, and Madan [2003], Bollen and Whaley [2004], Carr and Wu [2009], and Driessen, Maenhout, and Vilkov [2009].

[8] See Bollen and Whaley [2004], Garleanu, Pedersen, and Poteshman [2008], and Lakonishok, Lee, Pearson, and Poteshman [2007].

[9] Lemmon and Ni [2014] show that individual investors' sentiment affects the demand and pricing for equity options but not for index options.

[10] See Boyer, Mitton, and Vorkink [2010] and Boyer and Vorkink [2014].

The idiosyncratic VRP is estimated to be -11.2%. The negative price is consistent with the notion that options on stocks with high idiosyncratic volatilities attract high demand from speculators, and that constrained financial intermediaries charge extra compensation for supplying these options because of their high hedging costs (Cao and Han [2013]). The finding complements the literature on the pricing of idiosyncratic volatility in financial markets. Previous studies mainly focus on the stock market.[11]

I construct an idiosyncratic VIX portfolio, whose payoff approximates the realized idiosyncratic variance of the firm's stock return. In a cross-sectional regression, HHI negatively predicts the return of idiosyncratic VIX portfolio, suggesting that institutions with concentrated positions in the firm are sensitive to idiosyncratic volatility and pay a higher premium to hedge it.

The rest of this paper is organized as follows. Section 2 presents the construction of VIX portfolio and HHI. Section 3 investigates how HHI affects firm's VRP. Section 4 presents a decomposition of VRP and explores the effect of HHI on the systematic and idiosyncratic components of VRP. Section 5 reports the profitability of trading strategies. Section 6 offers concluding remarks.

1.2 Data Construction

This section presents the data steps to construct VIX portfolio and Herfindahl-Hirschman Index (HHI) of the firm's stocks.

[11] Ang, Hodrick, Xing, and Zhang [2006] find that idiosyncratic volatility negatively predicts future stock returns in the cross section. An exception is Cao and Han [2013] who find that idiosyncratic volatilities negatively predict the cross-sectional delta-hedged option returns.

1.2.1 VIX portfolio

I construct the VIX portfolio following Heston and Li [2020]. The payoff of VIX portfolio closely approximates the realized variance of stock return,[12] defined as the sum of squared daily stock return. The return of VIX portfolio directly measures VRP.

VIX portfolio is composed of two parts: a static position in a portfolio of out-of-the-money (OTM) options and a daily hedged position in the underlying stock. The option position is constructed based on CBOE White Paper[13] as follows:

$$V(t,T) = 2\sum_i \frac{O(K_i,t,T)\Delta_i}{K_i^2}, \tag{1.1}$$

where: $V(t,T)$ is the time t price of option position maturing at T; $O(K,t,T)$ represents time t price of an OTM call or put with strike price K and expiration T; K_i are the available strike prices of the firm's option contracts; Δ_i is the distance between adjacent strikes.

To make the VIX reflect the future 30 days volatility, CBOE does interpolation using near-term and next-term options. This paper does not follow this standard. Instead, I form the option position in the VIX portfolio on the third Friday of each month (t) and hold options to maturity, which is the third Friday of the subsequent month (T). By avoiding interpolation, I do not need to hold two option portfolios with different maturities.

[12] The detailed proof is in the appendix.
[13] It can be found at https://www.cboe.com/micro/vix/vixwhite.pdf.

By augmenting the static option position with a daily hedged stock position whose current price equals 0, I get the VIX portfolio, whose return equals

$$r_{hedged}(t,T) = \frac{V(T,T) - 2\left(\frac{S(T)}{S(t)(1+r_f)^{T-t}} - 1\right) + 2\sum_{u=t+1}^{T}(r(u) - r_f)}{V(t,T)} - 1, \qquad (1.2)$$

where: $S(t)$ is the stock price at time t; r_f is the daily risk-free interest rate; $r(u)$ represents the stock return on day u, which is a day between time t and T.

In order to construct the VIX portfolio, investors need to: 1. take a static option position formed on time t with price $V(t,T)$ and held-to-maturity payoff $V(T,T)$; 2. short a static hedged stock position with 0 current price and a final payoff of $2(\frac{S(T)}{S(t)(1+r_f)^{T-t}} - 1)$; 3. take a daily hedged stock position with 0 current price and daily payoff $r(u) - r_f$.

Since I only use options with available strike prices to form VIX portfolio in (1.1), the payoff of the VIX portfolio only approximately equals realized variance, with errors caused by discreteness of the strike interval. To gauge the tracking error, I compare the return in (1.2) with the variance swap return (VSR), defined following Carr and Wu [2009]:

$$VSR(t,T) = \frac{\sum_{u=t+1}^{T} r(u)^2}{V(t,T)} - 1. \qquad (1.3)$$

I construct VIX portfolios for both individual firms and the S&P 500 Index. I call them equity and index VIX portfolios, respectively. For index VIX portfolio, the correlation between its actual return and VSR is 0.99. Its payoff is very close to the realized variance over the month. As indicated in Figure 1.1, index VIX return closely tracks VSR during the sample period. I calculate returns of VIX portfolios for all optionable firms in the OptionMetrics Database, which gives a larger cross-section than previous studies.[14] The median of within-firm time-series correlation between the firm's equity VIX return and VSR equals 0.88. By forming portfolios, firm-level approximation errors could be diversified away. The correlation between the return of cross-sectionally equally weighted (EW) equity VIX portfolio and EW VSR is 0.91. Since most stocks have the same discrete intervals across strike prices, the error caused by discrete strike intervals would be differenced out when I form long-short trading strategies.

Option data is drawn from the OptionMetrics Ivy DB database. The dataset contains information on the entire U.S. equity option market and includes daily closing bid and ask quotes, open interest, and trading volume of each option. Implied volatility, option's delta, vega, and other Greeks are computed by OptionMetrics. The zero-coupon rate of appropriate maturity (interpolated when necessary) from OptionMetrics is used as the risk-free rate. Option positions in VIX portfolios are formed on the third Friday of each month and are held to maturity, which is the third Friday of the subsequent month. Sample period is from January 1996 to December 2017.

I construct VIX portfolios for all optionable firms in OptionMetrics, with the following filters applied: (1) to avoid extremely small and illiquid stocks, the underlying stock prices should be at least $5, (2) delete firm-month observations in which

[14] Carr and Wu [2009] conduct their study using five stock indexes and 35 individual stocks; Driessen, Maenhout, and Vilkov [2009] look at the VRP of S&P 100 Index and its constituent firms.

there are stock splits, (3) following Driessen, Maenhout, and Vilkov (2009), I discard options with zero bid prices and with missing implied volatility or delta (which occurs for options with nonstandard settlement or for options with intrinsic value above the current mid price), (4) delete options whose ask price is lower than bid price, (5) filter option contracts following CBOE White Paper, (6) option contracts with zero open interest are removed, in order to eliminate options with no liquidity, (7) delete options whose prices violate arbitrage bounds, (8) the midpoint price of option needs to be at least $0.125, (9) following Conrad, Dittmar, and Ghysels [2013], to reduce the bias caused by asymmetry in the domain of integration in equation A1, equal number of OTM calls and puts are used to construct VIX portfolio, and (10) exclude firm-month observations if the underlying stock pays a dividend during the remaining life of the option. Thus, options in my sample are close to the European style. Also, VIX portfolio assigns a higher weight on OTM puts, whose early exercise premium is lower. So, the early exercise premium of VIX portfolio is expected to be low. The final sample includes 138,339 firm-month observations and 5,012 unique stocks over the sample period. To pass the option filters, stocks in the sample tend to be relatively large stocks with liquid option markets. Results in this paper are not driven by small stocks.

Table 1.1 reports summary statistics. There are 526 stocks per month on average. Equity VIX portfolio consists of 6 option contracts on average. For index VIX portfolio, the average number of contracts is 84. Index VIX return has a mean of -23.24% per month. The large negative return reflects the large negative VRP embedded in index options documented by Carr and Wu [2009] and Driessen, Maenhout, and Vilkov [2009].

The pooled sample mean of equity VIX return is -5.13%. Each month, I equally weight firms' equity VIX portfolios. The time-series average of the equally weighted (EW) equity VIX return is -4.82%, which is much less negative than that of the index. This is broadly consistent with the result in previous literature stating that VRP of individual stocks are much less negative than that of the index.

For each firm, $\beta_{Index\,VIX\,Return}$ is the exposure of its VIX return to index VIX return. The average exposure across firms is 0.33. Corr(Equity VIX Return, Stock Return) is the firm-level time-series correlation between equity VIX return and the underlying stock return. The mean correlation across firms is -0.26, reflecting a leverage effect. To calculate the exposure and correlations, firms are required to have at least 30 observations. There are 1,389 firms meeting this requirement.

Other databases are used to extract the information needed later in this paper. Information about stock returns, accounting data, and analyst forecasts are obtained from CRSP, COMPUSTAT, and I/B/E/S, respectively. The Fama-French common risk factors are taken from Kenneth French's website.

1.2.2 HHI of institutional ownership

I use Thomson Reuters S12 Database to construct the quarterly HHI of mutual fund ownership of the firm's equity shares. The database includes all registered domestic mutual funds filing with the SEC and their equity holdings. A more aggregate level HHI is constructed using the S34 Database, which covers the holdings of entire investment companies, often called 13f institutions. S12 and S34 differ in their levels of coverage: almost every fund in the S12 set has a manager in the S34 set, and the latter reports the aggregated holdings of all funds under the manager's control. For example, Fidelity reports as a single entity and aggregates the holdings of all funds and trusts that it manages into its quarterly 13f filings, whose information would be included in the S34. Fidelity also reports holdings of its individual funds, whose information is included in the S12.

For each firm, its HHI of mutual fund ownership is constructed in the following steps: First, delete observations whose file date and report date are not in the same quarter, in order to avoid stale reports. Second, delete observations with missing fund assets. Third, for each firm, calculate the total number of shares owned by all mutual funds and the share proportion owned by each fund. Fourth, calculate the firm's HHI as the sum of squared share proportion owned by each fund i as follows:

$$Firm's\ Mutual\ Fund\ HHI = \sum_{i}^{N} \left(\frac{Shares_i}{Total\ Shares_{Mutual\ Fund}} \right)^2,$$

where N is the total number of funds that hold the firm's stocks. The institutional level HHI could be calculated in the same method using the S34 dataset. It could also be downloaded directly from the WRDS TR 13-F Stock Ownership database.

The decision to scale the share holding of each fund (institution) by total mutual fund (institution) share holdings, instead of total shares outstanding of the firm, is not arbitrary and depends on whether small retail investors hedge their equity positions using equity options. Imagine two firms: Firm A and Firm B. Firm

A is 100% owned by one fund. 50% shares of Firm B is owned by one fund, with the other half owned by many small retail investors. Assume that small investors do not use options to hedge.[15] Then, all the hedging demands in equity option markets for both firms should come from only the fund that owns the firm. However, if I scale by total shares outstanding of the firm, Firm A's HHI equals 1, while Firm B's HHI equals 0.25. HHI calculated this way would be misleading as a proxy for hedging demand.

Panel B in Table 1.1 reports summary statistics of mutual fund and 13f institution level HHI. The average HHI of mutual funds is 0.139, higher than that of institutions (0.057). The fund-level HHI has a standard deviation of 0.196, more variable than that of the institution-level measure (0.069).

1.3 HHI and the Cross-Section of VIX Returns

This section examines how mutual fund HHI predicts cross-sectional equity VIX returns, which is a direct measure of firm VRP. HHI is interpreted as a firm-level proxy for variance risk hedging demand in equity option markets. Intuitively, an increase in mutual funds ownership concentration in the underlying equity market drives up their hedging demand for equity options, and dealers charge a higher premium to absorb the increased order imbalances. Appendix B presents a simple model built on Smith [2019] to motivate the HHI measure: In a stochastic volatility

[15] Lakonishok et al (2007) examine households' holdings from a large discount brokerage firm. They find that even though account holdings are predominantly common stocks, only 1.3% positions are equity options, and less than half of those option positions come from accounts that hold the underlying stock. Therefore, this assumption is relatively innocuous.

setting, investors' equity positions expose them to variance risk, and they hedge the risk by purchasing a variance derivative with a payoff of realized variance. In equilibrium, each investor's hedging demand for the variance derivative is a quadratic function of her equity holding. Thus, the aggregate hedging demand of the firm's equity holders is proportional to HHI.

1.3.1 VIX return predictability of HHI

This section examines and compares the VIX return predictability of mutual fund and institution level HHI. There is a trade-off between granularity and coverage: The fund level measure is constructed from the S12 database, which is more granular than S34. Due to managerial compensation incentives, fund managers may make hedging decisions based on their own fund holdings and not on the aggregate fund family holdings. In this case, fund level HHI is a better proxy for hedging demand than institution level HHI. On the other hand, S34 has a broader coverage than S12. In addition to mutual funds, S34 includes the holdings of pension funds, insurance companies, and endowments. The broader coverage can make institution level HHI a better proxy.

I run monthly Fama and MacBeth [1973] cross-sectional regression

$$r_{i,t+1} = \alpha_t + \gamma_t HHI_{i,t} + \theta_t X_{i,t} + \epsilon_{i,t+1},$$

to examine the predictability of HHI on the one-month-ahead equity VIX returns. As a control variable, holdings of mutual fund (institution) is calculated as the firm's total shares held by all mutual funds (institutions) divided by the firm's total number of shares outstanding. Schürhoff and Ziegler [2011] find that holdings of mutual fund positively predict cross-sectional equity variance swap returns. The reason is that mutual funds sell options on average. This supply pressure makes options cheaper and firms' VRP less negative.

Table 1.2 reports the regression results. When fund level HHI is used alone as a predictor, its coefficient estimate is -0.24, with a t-statistic of -7.17. A standard deviation increase in HHI decreases the monthly option return by 4.7%. Hedging demands for equity options are higher among firms with larger HHI, which would push up option prices and make firms' VRP more negative. Controlling for share proportion owned by mutual funds only slightly changes the coefficient estimate and t-statistic of HHI. The coefficient estimate of holdings of mutual funds is weakly significant and positive. Institution level HHI exhibits a similar pattern. Unlike mutual funds, holdings of institutions have a weaker and insignificant positive effect on option returns. A possible reason is that 13f institutions other than mutual funds demand equity options, which counteracts the net selling effect of mutual funds. The story is supported by specification (5): In a multivariate regression, the coefficient of holdings of institution is -0.075 with a t-statistic of -3.02. Whereas, the coefficient of mutual fund holdings is significantly positive.

To do a horse race between the fund and institution level measure, I run a multivariate regression including all four variables in Column (5). The coefficient estimate of fund level HHI is only slightly affected. However, the coefficient estimate and t-statistic of institution level HHI are more than halved. This suggests that mutual fund HHI constructed from more granular level data is a better proxy for hedging demand.

Garleanu, Pedersen, and Poteshman [2008] document a net short position of end-users in equity option markets. Lakonishok et al. (2007) find that directional hedging account for a small fraction of trading in equity option markets. Their results suggest that hedging demand is less important in determining the overall level of option activity and returns in equity option market. However, the evidence documented by the two papers is on an aggregate level. The potential heterogeneity in hedging demands across firms can cause a large impact on option returns.

1.3.2 Robustness checks

This section checks whether the predictability of HHI can be explained by other option return predictors. I also use delta-hedged call and put returns in Bakshi and Kapadia [2003a] as additional testing assets. The return predictability of HHI cannot be absorbed by other predictors, size, number of fund holders for the firm's stocks, and industry effects. I also find no evidence supporting that HHI is a proxy for insider information about future stock return or volatility.

Control variables are as follows: volatility-related mispricing measures including idiosyncratic volatility (IVOL) documented in Cao and Han [2013], log difference between historical volatility and equity VIX (HV-VIX) modified from the volatility deviation measure in Goyal and Saretto [2009]; firm characteristics studied in Cao, Han, Tong, and Zhan [2017], including short-term stock return reversal

($RET_{t-1,t}$), stock return momentum ($RET_{t-12,t-1}$), long-term stock return reversal ($RET_{t-36,t-12}$), size (Ln(ME)), book-to-market (Ln(BM)), analyst earnings forecast dispersion (Analyst Dispersion), cash holdings (CH), profitability (Profit), new issues (Issue); higher-order moments of stock returns calculated using historical one-year daily data: skewness (Rolling Skew) and kurtosis (Rolling Kurt); the risk-neutral skewness of stock returns inferred from a portfolio of options (RN Skew) is included as a measure for jump risk (Bakshi, Kapadia, and Madan [2003]); Amihud illiquidity measure (Amihud) is calculated for each stock as a proxy for the underlying stock's liquidity (Amihud [2002]); the percentage bid-ask spread of equity VIX portfolio is used as a proxy for option liquidity. Detailed variable constructions are in the appendix.

Table 1.3 report results of the following Fama-MacBeth regression:

$$r_{i,t+1} = \alpha_t + \gamma_t HHI_{i,t} + \theta_t Controls_{i,t} + \epsilon_{i,t+1}.$$

In specifications (1) and (2), fund and institution level HHI both significantly and negatively predict equity VIX returns. The coefficient on fund level HHI is -0.21 with a t-statistic of -4.46; the coefficient on institution level HHI is -0.279 with a t-statistic of -4.01. When I include both measures in specification (3), the coefficient of fund level HHI remains significant with a t-statistic of -3.52. However, the coefficient of institution level HHI becomes insignificant, confirming the early finding in Table 1.2 that mutual fund HHI constructed from more granular level data is a better proxy. In Specifications (4) and (5), fund level HHI also negatively predicts delta-hedged call and put returns with similar t-statistics.

Firm size and HHI are negatively correlated with an average cross-sectional correlation of -0.38. To control for the potential nonlinear pricing relation between the two variables, I implement a double-sort procedure, with results reported in Panel A of Table A1.1. Returns sorted by HHI are significant in every size quintile. The information contained in HHI cannot be absorbed by size.

Another concern is that the predictability is related with the number of fund holders in the firm: when a firm is owned by fewer funds, HHI becomes larger by definition. In fact, their correlation is -0.43. I implement the same double-sort procedure: first sort firms into quintiles by the number of fund holders, then further sort each quintile by HHI. Results are reported in Panel B of Table A1.1. Returns sorted by HHI are significant in groups with both low and high number of fund holders. There are no systematic pattern showing that the predictability is related with the number of fund holders. Adding number of fund holders as a variable in Table 1.3 does not predict option returns and makes little difference in the return predictability of HHI.

I further check whether option return predictability of HHI comes from its ability to predict future stock return or variance of the underlying firm. I run Fama-MacBeth regression and use HHI to predict one-month-ahead stock return and realized variance, respectively, controlling for variables in Table 1.3. Panel C in Table A1.1 reports the results. The coefficients of HHI are insignificant. Therefore, it is implausible that HHI contains information about future stock return or variance.

Since index funds are unlikely to use equity options, their holdings should not contain information about hedging demand. In an unreported test, I calculate HHI using only stock holdings of index funds and find that the index fund HHI does not predict option return.

To remove industry effect, I classify firms into 10 industries, following the procedure in Kenneth French's data library. I demean firms' VIX returns by industry average each month and run the same regressions. Results (unreported for brevity) are very similar.

This section shows that fund level HHI cannot be fully absorbed by previously documented option return predictors. Since institution level HHI loses significance after including fund level HHI and other controls, the rest of this paper will focus on the mutual fund level measure.

1.3.3 HHI of option funds and non-option funds

This section examines the explanatory power of HHI of option funds and non-option funds[16] on equity VIX returns, respectively. All HHIs in this and next section are constructed using Morningstar U.S. equity mutual fund holdings data from 1996 to 2015 (4509 funds in total).[17] [18] I find that the explanatory power of HHI comes from option funds and especially from funds that long puts. Funds that specialize in selling options, i.e. covered call strategy, have positive, instead of negative, effect

[16] If a mutual fund has equity options in its portfolio, I call it "option fund". If a fund never holds equity options, I call it "non-option fund".

[17] I am especially grateful to David Hunter for sharing this dataset. The dataset is used in his paper Hunter [2015] "Mind the Gap: The Portfolio Effects of 'Other' Holdings", available at https://ssrn.com/abstract=3684031.

[18] A limitation of this dataset is that it does not cover the holdings of alternative funds, which are heavy option users according to Deli, Hanouna, Stahel, Tang, and Yost [2015].

on option returns. This is inconsistent with the story that the predictability of HHI comes from funds with skills in identifying overvalued options and sell them to generate alpha. Another finding is that option funds do not have higher alphas relative to non-option funds. This is inconsistent with the story that funds use options for informed speculation. I also find that the predictability of HHI comes from funds that overweight the firm relative to their benchmark indexes, consistent with a hedging story.

An important advantage of the Morningstar dataset over the CRSP Mutual Fund database is that it provides non-equity fund holdings, including options. This allows me to identify mutual funds that actually trade equity options and separately study the effect of their ownership on VRP. However, unlike equity holdings, funds report option holdings in a nonstandard way: most of the option holdings do not have common identifiers like CUSIP; funds usually do not report important characteristics of option contracts, like strike price and maturity; and underlying firm names are abbreviated, and sometimes funds use tickers instead of names.

To extract equity option holdings, I follow procedures used in Cici and Palacios [2015]: I use the security names of fund holdings as the main input, and identify observations that contain the "Call" or "Put" text strings in the names; I then use visual inspection to remove misclassification and index options and only keep equity options. The final sample contains 48,664 observations. 607 out of 4509 equity funds utilized equity options during the sample period.

Next, I classify all equity funds into option funds and non-option funds and study the effects of their stock ownership on VRP, respectively. Panel A in Table 1.4

reports the average coefficients of Fama-MacBeth regressions. HHI MStar is constructed using only the stock holdings of U.S. equity funds in Morningstar. HHI Non MStar is constructed from funds in S12 but uncovered by the Morningstar dataset. I construct this variable to check whether using only U.S. equity funds in Morningstar would lose information in predicting option returns. HHI Overweight (Underweight) is constructed using the holdings of funds in Morningstar that overweight (underweight) the firm relative to their benchmark indexes.[19] If the predictability comes from hedging demand, it should be driven by funds that overweight the firm. HHI Option Fund is constructed using only the 607 option funds. HHI Put Fund is constructed using only funds that use puts. If a fund uses volatility strategy like straddle or collar, it would be classified into this category. HHI Call Fund is constructed using funds that only use calls and never use puts. The union of Put Funds and Call Funds equals total Option Funds. HHI Put Short is constructed using put funds that only short puts but never long puts. HHI Put Long is constructed using put funds that long puts. The union of funds in Put Short and Put Long equals total Put Funds. HHI Call Short is constructed using call funds that only short calls but never long calls. HHI Call Long is constructed using call funds that long calls. The union of funds in Call Short and Call Long equals total Call Funds. The sample includes: 607 option funds, 343 put funds, 264 call funds, 243 long put funds, 100 short put funds, 94 long call funds, and 170 short call funds. In each column, I control for the corresponding share proportions owned by each fund category. For

[19] I download benchmarks of mutual funds from the Morningstar Direct platform. I use portfolio holdings of iShares ETFs to proxy the composition and weights of stocks in the benchmarks.

brevity, their coefficients are unreported here.

In Column (1), HHI MStar negatively predicts VIX returns. Column (2) shows that funds in S12 uncovered by the Morningstar dataset also negatively predict option returns, controlling for HHI MStar. Thus, by restricting the sample to only U.S. equity funds, HHI loses some option return predictability. In Column (3), HHI Overweight negatively predicts VIX returns, while the coefficient of HHI Underweight is insignificant. This is consistent with a hedging story.[20] In Column (4), HHI Option Fund crowds out the explanatory power of HHI MStar. This is expected because it should be the ownership of option funds that affects the demand for options. Results in Columns (5) and (6) both suggest that the negative effect of HHI Option Fund comes from put funds, who are more likely to use options for hedging, but not from call funds. In Column (6), the coefficient of HHI Call Fund is positive and weakly significant. A potential explanation is that many call funds use covered-call strategy and sell calls, which pushes down option prices. Column (7) shows that it is the funds that long puts who are driving the option return predictability. They are the type of funds who are most likely to use options for hedging purpose. An alternative story for the negative predictability of HHI is that some funds have skills in identifying overvalued options and sell them to generate alpha, instead of hedging. The positive coefficient of HHI Call Short and insignificantly negative coefficient of HHI Put Short are inconsistent with this story.

To check how long the predictability of HHI lasts, I run a Fama-MacBeth

[20]In unreported test, I find that neither HHI Overweight nor Underweight predicts future stock returns. This is inconsistent with an information channel.

regression regressing firms' VIX returns on the lagged n (1 to 12) month HHI constructed from option funds. Figure 1.2 plots the coefficient estimates of HHI (solid blue line) and the 95% confidence intervals (dashed black lines) with respect to month lags. The coefficients remain significant for up to 6 months. Contrary to the demand pressure pattern in stock market, there is no reversal in option market. A potential explanation is that options expire each month and there will be no reversal following high demands.

To check whether funds trade options for hedging or speculation, I compare the risk profiles of option and non-option funds under three Morningstar investment categories: Domestic Blend, Domestic Growth, and Domestic Value. For each fund, I compute its alpha relative to Carhart [1997] four-factor model, standard deviation, skewness, and kurtosis of monthly fund returns using CRSP mutual funds database. To get a precise estimate, I delete funds with less than 24 observations during the sample period. When a fund has multiple share classes, I take average. To check how concentrated a fund's portfolio is, for each fund, I compute the HHI of its equity holdings at each quarter and then take time-series average. To compare, I use a two-sided t-test to check the differences in mean estimates of the above fund characteristics between non-option funds and option, put, and call funds, respectively. All variables are winsorized at 0.5% level.

Table A1.2 reports the differences in mean estimates and associated p-values. Users/Total is the proportion of certain type of funds under a specific Morningstar category. For example, 11.03% (5.71%) in the first row means that 11.03% (5.71%) of domestic blend funds use equity options (puts). In every case, alphas are not significantly different among non-option, option, put, and call funds. The finding is inconsistent with the story that funds use options to do informational bets.

Among blend and value funds, option funds (specifically put funds) hold more concentrated equity portfolios than non-option funds. The average portfolio HHI of put funds is 0.32% (0.70%) higher than that of non-option funds in the category of blend (value) funds. Given that the average fund portfolio HHI is 2.11%, the differences are sizable. The standard deviation of put funds is not significantly larger than that of non-option funds. Conditional on the fact that put funds hold more concentrated portfolios, it is possible that they trade options to reduce their risk profiles to a similar level of non-option funds.

Overall, results in this section suggest that the negative effect of HHI on VRP comes from funds that actually use equity options, especially long puts. The comparison of risk profiles among funds is inconsistent with the hypothesis that mutual funds use equity options for informed speculation.

1.3.4 Mutual fund option market activity and HHI

This section directly checks the link between HHI and fund option demands. I examine the relation between HHI constructed from option funds and fund option market activity (FOMA). $FOMA_{i,t}$ is defined as the aggregate holdings on firm i's options across equity funds at the end of quarter t, scaled by the total dollar open interest of firm i's option market. $FOMA_{i,t}$ essentially measures firm i's option market share held by all U.S. equity funds at quarter t. I find that when a firm's

HHI increases, FOMA also increases.

I use the Morningstar dataset in last section to construct FOMA. Again, a caveat of this dataset is that it does not cover alternative funds, which are heavy option users according to Deli et al. (2015). Thus, FOMA calculated here is a lower bound for mutual funds equity option market shares, which is a limitation of this study. To construct FOMA, first, I match each option holding with the underlying firm. Since option holdings do not have common identifiers, I first use a name-matching algorithm based on spelling distance to match security names with firm names. Funds report the security names of option holdings in a nonstandard way: Most of the times, funds use abbreviations in firm names. Sometimes funds use tickers instead of firm names. For those firms, I use visual inspections to pick them out and match their security names with firm tickers. Then I do final visual inspections to filter out misclassification. Second, I aggregate holdings on firm i's options across equity funds at the end of each quarter. Third, using the Option-Metrics Database, I calculate the total dollar open interest for each firm at the end of each quarter and match with the observations in last step to calculate $FOMA_{i,t}$. The final sample has 19,932 firm-quarter observations with non-missing FOMA and 1,793 unique firms.

To check how HHI is related with FOMA, I sort firms into deciles by option funds HHI and report the average FOMA for each decile in Panel A of Table 1.5. When HHI increases from Decile 1 to Decile 10, FOMA monotonically increases from 0.38% to 5.34%.

To control for other variables, I run the following quarterly panel regression:

$$FOMA_{i,t} = \alpha_i + \gamma HHI_{i,t} + \delta Controls_{i,t} + \varepsilon_{i,t},$$

where: α_i is the firm fixed effect. Control variables include: firm size (Ln(ME)), book-to-market (Ln(BM)), short-term stock return reversal ($RET_{t-1,t}$), stock return momentum ($RET_{t-12,t-1}$), idiosyncratic volatility (IVOL) calculated from Fama-French 3-factor model using past one-month daily data, total volatility of stock return (VOL) calculated using past one-month daily data, number of analysts following the firm (Analyst Number), and the divergence of analysts' opinions (Analyst Dispersion). Control variables common to all firms at quarter t are also included: $Index\ Return_{t-6,t}$ is the return of the S&P 500 Index over the past 6 months; Index VIX is the S&P 500 Index VIX at time t; Index RN Skew is the risk-neutral skewness of the S&P 500 Index at time t. Standard errors are clustered at firm and quarter levels.

Table 1.5 reports the regression results. Controlling for the share proportion of the firm owned by all option funds, HHI is positively significant at the 1% level, with a t-statistic of 4.51. Adding other control variables, HHI remains significant at the 1% level, with a t-statistic of 2.60. The coefficient of size is negative. For large firms, mutual funds play a less important role in their equity option markets because there are many other investors demanding options of those firms. The coefficient of idiosyncratic volatility (IVOL) is positive, meaning that funds take larger option market shares for firms with higher IVOL. A possible explanation is that funds use equity options to hedge firms' IVOL.

To check whether the positive relation between HHI and FOMA is caused by firms with illiquid option markets (the denominator of FOMA), I examine how HHI is related to the firm's option market activity. Following Roll, Schwartz, and Subrahmanyam [2010], I use O/S, the option/stock dollar volume, to measure option market activity. It is calculated as the option dollar open interest scaled by the stock's monthly dollar trading volume. I multiply O/S by 100 and convert it to percent. Then I run the same panel regression using O/S as the dependent variable. The coefficient of HHI is positively significant at the 1% level, with a t-statistic of 2.73. Thus, when a firm's HHI increases, the firm's equity option market also becomes more active.

Overall, this section documents a positive relation between HHI and mutual funds option market activity, consistent with HHI being a proxy for fund option demands.

1.3.5 Demand pressure and price impact in equity option markets

If the predictability of HHI[21] comes from the increased hedging demand driving up option prices, there are two necessary components: demand pressure and price impact in option market. The predictability should be positively related with order

[21] Last two sections construct HHI using only U.S. equity mutual funds holdings in the Morningstar Dataset. Starting from this section, I get back to before and use HHI constructed from all funds in the S12 dataset because of its broader coverage.

imbalance times the option price impact of demand pressure as follows:

$$Predictability\ of\ HHI \propto \underbrace{d}_{Demand\ Pressure} \times \underbrace{\frac{\partial p}{\partial d}}_{Price\ Impact}.$$

Demand pressure is larger when mutual funds are more likely to use options to hedge. Garleanu et al. (2008) show that the price impact component: $\frac{\partial p}{\partial d} = \gamma(R_f - 1) \times Option\ Unhedgeable\ Risk$, where γ is option dealer's risk aversion. There are three forms of option unhedgeable risks: stochastic volatility risk, jump risk, and delta-hedging cost. I check whether the pattern of predictability is consistent with each component by testing some related theories in the literature.

First, I test four hypotheses related with when mutual funds tend to use derivatives to hedge and cause demand pressures in option markets: 1. Funds are more likely to use options to reduce risks following lower performance, which leads to unexpected fund outflows and makes fund portfolios riskier (Koski and Pontiff [1999]; Cao, Ghysels, and Hatheway [2011]). What is more, at the end of the year, due to window dressing purpose, loser funds have lower hedging motives and winners tend to hedge more in order to preserve good results (Brown, Harlow, and Starks [1996]; Chevalier and Ellison [1997]); 2. Funds with higher flow volatilities tend to use options to manage risks because their investor bases are less stable. Hypothesis 1 and 2 are both related with the flow-based motivation for mutual fund derivative use proposed by Koski and Pontiff [1999]; 3. When firms are overweighted by mutual funds relative to benchmark, their fund holders are more likely to use those firms' options to hedge; 4. Mutual funds with higher portfolio concentration tend to take hedging positions in option markets. Hypothesis 3 and 4 are both related with fund managers' career concern discussed in Cohen, Polk, and Silli [2010]: A heavy bet on a small number of positions can, in the presence of bad luck, cause the manager to lose her job and the manager tends to be more risk averse.

Second, I test four hypotheses related with option price impacts based on model predictions in Garleanu et al. (2008): 5. The predictability is stronger during periods in which intermediaries suffer tighter funding liquidity constraint. Because intermediaries would be more risk averse and facing higher effective risk-free rates. They charge higher compensation for bearing order imbalances, leading to larger price impacts. 6. Since options written on stocks with higher idiosyncratic volatilities have potentially higher stochastic volatility risk and are thus more difficult to hedge (Cao and Han [2013]), dealers charge higher premiums, leading to larger price impacts; 7. Options written on stocks with higher jump risk have larger price impacts; 8. Options written on illiquid stocks have larger price impacts because it is more costly to do high-frequency delta hedge for those options. In summary, options mentioned above have larger price impacts and their pricings are more sensitive to order imbalance. A given level of order imbalance can cause a larger cross-sectional dispersion in those stocks' option returns.

To test the first four hypotheses regarding demand pressure, I sort firms into three groups (Low, Medium, and High) at each month t, respectively, by: the average of past quarter adjusted returns of mutual funds holding firm i, the average of past-12-month flow volatilities of mutual funds holding firm i, the deviation of firm i's weight in fund industry from its market weight, and the average of portfolio concentrations (measured as HHI) of mutual funds holding firm i. Among each subgroup, I run the Fama-MacBeth regression $r_{i,t+1} = \alpha_t + \gamma_t HHI_{i,t} + \theta_t X_{i,t} + \epsilon_{i,t+1}$, where: $r_{i,t+1}$ is firm i's VIX return; $X_{i,t}$ is a set of control variables as those in Table 1.3.

To construct the above mutual fund characteristics, I first find all mutual funds (excluding index funds, ETF, and ETN) that hold firm i's stock at each month. I take fund returns from CRSP Mutual Fund database and adjust them by Morningstar investment category. I calculate fund flow at month t as:

$$\frac{TNA_t - (1 + r_t)TNA_{t-1}}{TNA_{t-1}},$$

where TNA_t and r_t are the fund's total net asset and monthly return at month t, respectively. I construct fund portfolio concentrations, measured as HHI, using equity holdings in S12 database. To calculate how much each firm is overweighted by fund industry, I use the aggregate stock market as the benchmark and compute the deviation of a firm's weight in total asset of fund industry from its weight in aggregate stock market.

Panel A shows the coefficients of HHI in Low, Medium, and High groups. The patterns are consistent with Hypothesis 1, 2, 3, and 4. The negative predictability is concentrated among firms with mutual fund holders that suffer recent lower performance and have higher flow volatilities and portfolio concentrations. The predictability is also stronger among firms overweighted by mutual fund industry. In order to test the year-end effect documented by Cao, Ghysels, and Hatheway

[2011], who find that winner funds are more likely to use derivatives to reduce risks for managerial incentives at year-end, I split sample periods into non-year-end and year-end (the last quarter of year) when I sort firms by their fund holders' past performances. In the row "Year-end", I sort firms by the average of their fund holders' up-to-date returns during the year adjusted for investment category. The predictability is concentrated among firms held by winner funds at year-end, consistent with the hypothesis.

To test Hypothesis 5, I use TED spread as a proxy for intermediary funding liquidity constraint. TED spread is related with dealers' risk aversion and effective risk-free rate. Data is taken from the Federal Reserve Bank of St.Louis. I split the sample period into three sub-periods (Low, Medium, and High) based on the level of TED spread and run monthly cross-sectional regression $r_{i,t+1} = \alpha_t + \gamma_t HHI_{i,t} + \theta_t X_{i,t} + \epsilon_{i,t+1}$ among each sub-period.

Panel B in Table 1.6 reports the coefficients of HHI in the three sub-periods. The negative predictability of HHI disappears in low TED spread period. As TED spread increases, the coefficients become significant. This pattern is consistent with the story that price impact is stronger during periods in which intermediaries suffer tighter funding liquidity constraint.

To test Hypothesis 6, 7, and 8 regarding option unhedgeable risk, I sort firms into three groups at each month t, respectively, by: firm i's idiosyncratic volatility, estimated from Fama-French three-factor model, as a proxy for stochastic-volatility risk; absolute value of the skewness of firm i's stock return as a proxy for jump risk, because both positive and negative jumps make options difficult to hedge; Amihud illiquidity measure as a proxy for high-frequency delta hedging cost. I run the same Fama-MacBeth regression as before. Results in Panel C display patterns consistent with Hypothesis 6, 7, and 8: the negative predictability of HHI is stronger among firms with higher idiosyncratic volatilities, jump risks, and stock market illiquidities.

Overall, the option return predictability of HHI displays patterns consistent with findings in related literature, adding more validities for HHI being a proxy for hedging demands.

1.4 HHI and the Price of Systematic and Idiosyncratic Variance

This section estimates the systematic and idiosyncratic VRP in equity option markets and shows that HHI is negatively related with each component. I first show that systematic variance risk is underpriced in equity options relative to index options, which helps explain the puzzle that equity options seem cheaper than index options. The underpricing is related to different demand patterns and compositions of traders in index and equity option markets, and is more pronounced among firms with lower HHI. In order to examine how HHI affects the idiosyncratic VRP, I construct a firm-level idiosyncratic VIX portfolio, whose payoff approximates the realized idiosyncratic variance of the firm's stock return. I find that HHI negatively predicts cross-sectional idiosyncratic VIX returns. Intuitively, for firms with higher HHI, some institutional investors are more likely to take large positions in those firms. They are more sensitive to both systematic and idiosyncratic variances and pay higher insurance premiums, leading to more negative systematic and idiosyncratic VRP.

1.4.1 Decomposing VRP in equity option markets

Assuming that individual stock returns follow the market model, I can decompose a stock's total VRP into systematic and idiosyncratic components. I start by estimating the following market-model regression for each firm i:

$$r_{i,t}^{Stock} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t}, \tag{1.4}$$

where: $r_{i,t}^{Stock}$ is the stock return of firm i at month t; $r_{m,t}$ is the market return, proxied by S&P 500 Index return; α_i and β_i are coefficients to be estimated for each firm i.

The realized variance of stock return at month $t+1$ is

$$RV_{i,t+1} = \beta_i^2 RV_{m,t+1} + RV_{\varepsilon,i,t+1}, \tag{1.5}$$

where: $RV_{i,t+1}$ is firm i's realized variance at month $t+1$; $RV_{m,t+1}$ is the realized variance of S&P 500 Index return; $RV_{\varepsilon,i,t+1}$ is the realized variance of firm i's idiosyncratic return.

At the end of month t, I take conditional variance of (1.4) under the risk-neutral measure:

$$VIX_{i,t}^2 = \beta_i^2 VIX_{m,t}^2 + VIX_{\varepsilon,i,t}^2, \tag{1.6}$$

where: $VIX_{i,t}^2$ is the expectation of firm i's total variance at month $t+1$ under risk-neutral measure; $VIX^2_{m,t}$ is the risk-neutral expectation of market variance at month $t+1$; $VIX^2_{\varepsilon,i,t}$ is the expectation of firm i's idiosyncratic variance.

Equation (1.5) and (1.6) imply

$$\underbrace{\frac{RV_{i,t+1} - VIX^2_{i,t}}{VIX^2_{i,t}}}_{VRP_{i,t+1}} = \beta_i^2 \frac{RV_{m,t+1} - VIX^2_{m,t}}{VIX^2_{i,t}} + \frac{RV_{\varepsilon,i,t+1} - VIX^2_{\varepsilon,i,t}}{VIX^2_{i,t}}. \tag{1.7}$$

The term on the left-hand side is firm i's variance risk premium at month $t+1$, denoted as $VRP_{i,t+1}$. Carr and Wu [2009] use it to measure VRP. To recover the systematic and idiosyncratic components from $VRP_{i,t+1}$, I rewrite (1.7) as

$$\begin{aligned}
\underbrace{\frac{RV_{i,t+1} - VIX^2_{i,t}}{VIX^2_{i,t}}}_{VRP_{i,t+1}} &= \frac{\beta_i^2 VIX^2_{m,t}}{VIX^2_{i,t}} \cdot \frac{RV_{m,t+1} - VIX^2_{m,t}}{VIX^2_{m,t}} + \frac{VIX^2_{\varepsilon,i,t}}{VIX^2_{i,t}} \cdot \frac{RV_{\varepsilon,i,t+1} - VIX^2_{\varepsilon,i,t}}{VIX^2_{\varepsilon,i,t}} \\
&= w_{i,t} \cdot \underbrace{\frac{RV_{m,t+1} - VIX^2_{m,t}}{VIX^2_{m,t}}}_{Systematic\ VRP\ (SVRP)} + (1 - w_{i,t}) \cdot \underbrace{\frac{RV_{\varepsilon,i,t+1} - VIX^2_{\varepsilon,i,t}}{VIX^2_{\varepsilon,i,t}}}_{Idiosyncratic\ VRP\ (IVRP)} \\
&= IVRP_{i,t+1} + w_{i,t}(SVRP_{t+1} - IVRP_{i,t+1}),
\end{aligned} \tag{1.8}$$

where: $w_{i,t} = \frac{\beta_i^2 VIX^2_{m,t}}{VIX^2_{i,t}}$; $SVRP$ is the systematic variance risk premium embedded in equity options; $IVRP$ is the idiosyncratic variance risk premium. The second equality holds because $VIX^2_{\varepsilon,i,t} = VIX^2_{i,t} - \beta_i^2 VIX^2_{m,t}$, by (1.6).

I estimate the systematic and idiosyncratic VRP in equity option markets by running a monthly cross-sectional regression, as follows:

$$VRP_{i,t+1} = \lambda_{0,t+1} + \lambda_{1,t+1} w_{i,t} + \varepsilon_{i,t+1}. \tag{1.9}$$

The independent variable in (1.9) is $w_{i,t}$. To avoid forward-looking bias, $\beta_{i,t}$ is estimated by running rolling regression (1.4) at the end of each month t, using the past year daily stock return.[22] $VIX^2_{m,t}$ and $VIX^2_{i,t}$ are calculated following the construction of VIX portfolio. According to (1.8), the price of systematic and idiosyncratic variance risk equal

$$\begin{aligned} Price\ of\ Systematic\ Variance &= \overline{\lambda_0} + \overline{\lambda_1}, \\ Price\ of\ Idiosyncratic\ Variance &= \overline{\lambda_0}, \end{aligned} \tag{1.10}$$

where: $\overline{\lambda_0}$ and $\overline{\lambda_1}$ are the time-series averages of $\lambda_{0,t}$ and $\lambda_{1,t}$, estimated from (1.9).

Panel A of Table 1.7 reports coefficients of the regression:

$$r_{i,t+1} = \lambda_{0,t+1} + \lambda_{1,t+1} \cdot w_{i,t} + \varepsilon_{i,t+1}, \tag{1.11}$$

where $r_{i,t+1}$ is firm i's one-month-ahead VIX return.

According to (1.10), the price of systematic variance risk equals

$$\overline{\lambda_0} + \overline{\lambda_1} = -11.2\% + 23.5\% = 12.3\%.$$

$\lambda_{0,t+1} + \lambda_{1,t+1}$ and index VIX return have a correlation of 0.57. A t-test shows that $\lambda_{0,t+1} + \lambda_{1,t+1}$ is statistically positive. This is contrary to the largely negative index VIX return.[23] A detailed explanation for the differential pricing is examined

[22] To ensure the precision of the estimate, I require at least 120 daily observations in the rolling regression. Changing the rolling window to 6 month or using whole sample realized β_i does not change the qualitative results.

[23] To make sure that the result is not caused by using firms not included in the S&P 500 Index, I rerun the above regression with only firms included in the index each month. The price of

in the next section. If the price of systematic variance embedded in equity options, $VIX^2_{m,t}$, is priced the same as that in index options, $\overline{\lambda_0} + \overline{\lambda_1}$ should be negative instead of positive.

The underpricing of systematic variance risk in equity option markets offers an alternative explanation for the stylized fact that individual firms' VRP are less negative than index VRP. To reconcile the difference, Driessen, Maenhout, and Vilkov [2009] decompose index VRP into VRP of constituent firms and correlation risk premium. They assume no-arbitrage between index and equity option markets and attribute the largely negative index VRP to correlation risk premium. The no-arbitrage assumption can be strong given the documented mispricings in option market: Eisdorfer, Sadka, and Zhdanov [2017] document that options held from one expiration date to the next achieve significantly lower returns when there are four versus five weeks between expiration dates because of investor inattention to exact expiration date; Jones and Shemesh [2018] find that option returns are significantly lower over nontrading periods because of the incorrect treatment of stock return variance over those periods; Lemmon and Ni [2014] find that individual investors' sentiment affects the demand and pricing for equity options but not for index options. The no-arbitrage assumption can be questionable, especially in equity option markets given their large presence of less sophisticated individual investors.

Instead, this paper argues that individual firm's VRP would have been more negative if systematic variance risk has the same price in the two markets. In

systematic variance is estimated to be 11.15%, close to 12.3%. I also use the method in Fama and MacBeth [1973] to estimate the systematic VRP: For each firm, I run a full-sample monthly time-series regression of equity VIX returns on index VIX return and get each firm's exposure; then I estimate systematic VRP via cross-sectional regression. The estimate equals 9.08%.

a related paper, Barras and Malkhozov [2016] find that systematic variance risk has two prices in index option market and stock market because of the financial constraints faced by intermediaries in supplying index options. This paper focuses on the difference between index option and equity option markets, which are supposed to be more closely related.

The intercept $\overline{\lambda_0}$ equals -11.2%, with a t-statistic of -7.24, suggesting that investors pay a premium for idiosyncratic variance. This is consistent with the notion that options on stocks with high idiosyncratic volatility attract high demand and that constrained financial intermediaries charge extra compensation for supplying these options because of their high hedging costs (Cao and Han [2013]). Ang et al. (2006) find that idiosyncratic volatility negatively predicts future cross-sectional stock returns. Cao and Han [2013] find that idiosyncratic volatility negatively predicts future cross-sectional delta-hedged option returns. My finding complements the literature by showing that idiosyncratic variance has a negative price in equity option markets.

This section documents a positive price of systematic variance and a negative price of idiosyncratic variance in equity option markets. The two combined conform to a close-to-zero and much less negative firm-level VRP. The finding that systematic variance risk has two prices in index and equity option markets helps explain why equity options seem cheaper than index options.

1.4.2 HHI and the price of systematic variance risk

This section explores how HHI is related with the price of systematic variance risk embedded in equity options. I make a conjecture that the underpricing of systematic variance risk in equity option markets is related with different demand patterns and compositions of traders in index and equity option markets: Equity options are less used for hedging purpose than index options are; In addition, Lemmon and Ni [2014] find that individual investors have a larger impact in equity option markets than in index option market. I hypothesize that in equity option markets, compared with less sophisticated individual investors who are more likely to chase a firm's idiosyncratic variance for lottery-like payoffs,[24] institutional investors who take large positions in the firm, i.e. firm with high HHI, pay more attention to systematic variance, which will be priced more consistently with that embedded in index options. According to the hypothesis, systematic VRP inferred from firms with higher HHI should be closer to that inferred from index options.

To test the hypothesis, I estimate systematic VRP from groups of firms with different HHI. Each month, I first rank firms into three groups by their size and further sort each size group into three subgroups by HHI. Within each size-HHI subgroup, I run regression (1.11), and report prices of systematic variance risk in Panel B of Table 1.7.

[24] See Boyer, Mitton, and Vorkink [2010] and Boyer and Vorkink [2014] for details about the link between a firm's idiosyncratic volatility and skewness in stock and option markets. Boyer, Mitton, and Vorkink [2010] find that a firm's idiosyncratic volatility strongly and positively predicts the idiosyncratic skewness of its future stock returns. Boyer and Vorkink [2014] find a strong negative relationship between skewness and equity option returns and attribute it to the demand pressure caused by investors' preference for lottery-like options.

Within each size tercile, the estimated price is decreasing as HHI increases. The price inferred from HHI 3, the group of firms with the highest HHI, is not statistically positive and closer to that estimated from index options. The pattern is consistent with the hypothesis and suggests that the underpricing of systematic variance is more pronounced among firms with lower HHI.

Size and HHI are negatively correlated with each other. However, they both have a negative relation with systematic VRP. Therefore, the pattern in Panel B is not caused by the correlation between size and HHI. The two variables capture different information contents related to systematic VRP embedded in equity options.

1.4.3 Controlling for variance-related option mispricing

This section examines whether the profit of trading strategy exploiting systematic variance risk mispricings can be explained by other variance-related option mispricing in the literature. I use $w_{i,t}$, defined as $\frac{\beta_{i,t}^2 VIX_{M,t}^2}{VIX_{i,t}^2}$, to measure firm i's degree of systematic variance risk mispricing. The higher $w_{i,t}$ is, the larger is the proportion of systematic variance in firm i's total variance under risk-neutral measure.

I use a double-sort procedure to control for variance mispricing measures in equity options documented by previous studies. Goyal and Saretto [2009] find that the log difference between historical realized volatility and ATM implied volatility predicts cross-sectional option returns. Their option portfolios consist of only ATM options. Since VIX portfolio includes options with all moneynesses, I modify their measure as $log(\frac{RV_{i,t-12,t}}{VIX_{i,t}^2})$,[25] where $RV_{i,t-12,t}$ is firm i's historical variance estimated

[25] Using their original measure yields stronger results.

using daily stock return over the past 12 months. I call it $HV - IV$. Another measure is idiosyncratic volatility (IVOL) documented by Cao and Han [2013].

Each month, I first sort firms into quintiles based on $HV - IV$ or IVOL and then sort each quintile by $w_{i,t}$. All portfolios are equally weighted. Alpha is calculated from the Fama-French 5 factors (Fama and French [2015]), stock momentum, and index VIX return. Table A1.3 presents average monthly returns. In Panel A, after controlling for $HV - IV$, the strategy that long VIX portfolios of firms with high $w_{i,t}$ and short those with low $w_{i,t}$ delivers a significantly positive return in every quintile. The alpha is even higher than the raw return, because the trading strategy is constructed to have a positive exposure to the negative index VIX return. Panel B shows the result controlling for IVOL. The pattern is the same as in Panel A.

In unreported diagnostics, I use a Fama-MacBeth regression to check whether $w_{i,t}$ can be explained by firm characteristics. After controlling for characteristics, the coefficient estimate of $w_{i,t}$ remains highly significant with a t-statistic of 6.50. It cannot be subsumed by firm characteristics.

1.4.4 HHI and the price of idiosyncratic variance risk

This section examines the relation between HHI and idiosyncratic VRP. I construct a firm-level idiosyncratic VIX portfolio, whose payoff approximates the realized idiosyncratic variance of the firm's stock return. Then I use Fama-MacBeth regression to examine the cross-sectional relation between HHI and idiosyncratic VRP.

Firm i's idiosyncratic VIX portfolio is constructed by long 1 unit of firm i's VIX portfolio and short $\beta^2_{i,t}$ unit of index VIX portfolio. Based on equation (1.5), the portfolio payoff should approximate firm i's idiosyncratic variance over the next month.

I first check the tracking performance of idiosyncratic VIX portfolios. Table A1.4 reports summary statistics of idiosyncratic VIX return. Idiosyncratic VIX returns are quite volatile with a monthly standard deviation of 176.1%, twice of that of VIX returns. To avoid extreme observations, I apply the following filtering rules at each month: Delete firms with negative idiosyncratic VIX prices and firms with idiosyncratic VIX price below the 5 and above the 95 percentile. The average idiosyncratic VIX return is 10.86%, close to the average idiosyncratic VSR, defined as

$$Idio\,VSR_{i,t,T} = \frac{\sum_{u=t+1}^{T} r^2_{i,u} - \beta^2_{i,t,T} \sum_{u=t+1}^{T} r^2_{m,u}}{VIX^2_{i,t,T} - \beta^2_{i,t} VIX^2_{m,t,T}} - 1, \tag{1.12}$$

where: $\beta_{i,t,T}$ is the realized β of firm i during period t to T by running regression (1.4); $\beta_{i,t}$ in denominator is rolling 1 year β; $r_{i,u}$ is firm i's stock return on day u; $r_{m,u}$ is index return on day u; $VIX^2_{m,t,T}$ and $VIX^2_{i,t,T}$ are the prices of index and firm i's VIX portfolio at month t.

To calculate time-series correlation between idiosyncratic VIX return and idiosyncratic VSR for each firm, I require firms to have at least 30 observations. The average correlation equals 0.62. The median correlation is 0.72. The tracking error could be diversified away by forming equally weighted (EW) portfolio each month. The correlation between the EW idiosyncratic VIX return and VSR equals 0.79.

The average of idiosyncratic VIX return is positive. This seems to contradict the negative price of idiosyncratic variance documented before. The seeming contradiction is caused by the underpriced systematic variance risk in equity option markets: When investors long systematic variance embedded in equity options at a lower price and short systematic variance at a higher price by selling index options, they earn a positive return. This cross-market arbitrage turns negative idiosyncratic VRP into positive portfolio returns.

Table 1.8 reports the results. In a cross-sectional regression, HHI negatively predicts one-month ahead idiosyncratic VIX returns. The coefficient of HHI is -0.397 with a t-statistic of -5.90. It remains highly significant after controlling for other predictors. The negative predictability suggests that for firms in which institutional investors take more concentrated positions, institutions are more sensitive to those firms' idiosyncratic variances and pay a higher premium on option markets to hedge.

1.5 Trading Strategies

This section explores the profitabilities of two trading strategies. The first strategy sorts firms by mutual fund HHI. The second strategy sorts firms by $w_{i,t}$ to exploit the systematic variance risk mispricing. I implement the two strategies with both VIX portfolios and delta-hedged call and put options.

At each month, I sort firms into deciles by $-HHI_{i,t}$ or $w_{i,t}$ and equally weight firms. I sort by negative HHI in order to generate an increasing pattern of returns. Alpha is calculated from Fama-French 5 factors, stock momentum, and S&P 500

Index VIX return. To account for the potential nonnormality of option returns, I also report the 99% bootstrap confidence intervals for the risk-adjusted long-short portfolio returns. Table 1.9 presents average monthly returns.

Panel A reports returns sorted by $-HHI_{i,t}$. Monthly decile returns of VIX portfolios increase from -10.87% to -0.91% as $-HHI_{i,t}$ increases. A long-short trading strategy generates a monthly return of 9.96% with a t-statistic of 5.89. The annual Sharpe Ratio is 1.26. Trading delta-hedged call and put also yields significantly positive returns, equal to 0.88% and 1.17%, respectively.

Panel B reports returns sorted by $w_{i,t}$. Monthly decile returns of VIX portfolios monotonically increase from -13.3% to 4.21% as $w_{i,t}$ increases. A long-short trading strategy generates a monthly return of 17.5% with a t-statistic of 8.23. The Sharpe Ratio is 1.76. The alpha is 20.8%, even higher than the raw return. This is because the trading strategy has a positive exposure to the index VIX return, which is largely negative. Trading delta-hedged call and put also yields significantly positive returns, equal to 1.50% and 1.75%, respectively.

For previous results, I assume that options can be bought and sold at the midpoint of bid and ask quotes. To take into account the costs associated with buying or selling options, I assume the effective option spread equals 50%, 75%, and 100% of the quoted spread. Effective spread is defined as twice the difference between the actual execution price and the midpoint at the time of order entry. The column "MidP" in Table A1.5 corresponds to zero effective spread, i.e., options are traded at midpoint. An effective-to-quoted spread ratio of 50% is equivalent to paying half of quoted bid-ask spread. De Fontnouvelle, Fishe, and Harris [2003] and

Mayhew [2002] show that the typical spread ratio is less than 0.5. Muravyev and Pearson [2019] show that effective spreads of traders who time executions are less than 40% of the conventional measures.

Table A1.5 examines the impact of option bid-ask spreads on the profitability of strategies. Returns in "All" columns are calculated using all firms at that month. Returns in "Low Bid-Ask Spread" columns are calculated using firms with percentage bid-ask spread lower than the median bid-ask spread of that month, in order to avoid illiquid options.

In Panel A, the monthly return of long-short VIX portfolios sorted by $-HHI_{i,t}$ becomes insignificant under 50% ratio case. Delta-hedged ATM call return remains significant when the ratio is 50% and even significant under the 75% case if only liquid options with lower-than-median bid-ask spreads are traded. The strategy is most profitable for puts: When the ratio is 75%, the mean return is 0.22%, with a t-statistic of 2.46; by only trading liquid options, the mean return after full bid-ask spread is 0.32%, with a t-statistic of 3.02.

In Panel B, when the ratio increases to 50%, the monthly return of long-short VIX portfolios sorted by $w_{i,t}$ decreases to 6.61%, with a t-statistic of 3.15. It becomes insignificant when the ratio raises to 75%. By only trading firms with lower-than-median bid-ask spreads, the monthly VIX return remains significant at 6.62%, with a t-statistic of 2.52, under the 75% case. Delta-hedged ATM call and put returns remain highly significant under the 75% case. By trading only liquid options, returns are statistically positive even when the whole bid-ask spreads are considered.

To conclude, option bid-ask spreads reduce the profits of trading strategies but do not eliminate them at reasonable estimates of effective spreads. By avoiding illiquid options, most strategies deliver statistically positive returns when the effective-to-quoted spread ratio equals 75%.

1.6 Conclusion

This paper finds that institutional stock holdings negatively predict cross-sectional option returns. Evidence is consistent with a hedging and demand pressure channel: In a simple model, HHI of stock holdings is proportional to stock holders' aggregate hedging demand for options against variance risks originated from their stock positions. For stocks with more concentrated ownership, some institutions are more likely to overweight them and demand more of their options to hedge. To absorb the order imbalances, dealers sell options and charge higher prices, leading to lower option returns. Using option holdings of U.S. equity mutual funds, I find that the negative predictability of HHI comes from funds that overweight the firm relative to their benchmark indexes and funds that use equity options, especially those long puts. I also document a positive correlation between funds' stock concentration and their option share in the same firms, directly linking firm's HHI with their fund holders' option demand.

I also validate the channel by testing related theories in the literature. Theories suggest that the predictability should be stronger when mutual funds are more likely to use options to hedge and among firms with higher option price impacts.

Consistent with predictions, I find that the negative predictability is stronger among firms with mutual fund holders that suffer recent lower performance and have higher flow volatilities and portfolio concentrations, among firms overweighted by mutual funds, as well as among firms with higher option market making costs.

I decompose firm's total VRP into systematic and idiosyncratic components. The price of systematic variance risk estimated from equity options is positive, instead of negative as that implied by S&P 500 Index options. This differential pricing is more pronounced among firms with lower HHI and can help explain the puzzle that individual firm's VRP is less negative than that of the index. This pattern is related with different demand patterns and compositions of traders in index and equity option markets: institutional investors who hold concentrated positions in firms with higher HHI are more sensitive to systematic variance, which will be priced more consistently with that embedded in index options.

This figure plots the monthly index VIX return (blue solid line) and variance swap return (red dashed line) defined in (1.3). The sample period is from January 1996 to December 2017. Markers indicate the returns for the October 1997 Mini Crash caused by the Asian economic crisis, the 1998 collapse of Long Term Capital Management (LTCM), the March 2000 Dot-com Bubble, the 2008 collapse of Lehman Brothers (Lehman), the April 2010 Greece Debt Crisis, and the August 2011 Black Monday following the downgrade of the U.S. sovereign debt.

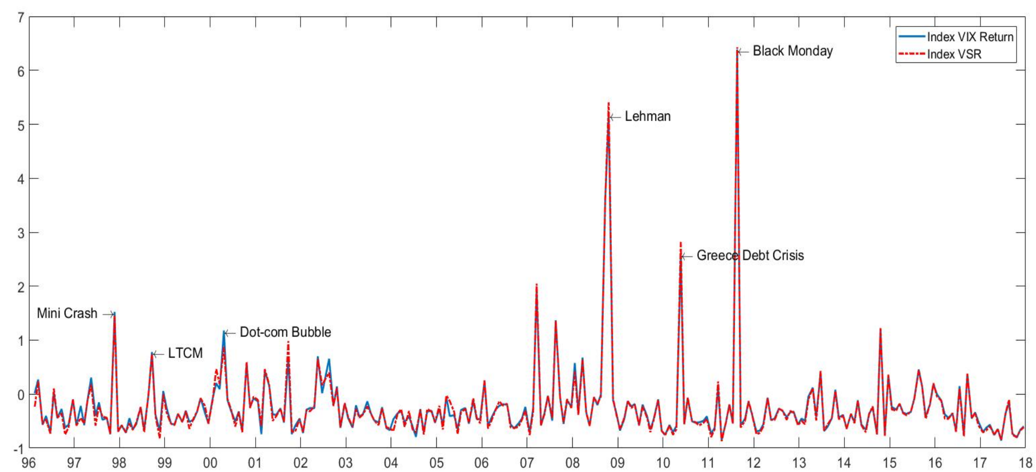

Figure 1.1: **Index VIX Return and Variance Swap Return**

In a Fama-MacBeth regression, I regress firms' equity VIX returns on lagged n (1 to 12) month HHI constructed from option funds in Morningstar dataset, controlling for other option return predictors in Table 1.3. The figure plots the coefficient estimates of HHI (solid blue line) and the 95% confidence intervals (dashed black lines).

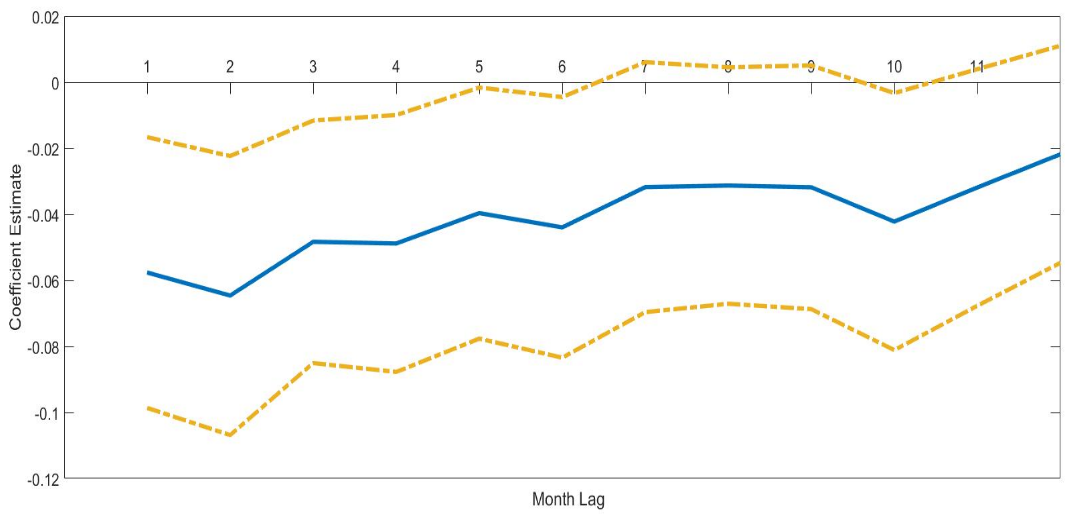

Figure 1.2: **Option Return Predictability of Lagged HHI Option Fund**

Table 1.1: **Summary Statistics**

The sample period is from January 1996 to December 2017. I pick all optionable firms in the OptionMetrics Database. There are 138,339 firm-month observations in total. Number of Firms Each Month is the number of firms each month in my sample. Number of Option Contracts is the number of option contracts used to construct equity VIX portfolio for each firm. Index (Equity) VIX Return is the actual return of the index (equity) VIX portfolio. Equity VSR (Variance Swap Return) is defined as the realized variance of equity return divided by the price of equity VIX portfolio minus 1. EW (Equally Weighted) Equity VIX Return is the cross-sectional average of equity VIX Return at each month. $\beta_{Index\,VIX\,Return}$ is the firm-level exposure of equity VIX return to index VIX return. Corr(Equity VIX Return,Equity VSR) is the firm level time series correlation between equity VIX return and equity VSR. Corr(Equity VIX Return,Stock Return) is the firm level time-series correlation between the equity VIX return and stock return. HHI Mutual Fund (Institution) is the Herfindahl-Hirschman Index (HHI) of mutual fund (institution) ownership of the firm's stocks. It measures the ownership concentration among mutual funds (institutions) that are shareholders of the company.

	Mean	Std	10%	25%	50%	75%	90%
Panel A: VIX return.							
Number of Firms Each Month	526	214	260	335	503	700	831
Number of Option Contracts	6.41	4.53	4.00	4.00	4.00	8.00	10.00
Index VIX Return(%)	-23.24	72.66	-67.99	-56.43	-37.18	-13.80	18.44
Equity VIX Return(%)	-5.13	91.98	-62.01	-45.20	-21.39	13.83	68.07
EW Equity VIX Return(%)	-4.82	28.13	-30.20	-22.25	-11.30	4.05	25.44
$\beta_{Index\,VIX\,Return}$	0.33	0.36	-0.02	0.15	0.31	0.50	0.74
Corr(Equity VIX Return,Equity VSR)	0.75	0.31	0.35	0.68	0.88	0.95	0.98
Corr(Equity VIX Return,Stock Return)	-0.26	0.23	-0.51	-0.41	-0.29	-0.13	0.04
Panel B: Herfindahl-Hirschman Index.							
HHI Mutual Fund	0.139	0.196	0.024	0.035	0.065	0.142	0.343
HHI Institution	0.057	0.069	0.026	0.032	0.042	0.058	0.089

Table 1.2: **HHI and Equity VIX Returns**

This table reports the results of cross-sectional regression: $r_{i,t+1} = \alpha_t + \gamma_t HHI_{i,t} + \theta_t X_{i,t} + \epsilon_{i,t+1}$, where $r_{i,t+1}$ is the one-month-ahead equity VIX return of firm i. HHI Mutual Fund (Institution) is the Herfindahl-Hirschman Index (HHI) of mutual fund (institution) ownership of the firm's stocks. Holdings of Mutual Fund (Institution) are calculated as the firm's total shares held by mutual funds (institutions) divided by the total number of shares outstanding. The associated t-statistics are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The sample period is from January 1996 to December 2017.

	(1)	(2)	(3)	(4)	(5)
HHI Mutual Fund	-0.240***	-0.232***			-0.229***
	(-7.17)	(-6.41)			(-5.19)
Holdings of Mutual Fund		0.132*			0.299***
		(1.90)			(3.57)
HHI Institution			-0.396***	-0.383***	-0.194***
			(-7.11)	(-6.41)	(-2.87)
Holdings of Institution				0.007	-0.075***
				(0.39)	(-3.02)
Intercept	-0.024	-0.038*	-0.025	-0.025	0.004
	(-1.24)	(-1.69)	(-1.36)	(-0.96)	(0.15)
Adj. R^2	0.004	0.006	0.004	0.006	0.008

Table 1.3: **Robustness of HHI**

This table reports the average coefficients of monthly Fama-MacBeth regressions of equity VIX returns in one month ahead on the latest available institutional and mutual fund holdings. Control variables include idiosyncratic volatility (IVOL, Cao and Han (2013)), log difference between historical volatility and equity VIX (HV-VIX, modified from Goyal and Saretto (2009)), short-term stock return reversal ($RET_{t-1,t}$), momentum ($RET_{t-12,t-1}$), long-term stock return reversal ($RET_{t-36,t-12}$), size (Ln(ME)), book-to-market (Ln(BM)), risk-neutral skewness of stock returns (RN Skew, Bakshi, Kapadia, and Madan (2003)), rolling 1 year skewness and kurtosis of stock returns (Rolling Skew and Kurt), analyst dispersion, cash holdings (CH), profitability (Profit), new issues (Cao, Han, Tong, and Zhan (2017)), Amihud illiquidity measure over the previous month (Amihud (2002)), and the percentage bid-ask spread of the option portfolio (Option Bid-Ask Spread). To check the robustness, results using delta-hedged ATM call and put option gains until maturity (calculated as Bakshi and Kapadia (2003)) are also reported. The associated heteroskedasticity-robust t-statistics are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The sample period is from January 1996 to December 2017.

	Equity VIX Return			Delta Call	Delta Put
	(1)	(2)	(3)	(4)	(5)
HHI Mutual Fund	-0.210***		-0.191***	-0.008***	-0.012***
	(-4.46)		(-3.52)	(-3.32)	(-4.54)
Holdings of Mutual Fund	0.208**		0.168	0.012***	0.015***
	(2.30)		(1.56)	(2.62)	(3.78)
HHI Institution		-0.279***	-0.127		
		(-4.01)	(-1.63)		
Holdings of Institution		0.042**	0.015		
		(2.33)	(0.56)		
IVOL	-1.273***	-1.315***	-1.348***	-0.171***	-0.186***
	(-3.22)	(-3.18)	(-3.33)	(-6.40)	(-7.32)
HV-VIX	0.328***	0.333***	0.331***	0.024***	0.025***
	(11.16)	(11.25)	(11.09)	(11.92)	(13.94)
$RET_{t-1,t}$	-0.121***	-0.121***	-0.117***	-0.003	-0.008***
	(-2.92)	(-2.92)	(-2.84)	(-1.12)	(-3.38)
$RET_{t-12,t-1}$	0.039***	0.037***	0.037***	0.001	0.002**
	(2.90)	(2.79)	(2.74)	(1.17)	(2.54)
$RET_{t-36,t-12}$	0.026***	0.026***	0.025***	0.001	0.001*
	(3.07)	(3.15)	(2.97)	(1.06)	(1.76)
Ln(ME)	-0.001	0.000	-0.002	-0.000	0.000
	(-0.18)	(0.08)	(-0.36)	(-0.52)	(1.01)
Ln(BM)	0.014***	0.012***	0.012***	0.001**	0.001**
	(3.12)	(2.61)	(2.78)	(2.30)	(2.40)
RN Skew	0.023**	0.023**	0.024**	-0.002***	0.001
	(2.11)	(2.09)	(2.14)	(-5.28)	(1.40)
Rolling Skew	0.001	0.001	0.001	0.000	0.000
	(0.21)	(0.27)	(0.30)	(0.01)	(0.13)
Rolling Kurt	-0.004***	-0.004***	-0.004***	-0.000***	-0.000***
	(-7.06)	(-7.32)	(-7.09)	(-6.74)	(-7.66)
Analyst Dispersion	-0.028*	-0.026*	-0.026	-0.003***	-0.003***
	(-1.81)	(-1.65)	(-1.63)	(-2.68)	(-2.70)
CH	0.044**	0.048**	0.046**	-0.000	-0.000
	(2.11)	(2.32)	(2.19)	(-0.11)	(-0.24)
Profit	-0.004	-0.005	-0.004	-0.000	-0.000
	(-0.67)	(-0.81)	(-0.73)	(-0.49)	(-0.72)
Issue	0.046	0.049*	0.042	0.001	0.001
	(1.56)	(1.68)	(1.45)	(0.61)	(0.63)
Amihud	0.517	-0.647	0.230	-0.360**	-0.542***
	(0.24)	(-0.30)	(0.11)	(-2.50)	(-3.50)
Option Bid-Ask Spread	0.024	0.017	0.015	0.009**	0.006**
	(0.62)	(0.45)	(0.41)	(2.32)	(2.03)
Intercept	-0.048	-0.079	-0.030	-0.003	-0.009**
	(-0.57)	(-1.04)	(-0.37)	(-0.78)	(-2.30)
Adj. R^2	0.058	0.058	0.059	0.087	0.085

Table 1.4: **HHI and Risk Profiles of Option Funds and Non-option Funds**

This table examines the cross-sectional explanatory power of ownership concentration of option funds and non-option funds on equity VIX returns, respectively. In each column, I control for the corresponding share proportions owned by each fund category. HHI MStar is constructed using the holdings of all U.S. equity funds in Morningstar dataset. HHI Non MStar is constructed using the holdings of funds in S12 but not covered by Morningstar dataset. HHI Overweight (Underweight) is constructed using the holdings of funds in Morningstar dataset that overweight (underweight) the firm relative to their benchmarks. HHI Option Fund is constructed using only funds that use equity options. HHI Put Fund is constructed using funds that use put options. HHI Call Fund is constructed using funds that only use calls and never use puts. HHI Put Short is constructed using put funds that only short puts but never long puts. HHI Put Long is constructed using put funds that long puts. HHI Call Short is constructed using call funds that only short calls but never long calls. HHI Call Long is constructed using call funds that long calls. The associated t-statistics are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HHI MStar	-0.086***	-0.086***		-0.053			
	(-3.67)	(-3.10)		(-1.64)			
HHI Non MStar		-0.048***					
		(-3.02)					
HHI Overweight			-0.224***				
			(-3.56)				
HHI Underweight			-0.040				
			(-1.41)				
HHI Option Fund				-0.049**	-0.003	-0.098***	
				(-2.53)	(-0.11)	(-5.00)	
HHI Put Fund					-0.074***		
					(-3.31)		
HHI Call Fund						0.029*	
						(1.67)	
HHI Put Long							-0.071***
							(-4.23)
HHI Put Short							-0.020
							(-1.35)
HHI Call Long							-0.015
							(-0.99)
HHI Call Short							0.018
							(1.13)
Intercept	-0.057**	-0.044*	-0.066**	-0.044*	-0.023	-0.037*	-0.005
	(-2.40)	(-1.71)	(-2.12)	(-1.77)	(-1.01)	(-1.74)	(-0.18)
Adj. R^2	0.008	0.011	0.011	0.010	0.009	0.009	0.013

Table 1.5: **Fund Option Market Activity and Option Funds HHI**

This table reports the results of quarterly panel regression: $FOMA_{i,t} = \alpha_i + \gamma HHI_{i,t} + \delta X_{i,t} + \varepsilon_{i,t}$, where: $FOMA_{i,t}$ is mutual fund option market activity of firm i at the end of quarter t, defined as the aggregate funds holdings at firm i's option market scaled by the total dollar open interest of firm i's option market. $O/S_{i,t}$ is firm i's option/stock dollar volume, defined as option dollar open interest scaled by the stock's monthly dollar trading volume. I multiply O/S by 100 to convert it to percent. Control variables $X_{i,t}$, such as Ln(ME), Ln(BM), IVOL, $RET_{t-1,t}$, $RET_{t-12,t-1}$ and Analyst Dispersion, are the same as in Table 1.3. VOL is the past-1-month total volatility of stock returns. Analyst Number is the number of I/B/E/S analysts making one-year forecasts on the firm. $Index\ Return_{t-6,t}$ is the return of S&P 500 Index over the past 6 months. Index VIX is the S&P 500 Index VIX at the end of month. Index Skew is the risk-neutral skewness of S&P 500 Index at the end of month. Standard errors are clustered at firm and month level. The associated t-statistics are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The sample period is from January 1996 to December 2015.

Panel A: Sort by HHI Option Fund.

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)
FOMA (%)	0.38	0.75	1.00	1.70	2.08	2.26	2.78	3.55	4.38	5.34

Panel B: Panel regressions.

	(1) FOMA	(2) FOMA	(3) O/S
HHI Option Fund	0.0355***	0.0205***	0.4669***
	(4.51)	(2.60)	(2.73)
Holdings of Option Fund	0.0224	0.0306	0.7481
	(0.47)	(0.63)	(0.69)
Ln(ME)		-0.0094***	0.1248**
		(-5.43)	(2.05)
Ln(BM)		-0.0036***	-0.0092
		(-2.74)	(-0.19)
IVOL		0.4922***	-8.9554**
		(4.28)	(-2.56)
VOL		-0.3983***	7.1567**
		(-4.50)	(2.35)
$RET_{t-1,t}$		0.0266***	-0.1886
		(6.11)	(-1.26)
$RET_{t-12,t-1}$		0.0045**	-0.1205**
		(2.50)	(-2.00)
Analyst Number		0.0001	-0.0078
		(0.52)	(-1.27)
Analyst Dispersion		0.0002	0.0047
		(1.19)	(1.11)
$Index\ Return_{t-6,t}$		-0.0025	-0.4074*
		(-0.32)	(-1.79)
Index VIX		0.0002	-0.0071*
		(1.36)	(-1.75)
Index Skew		-0.0004	0.0785*
		(-0.37)	(1.84)
Observations	19142	17477	17448
adj. R^2	0.50	0.53	0.53
Firm FE	Yes	Yes	Yes

Table 1.6: **Option Demand Pressure and Price Impact**

This table reports the coefficients of HHI in the monthly Fama-MacBeth regression:

$$r_{i,t+1} = \alpha_t + \gamma_t HHI_{i,t} + \theta_t X_{i,t} + \epsilon_{i,t+1}.$$

$r_{i,t+1}$ is firm i's VIX return. $X_{i,t}$ is a set of control variables as those in Table 1.3. In Panel A, I sort firms into three groups at each month t, respectively, by the average of their fund holders': past quarter returns adjusted for investment category, past-12-month fund flow volatilities, and portfolio concentrations. To test the year-end hypothesis, I split sample periods into non-year-end and year-end periods when I sort firms by past fund returns. I also sort firms by the deviation of their weights in mutual fund industry from market weights (Benchmark Deviation). Panel B reports the coefficients among three sub-periods sorted by TED spread. In Panel C, I sort firms by three stock characteristics associated with option unhedgeable risk: firm i's idiosyncratic volatility, absolute value of the skewness of stock return, and Amihud illiquidity measure. The associated t-statistics are in parentheses. The sample period is from January 1996 to December 2017.

Panel A: Mutual fund characteristics.

	Low	Medium	High
Fund Past Performance	-0.424***	-0.205	-0.149
	(-3.08)	(-1.53)	(-1.37)
Non-year-end	-0.559***	-0.175	-0.100
	(-3.24)	(-1.19)	(-0.73)
Year-end	0.161	-0.200	-0.352**
	(0.63)	(-0.69)	(-2.02)
Fund Flow Volatility	-0.056	-0.164	-0.465***
	(-0.53)	(-1.10)	(-3.59)
Benchmark Deviation	-0.194	-0.178*	-0.200**
	(-1.24)	(-1.92)	(-2.54)
Fund Portfolio Concentration	-0.136	-0.252	-0.275**
	(-0.94)	(-1.28)	(-2.38)

Panel B: TED spread.

	Low	Medium	High
TED spread	-0.018	-0.328***	-0.295***
	(-0.30)	(-4.01)	(-3.14)

Panel C: Stock characteristics.

	Low	Medium	High
Stock Idiosyncratic Volatility	-0.107	-0.173	-0.206**
	(-0.83)	(-1.67)	(-2.19)
|Skew|	0.018	-0.276***	-0.297***
	(0.22)	(-2.70)	(-2.82)
Amihud Illiquidity	-0.288*	-0.200	-0.220***
	(-1.90)	(-1.30)	(-3.15)

Table 1.7: **Price of Systematic Variance in Equity Option Markets**

Panel A reports the average coefficients of the monthly Fama-MacBeth regression, $r_{i,t+1} = \lambda_{0,t+1} + \lambda_{1,t+1} \cdot w_{i,t} + \varepsilon_{i,t+1}$, where $r_{i,t+1}$ is the one-month-ahead VIX return and $w_{i,t}$ is defined as $\frac{\beta_{i,t}^2 VIX_{M,t}^2}{VIX_{i,t}^2}$. Results using delta-hedged ATM call and put option gains until maturity (calculated as in Bakshi and Kapadia (2003)) are also reported. Panel B reports the price of systematic variance risk (in percent) inferred from subgroups of firms with different sizes and mutual fund HHI. Each month, I first rank firms into three groups by their size; then firms within each size group are further sorted into three subgroups by HHI. I run the cross-sectional regression in Panel A, using only firms in each size-HHI subgroup. The associated t-statistics are in parentheses. *** denotes significance at 1%. The sample period is from Jan. 1996 to Dec. 2017.

Panel A: Price of systematic and idiosyncratic variances.

	VIX Return	Delta-hedged Call	Delta-hedged Put
Intercept	-0.112***	-0.008***	-0.012***
	(-7.24)	(-9.96)	(-14.07)
$w_{i,t}$	0.235***	0.019***	0.022***
	(7.35)	(10.65)	(12.66)
Adj. R^2	0.017	0.014	0.017

Panel B: HHI and price of systematic risk.

	HHI 1 (Low)	HHI 2	HHI 3 (High)
Size 1 (Low)	24.14	20.72	16.08
	(2.61)	(2.39)	(1.00)
Size 2	19.18	13.41	11.01
	(3.31)	(2.13)	(1.64)
Size 3 (High)	11.33	12.34	5.16
	(2.72)	(2.13)	(1.11)

Table 1.8: **HHI and Idiosyncratic VIX Returns**

This table reports the average coefficients of the monthly Fama-MacBeth regression of one-month-ahead idiosyncratic VIX returns on the latest available independent variables. The associated t-statistics are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The sample period is from January 1996 to December 2017.

	(1)	(2)	(3)
HHI Mutual Fund	-0.397***	-0.387***	-0.326***
	(-5.90)	(-5.55)	(-3.57)
Holdings of Mutual Fund		0.335**	0.507***
		(2.14)	(2.96)
IVOL			-4.099***
			(-5.13)
HV-VIX			0.945***
			(9.92)
$RET_{t-1,t}$			-0.227**
			(-2.43)
$RET_{t-12,t-1}$			0.046
			(1.64)
$RET_{t-36,t-12}$			0.039**
			(2.11)
Ln(ME)			0.020**
			(2.35)
Ln(BM)			0.033***
			(3.95)
RN Skew			0.051**
			(2.43)
Rolling Skew			0.003
			(0.36)
Rolling Kurt			-0.009***
			(-7.93)
Analyst Dispersion			-0.073***
			(-2.77)
CH			0.079**
			(2.09)
Profit			-0.016
			(-1.43)
Issue			0.128**
			(2.44)
Amihud			2.735
			(0.76)
Option Bid-Ask Spread			0.076
			(1.13)
Intercept	0.153***	0.129***	-0.239
	(5.39)	(3.81)	(-1.63)
Adj. R^2	0.005	0.007	0.071

Table 1.9: **Decile Portfolio Returns**

This table shows decile returns of two profitable trading strategies: sorting by $-HHI$ and $w_{i,t}$. I report long-short portfolio returns using VIX portfolios and delta-hedged at-the-money (ATM) call and put option. At each month, firms are ranked based on their $-HHI$ or $w_{i,t}$ and equally weighted within each decile. Alpha is calculated from the Fama and French (2015) 5 factors, stock momentum, and the S&P 500 Index VIX return in excess of risk-free rate. 99% CI is the 99% bootstrap confidence interval of alpha. SR is the annual Sharpe Ratio. Average monthly returns of these portfolios are presented. The t-statistics are reported in parentheses. Portfolio returns are expressed in percent. The sample period is from January 1996 to December 2017.

Panel A: Sort by $-HHI$

	1	2	3	4	5	6	7	8	9	10	10-1	Alpha	SR	99% CI
VIX Ret	-10.87	-6.95	-6.41	-5.37	-4.44	-4.71	-3.76	-3.21	-2.80	-0.91	9.96	12.50	1.26	[4.98,20.03]
											(5.89)	(7.37)		
Delta-hedged Call	-0.92	-0.61	-0.46	-0.33	-0.21	-0.25	-0.22	-0.20	-0.14	-0.04	0.88	0.86	1.93	[0.56,1.16]
											(9.05)	(8.17)		
Delta-hedged Put	-1.40	-0.97	-0.78	-0.65	-0.51	-0.55	-0.48	-0.45	-0.36	-0.24	1.17	1.15	2.71	[0.87,1.43]
											(12.69)	(11.56)		

Panel B: Sort by $w_{i,t}$

	1	2	3	4	5	6	7	8	9	10	10-1	Alpha	SR	99% CI
VIX Ret	-13.30	-11.01	-8.86	-6.01	-4.67	-3.31	-3.18	-1.81	-0.32	4.21	17.50	20.80	1.76	[11.57,30.03]
											(8.23)	(9.43)		
Delta-hedged Call	-1.27	-0.79	-0.51	-0.40	-0.32	-0.19	-0.15	-0.02	0.02	0.23	1.50	1.54	2.64	[1.13,1.95]
											(12.38)	(11.91)		
Delta-hedged Put	-1.75	-1.11	-0.87	-0.71	-0.58	-0.48	-0.42	-0.25	-0.22	0.00	1.75	1.80	3.46	[1.43,2.17]
											(15.69)	(15.12)		

1.7 Appendix

1.7.1 The Payoff of VIX Portfolio

This section follows Heston and Li [2020] and proves that the payoff of VIX portfolio approximately equals the realized variance of stock return.

Eqn (1.1) is a discrete version of the continuous integral in Carr and Madan (1998), who show that the price of a portfolio whose payoff equals to realized variance of stock return is

$$\hat{V}(t,T) = 2\int_0^\infty \frac{O(K,t,T)}{K^2}dK. \tag{A1}$$

Given stock price $S(T)$ at expiration, the option payoff $O(K,T,T)$ equals $Max(S(T)-K,0)$ for a call option and $Max(K-S(T),0)$ for a put option. In the absence of intermediate dividends, integrating these option payoffs over strike prices (A1) shows the terminal payoff of this idealized VIX portfolio with continuous strikes equals

$$\hat{V}(T,T) = -2\log(\frac{S(T)}{S(t)(1+r_f)^{T-t}}) + 2\left(\frac{S(T)}{S(t)(1+r_f)^{T-t}} - 1\right), \tag{A2}$$

where r_f is the daily risk-free interest rate, which is assumed to be constant over the life of the option. The first term in the payoff (A2) represents selling two units of the "log-portfolio". The second term represents a costless static hedge that leverages (the present value of) two dollars of stock at time t and holds this hedge position constant until expiration at time T. The combined payoff is a U-shaped function of the stock price, resembling a squared stock return. Therefore, the price of this portfolio represents the risk-neutral variance of stock return.

We can further reduce risk of the idealized VIX portfolio by daily-hedging instead of using a fixed static hedge just at time t. This replaces the second term of (A2) with daily delta hedging of the log-portfolio. Due to the special case of log-payoff (the first term on right-hand side in (A2)), the delta of the idealized VIX portfolio is model-free and equals $1/S(t)$. Thus, to delta-hedge the log-portfolio at daily frequency, investors need to buy $1/S(t)$ shares of stock for a price of $S(t)$ and rebalance the hedging position each day. The payoff of this daily hedged idealized VIX portfolio equals

$$\hat{V}_{hedged}(T,T) = -2\log(\frac{S(T)}{S(t)(1+r_f)^{T-t}}) + 2\sum_{u=t+1}^{T}(r(u) - r_f), \tag{A3}$$

where $r(u)$ represents the stock return on day u, which is a day between time t and T. We can replace the stock price in equation (A3) to express the payoff in terms of a telescoping series of daily stock returns $r(u)$ between t and T as follows:

$$\hat{V}_{hedged}(T,T) = -2\sum_{u=t+1}^{T}\log(\frac{1+r(u)}{1+r_f}) + 2\sum_{u=t+1}^{T}(r(u) - r_f). \tag{A4}$$

When daily stock returns and risk-free rates are small, a second-order Taylor series expansion shows that the payoff of this daily hedged option portfolio (A4) closely approximates the realized variance of stock return over time t to T as follows:

$$\hat{V}_{hedged}(T,T) = 2\sum_{u=t+1}^{T}[r(u) - r_f - \log(\frac{1+r(u)}{1+r_f})] \approx \sum_{u=t+1}^{T}(r(u) - r_f)^2 \approx \sum_{u=t+1}^{T} r(u)^2. \tag{A5}$$

Since the daily risk-free rate is very small, the last approximation holds.[26] Combine Equation (A2) and (A5), it is easy to see that the numerator of Equation (1.2) approximates realized variance.

1.7.2 Model Linking HHI with Aggregate Hedging Demand for VIX Portfolio

Building on the model in Smith [2019], I derive a positive relation between HHI and investors' aggregate hedging demand for the firm's VIX portfolio. Here I will give a brief summary of model setup in Smith [2019] and show how HHI could be extracted as an empirical proxy for hedging demand. Readers can refer to the original paper for more details.

It is a single-period model with a continuum of investors indexed on $[0, 1]$ with CARA utility $u(W) = -e^{-\frac{W}{\tau}}$. Three assets are traded: a risk-free asset with payoff normalized to one and unlimited supply; a risky asset (stock) that pays off $\tilde{x}$ at the end of period, with per-capita endowment of $\bar{z}$; a variance derivative (VIX portfolio) with payoff equal to the stochastic variance $\tilde{V}$ and 0 net supply. Define D_{S_i} and D_{D_i} as the ith trader's position in the stock and derivative after trade.

[26] $\sum_{u=t+1}^{T}(r(u) - r_f)^2$ and $\sum_{u=t+1}^{T} r(u)^2$ have a correlation of 1, and the average absolute value of percentage error is only 0.14%.

The critical assumption is that both the mean and variance of the stock's payoffs are unknown to investors: Given the realizations of two independent random variables, $\tilde{\mu}$ and $\tilde{V}$, payoff $\tilde{x}$ is normally distributed with mean $\tilde{\mu}$ and variance $\tilde{V}$: $\tilde{x}|\tilde{\mu}, \tilde{V} \sim N(\tilde{\mu}, \tilde{V})$. $\tilde{\mu}$ is assumed to be Gaussian: $\tilde{\mu} \sim N(m_\mu, \sigma_\mu^2)$. Assume that variance $\tilde{V} \in \{m_V - \sigma_V, m_V + \sigma_V\}$ with ex-ante equal probabilities.

Each investor i receives both a "mean" signal and a "risk" signal regarding $\tilde{\mu}$ and $\tilde{V}$, respectively: $\tilde{\varphi}_i = \tilde{\mu} + \tilde{n} + \tilde{\epsilon}_i$ and $\tilde{\eta}_i = \tilde{V} + \tilde{v} + \tilde{e}_i$, where $\tilde{\epsilon}_i \sim N(0, \sigma_\epsilon^2)$, $\tilde{n} \sim N(0, \sigma_n^2)$, $\tilde{e}_i \sim N(0, \sigma_e^2)$, and $\tilde{v} \sim N(0, \sigma_v^2)$. To prevent fully revealing equilibrium, investors have stochastic nontradable endowments of the two components of risk $\tilde{\mu}$ and $\tilde{V}$. Trader i's endowment of $\tilde{\mu}$ equals $\tilde{Z}_{\mu i} = \tilde{z}_\mu + \tilde{z}_{\mu i}$. Her endowment of $\tilde{V}$ equals $\tilde{Z}_{Vi} = \tilde{z}_V + \tilde{z}_{Vi}$.

To see why investors face variance risk, ignoring endowments for simplicity, consider investor i's expected utility conditional on $\tilde{V}$:

$$\begin{aligned} &E\{-exp[-\frac{1}{\tau}(D_{Si}(\tilde{x} - P_S) + D_{Di}(\tilde{V} - P_D))]|\Phi_i, \tilde{V}\} \\ &= -exp\{-\frac{1}{\tau}[D_{Si}(E(\tilde{\mu}|\Phi_i) - P_S) + D_{Di}(\tilde{V} - P_D) - \frac{D_{Si}^2}{2\tau}(Var(\tilde{\mu}|\Phi_i) + \tilde{V})]\}. \end{aligned} \tag{A6}$$

In equilibrium, investor i's stock and derivative positions satisfy

$$\begin{aligned} D_{S_i} &= \tau \frac{E(\tilde{x}|\Phi_i) - P_S}{Var(\tilde{\mu}|\Phi_i) + P_D} - \frac{\tilde{Z}_{\mu i} Var(\tilde{\mu}|\Phi_i)}{Var(\tilde{\mu}|\Phi_i) + P_D}, \\ D_{D_i} &= \underbrace{\frac{\tau}{2\sigma_V}[log(\frac{Pr(\tilde{V} = m_V + \sigma_V|\Phi_i)}{Pr(\tilde{V} = m_V - \sigma_V|\Phi_i)}) - log(\frac{-m_V + \sigma_V + P_D}{m_V + \sigma_V - P_D})] - \tilde{Z}_{Vi}}_{\textit{Speculating Demand}} + \underbrace{\frac{1}{2\tau} D_{Si}^2}_{\textit{Hedging Demand}}, \end{aligned} \tag{A7}$$

where: $\Phi_i \equiv \{\tilde{\varphi}_i,\ \tilde{\eta}_i,\ \tilde{Z}_{\mu i},\ \tilde{Z}_{Vi},\ P_S,\ P_D\}$ represent investor i's information set. P_S (P_D) is the price of stock (derivative). Investors' hedging demands for the variance derivative are a quadratic function of their equity holdings, as variance risk has a higher-order impact on investors' utility.

Above are the results in Smith [2019]. Next, I will show that HHI is proportional to the aggregate hedging demand for the variance derivative and it negatively predicts VRP.

Since the derivative market is in zero net supply, summing up the second equation in (A7) across investors in $[0, 1]$ yields

$$\underbrace{\frac{1}{2\tau}\int_0^1 D_{Si}^2}_{Aggregate\ Hedging\ Demand} = f(P_D), \tag{A8}$$

where $f(P_D)$ is an increasing function in P_D. By definition, we have

$$HHI \equiv \frac{\int_0^1 D_{Si}^2}{\bar{z}^2} \tag{A9}$$

Combining (A8) and (A9), we can conclude that HHI is proportional to aggregate hedging demand for variance derivative and is positively related with P_D. The unconditional VRP equals $\frac{m_V}{P_D}$. This means that HHI is negatively related to VRP.

1.7.3 Variable Construction

This section discusses the construction of control variables used in the paper.

- IVOL: idiosyncratic volatility of stock return, estimated from Fama-French 3 factors using rolling one-month daily data, following Ang, Hodrick, Xing, and Zhang [2006].

- HV-VIX: difference between historical volatility, estimated using rolling one-year daily stock return data, and equity VIX. It is modified from the volatility deviation measure in Goyal and Saretto [2009].

- $RET_{t-1,t}$: short-term stock return reversal, calculated as the past month cumulative stock return (Jegadeesh [1990]).

- $RET_{t-12,t-1}$: stock return momentum, calculated as the cumulative stock return over the 11 months ending at the end of previous month (Jegadeesh and Titman [1993]).

- $RET_{t-36,t-12}$: long-term stock return reversal, calculated as the cumulative stock return from the past 36 month to the past 12 month (De Bondt and Thaler [1985]).

- Ln(ME): firm size is measured as the natural logarithm of the market value of equity at June (Fama and French [1992]).

- Ln(BM): value is measured as the natural logarithm of book equity for the fiscal year-end in a calendar year divided by market equity at the end of December of that year, as in Fama and French [1992].

- RN Skew: risk-neutral skewness of stock returns estimated from a portfolio of OTM options (Bakshi, Kapadia, and Madan [2003]).

- Rolling Skew: historical stock return skewness, estimated using rolling one-year daily stock return data.

- Rolling Kurt: historical stock return kurtosis, estimated using rolling one-year daily stock return data.

- Analyst Dispersion: analyst earnings forecast dispersion, computed as the standard deviation of annual earnings-per-share forecasts scaled by the absolute value of the average outstanding forecasts (Diether, Malloy, and Scherbina [2002]).

- CH: cash-to-assets ratio, defined as the value of corporate cash holdings over the value of the firm's total assets (Palazzo [2012]).

- Profit: firm profitability, as in Fama and French [2006],calculated as earnings divided by book equity, in which earnings is defined as income before extraordinary items.

- Issue: new stock issues, as in Pontiff and Woodgate [2008], measured as the change in shares outstanding from 11 months ago.

- Amihud: Amihud illiquidity measure (Amihud [2002]) over the past 30 days, calculated as equation (1) in that paper. Amihud multiplies it by 10^6 to adjust the scale. To get a reliable estimate, I require at least 17 observations of daily stock returns over the past 30 days.

- Option Bid-Ask Spread: for equity VIX portfolio, it is the percentage bid-ask spread calculated as the absolute bid-ask spread divided by the midpoint price of the VIX portfolio; for delta-hedged call (put) portfolio, it is simply the percentage bid-ask spread of the call (put) option.

- Option Bid-Ask Spread: for equity VIX portfolio, it is the percentage bid-ask spread calculated as absolute bid-ask spread divided by midpoint price of the VIX portfolio; for delta-hedged call (put) portfolio, it is simply the percentage bid-ask spread of the call (put) option.

- Leverage Ratio: firm leverage ratio, calculated as

$$\frac{Book\ Value\ of\ Debt}{Market\ Value\ of\ Equity + Book\ Value\ of\ Debt}.$$

- Treasury Rate: yield on 10-year Treasury. Data is taken from Federal Reserve Bank of St. Louis.

- Term Spread: slope of the term structure, defined as ten-year minus two-year Treasure yields.

Table A1.1: **Robustness Checks**

In Panel A, I first sort firms into quintiles based on firm size at each month and then further sort each quintile by $-HHI$ Mutual Fund. In Panel B, I first sort by Fund Number, which is the number of fund holders holding the firm, and then sort by $-HHI$ Mutual Fund. Firms are equally weighted. Average monthly returns (in percent) of these portfolios are presented. In Panel C, I run Fama-MacBeth regression to check the predictability of HHI on future stock return and variance, respectively. Control variables are the same as those in Table 1.3. The t-statistics are reported in parentheses. The sample period is from January 1996 to December 2017.

Panel A: Sort first by size and then $-HHI$ Mutual Fund.

	$-HHI$					
Size	1(Low)	2	3	4	5(High)	5-1
1(Low)	-12.13	-8.58	-6.67	-5.18	-2.47	9.66
						(4.70)
2	-8.80	-6.46	-3.70	-4.23	-2.63	6.17
						(2.60)
3	-8.86	-5.84	-5.57	-3.90	-3.27	5.59
						(2.98)
4	-7.08	-4.00	-5.77	-2.72	-1.16	5.92
						(3.31)
5(High)	-4.36	-2.99	-2.41	-2.77	-0.99	3.37
						(2.07)

Panel B: Sort first by Fund Number and then $-HHI$ Mutual Fund.

	$-HHI$					
Fund Number	1(Low)	2	3	4	5(High)	5-1
1(Low)	-11.82	-9.22	-8.77	-5.41	-7.71	4.10
						(2.07)
2	-8.29	-5.35	-3.58	-4.90	-1.30	6.99
						(3.93)
3	-7.51	-4.09	-4.83	-3.31	-4.82	2.69
						(1.12)
4	-6.30	-4.94	-3.62	-3.37	-4.77	1.53
						(0.95)
5(High)	-5.49	-2.68	-1.56	-0.70	-0.59	4.90
						(2.66)

Panel C: Future stock return and variance.

	$Stock\ Return_{i,t+1}$		$Variance_{i,t+1}$	
	(1)	(2)	(3)	(4)
HHI Mutual Fund	-0.005		0.002	
	(-0.74)		(1.30)	
HHI Institution		0.001		-0.002
		(0.11)		(-0.86)
Controls	Yes	Yes	Yes	Yes
R^2	0.114	0.114	0.278	0.275

Table A1.2: **Characteristics of Option and Non-option Funds**

This table reports differences in risk profiles between different types of funds under different Morningstar investment categories. Users/Total is the proportion of certain type of funds under a specific Morningstar category. Portfolio Concentration is the Herfindahl Index of the fund's equity portfolio. Alpha is calculated using Carhart 4-factor model. Std, Skew, and Kurt are the standard deviation, skewness, and kurtosis of fund returns, respectively. All four variables are calculated using CRSP monthly mutual fund returns. Option - Non is the difference between option funds and no option funds. Put (Call) - Non is the difference between put (call) funds and no option funds. The p-value associated with a two-sample t-test is reported in parenthesis.

Fund Category	Characteristics	Option - Non	Put - Non	Call - Non
Domestic Blend	Users/Total	11.03%	5.71%	5.32%
	Portfolio Concentration (%)	0.32 (0.02)	0.32 (0.07)	0.32 (0.14)
	Alpha (%)	0.01 (0.72)	-0.01 (0.86)	0.02 (0.39)
	Std (%)	0.15 (0.22)	0.30 (0.12)	-0.01 (0.95)
	Skew	-0.01 (0.85)	0.03 (0.67)	-0.05 (0.25)
	Kurt	0.35 (0.47)	1.01 (0.25)	-0.37 (0.04)
Domestic Growth	Users/Total	14.51%	9.08%	5.43%
	Portfolio Concentration (%)	0.14 (0.15)	0.13 (0.27)	0.18 (0.32)
	Alpha (%)	0.02 (0.40)	0.03 (0.17)	-0.01 (0.74)
	Std (%)	0.30 (0.03)	0.23 (0.17)	0.40 (0.05)
	Skew	0.01 (0.78)	0.02 (0.77)	0.01 (0.93)
	Kurt	0.90 (0.03)	0.94 (0.08)	0.83 (0.20)
Domestic Value	Users/Total	11.70 %	6.09%	5.61%
	Portfolio Concentration (%)	0.28 (0.08)	0.70 (0.01)	-0.16 (0.38)
	Alpha (%)	0.02 (0.34)	0.03 (0.30)	0.01 (0.77)
	Std (%)	-0.03 (0.83)	-0.02 (0.94)	-0.04 (0.79)
	Skew	-0.01 (0.82)	0.01 (0.92)	-0.03 (0.46)
	Kurt	0.28 (0.57)	0.80 (0.36)	-0.29 (0.26)

Table A1.3: **Double-Sorted VIX Returns**

Each month, I first sort firms into quintiles based on $HV-IV$ or idiosyncratic volatility (IVOL). $HV-IV$ is defined as $log(\frac{RV_{i,t-12,t}}{VIX_{i,t}^2})$, where $RV_{i,t-12,t}$ is the realized variance of firm i's stock return over the past 12 months. IVOL is the rolling 1-month standard deviation of firm's idiosyncratic return calculated from Fama-French 3-factor model. Firms within each quintile are further sorted into quintiles based on $w_{i,t}$. All portfolios are equally weighted. Alpha is calculated from the Fama and French (2015) 5 factors, the Carhart (1997) momentum factor, and S&P 500 Index VIX return in excess of risk-free rate. Average monthly returns of these portfolios are presented. The t-statistics are reported in parentheses. Portfolio returns are expressed in percent. The sample period is from January 1996 to December 2017.

Panel A: Sort by $HV-IV$ and then $w_{i,t}$.

	$w_{i,t}$						
Value	1(Low)	2	3	4	5(High)	5-1	Alpha
1(Low)	-21.74	-18.28	-14.34	-12.06	-9.55	12.20	17.36
						(5.06)	(7.28)
2	-9.77	-6.70	-6.27	-4.47	-4.59	5.18	9.05
						(2.42)	(4.17)
3	-5.35	-2.51	-1.85	-2.93	-0.95	4.40	9.17
						(2.21)	(4.95)
4	-4.40	-2.94	-1.50	-1.20	2.18	6.58	8.48
						(2.80)	(3.37)
5(High)	-2.80	-0.69	3.17	1.09	7.55	10.35	11.16
						(3.82)	(3.80)

Panel B: Sort by IVOL and then $w_{i,t}$.

	$w_{i,t}$						
IVOL	1(Low)	2	3	4	5(High)	5-1	Alpha
1(Low)	-15.06	-8.28	-7.42	-3.75	-0.09	14.97	16.21
						(6.65)	(6.68)
2	-12.55	-8.70	-3.47	-2.04	3.86	16.41	19.90
						(6.62)	(7.94)
3	-9.02	-6.26	-1.73	-1.49	4.14	13.16	13.65
						(5.65)	(5.38)
4	-9.68	-4.92	-3.44	-2.15	2.94	12.62	14.92
						(5.25)	(5.76)
5(High)	-13.25	-7.73	-4.63	-2.86	0.16	13.41	16.66
						(5.59)	(6.52)

Table A1.4: **Summary Statistics of Idiosyncratic VIX Return**

Idiosyncratic VIX Return is the return of firm's idiosyncratic VIX portfolio. The price of idiosyncratic VIX portfolio of firm i at month t equals $VIX_{i,t}^2 - \beta_{i,t}^2 VIX_{M,t}^2$. Idiosyncratic variance swap return (VSR) is defined as the realized idiosyncratic variance divided by the price of idiosyncratic VIX portfolio minus 1. The equally weighted (EW) idiosyncratic VIX Return is the cross-sectional average of firms' VIX returns at each month. Corr(Idio VIX Return,Idio VSR) is the time-series correlation between idiosyncratic VIX return and idiosyncratic VSR for each firm. When calculating the correlations, firms are required to have at least 30 observations. Portfolio returns are expressed in percent. The sample period is from January 1996 to December 2017.

	Mean	Std	10%	25%	50%	75%	90%
Idio VIX Return (%)	10.86	176.1	-70.88	-47.39	-14.45	37.88	123.6
Idio VSR (%)	11.51	179.2	-70.9	-54.40	-25.54	24.89	108.4
Corr(Idio VIX Return,Idio VSR)	0.62	0.32	0.19	0.51	0.72	0.85	0.92
EW Idio VIX Return (%)	11.71	40.95	-18.65	-6.55	6.31	26.70	51.06
EW Idio VSR (%)	10.04	34.87	-26.91	-11.08	2.15	27.34	49.73

Correlation(EW Idio VIX Return , EW Idio VSR)	0.79

Table A1.5: **Impact of Transaction Costs**

Portfolios are formed as in Table 1.9. portfolio returns are computed from the midpoint price (MidP) and from the effective bid-ask spread (ESPR), estimated to be 50%, 75%, and 100% of the quoted spread (QSPR). Returns in "Low Bid-Ask Spread" columns are calculated using firms with percentage bid-ask spread lower than the median bid-ask spread of that month. Returns in "All" columns are calculated using all firms in that month. Average monthly returns of these portfolios are presented. The t-statistics are reported in parentheses. Portfolio returns are expressed in percent. The sample period is from January 1996 to December 2017.

Panel A: Sort by $-HHI$

	All				Low Bid-Ask Spread			
		ESPR/QSPR				ESPR/QSPR		
	MidP	50%	75%	100%	MidP	50%	75%	100%
VIX Ret	9.96	-0.40	-6.07	-12.19	8.88	3.07	0.13	-2.85
	(5.89)	(-0.25)	(-3.69)	(-7.15)	(4.26)	(1.50)	(0.06)	(-1.41)
Delta-hedged Call	0.88	0.22	-0.10	-0.43	0.90	0.51	0.31	0.12
	(9.05)	(2.34)	(-1.10)	(-4.52)	(7.57)	(4.37)	(2.71)	(1.02)
Delta-hedged Put	1.17	0.54	0.22	-0.10	1.05	0.69	0.50	0.32
	(12.69)	(5.95)	(2.46)	(-1.07)	(9.66)	(6.40)	(4.72)	(3.02)

Panel B: Sort by $w_{i,t}$

	All				Low Bid-Ask Spread			
		ESPR/QSPR				ESPR/QSPR		
	MidP	50%	75%	100%	MidP	50%	75%	100%
VIX Ret	17.50	6.61	0.70	-6.02	15.68	9.66	6.62	3.55
	(8.23)	(3.15)	(0.33)	(-2.79)	(5.93)	(3.68)	(2.52)	(1.35)
Delta-hedged Call	1.50	0.75	0.39	0.03	1.20	0.85	0.67	0.49
	(12.38)	(6.35)	(3.28)	(0.22)	(8.51)	(6.03)	(4.78)	(3.51)
Delta-hedged Put	1.75	1.06	0.70	0.35	1.32	0.99	0.83	0.66
	(15.69)	(9.56)	(6.38)	(3.16)	(9.17)	(6.94)	(5.80)	(4.66)

Chapter 2: Option Momentum

2.1 Introduction

Early tests of market efficiency examined autocorrelation of stock returns (Fama and French [1988]) as well as predictability of market variance (Canina and Figlewski [1993], Day and Lewis [1992], Lamoureux and Lastrapes [1993], Fleming [1998], and Christensen and Prabhala [1998]). While autocorrelation of aggregate stock market returns is weak, Jegadeesh [1990] and Jegadeesh and Titman [1993] document strong momentum in the cross-section of U.S. stock returns.[1] Moskowitz and Grinblatt [1999] and Grundy and Martin [2001] extended that cross-sectional predictability to stock industry returns, and Jostova, Nikolova, Philipov, and Stahel [2013] extended it to bond returns.[2] Predictability in the cross-section implies that at least some assets have predictable returns. Despite the relevance and success of momentum strategies across asset classes, the literature has not yet investigated momentum in the cross-section of option returns across different stocks.

In order to investigate option momentum, we need to calculate returns on

[1] Rouwenhorst [1998] and Griffin, Ji, and Martin [2003] confirmed this cross-sectional effect in other countries.

[2] Asness, Moskowitz, and Pedersen [2013] and Jegadeesh and Titman [2011] also review evidence of momentum across countries, currencies, and commodity futures. Our focus is on the cross-section of U.S. stock options.

benchmark option portfolios. The standard published benchmarks for option volatility are the Chicago Board of Options Exchange (CBOE) VIX portfolio of $S\&P$ 500 index options, and the corresponding equity-VIX portfolios for options on individual stocks. Carr and Wu [2009] and Britten-Jones and Neuberger [2000] derived formulas that link VIX to the value of swaps on realized variance. But these formulas are only approximate, because they require a continuum of strike prices, and because they make additional continuous-time diffusion approximations. For empirical work, it is difficult to verify the adequacy of these approximations across hundreds of different stocks.

This paper derives a new formula to calculate *exact* returns on tradable option strategies. These strategies employ equity-VIX portfolios of options on individual stocks, constructed by CBOE's standard "model-free" VIX weighting methodology. We calculate monthly returns on these portfolios, including daily dynamic hedges in the underlying stocks. The advantages of our approach are: 1) It provides *exact* returns on standard benchmark equity-VIX portfolios, 2) It uses a daily "model-free" hedge that does not require estimating any model parameters, and 3) It explains option returns with a simple "variance swap" decomposition into realized variance and option implied-variance. In other words, our methodology is the first to translate continuous-time variance swap intuition into exact predictions for discrete option data.

This paper explores predictability of monthly returns on equity-VIX portfolios of options across different $S\&P$ 500 stocks. It finds that positive returns (in the cross-section) strongly continue for 12 months. Unlike stock returns, option returns show no tendency to reverse the gains from momentum (De Bondt and Thaler [1985, 1987]). Instead, momentum continues periodically for up to 60 months. In particular, option momentum displays a quarterly pattern of continuation. This periodic pattern matches the quarterly pattern of stock momentum over the past year, documented by Heston and Sadka [2008].

Our new methodology allows a variance decomposition of momentum returns. The cross-section of realized variance is persistent, with a strong quarterly pattern. But the cross-section of option implied-variance is even more persistent than realized variance. In other words, overpriced options tend to stay overpriced, and underpriced options tend to stay underpriced. The cross-section of option implied-variance has a smaller seasonal pattern than realized variance, suggesting that markets do not fully anticipate the seasonality of market volatility. Even after we eliminate firm-month observations with dividend payments and earnings announcements, the momentum and seasonality patterns remain strong. This suggests that returns might be related to behavioral biases in forecasting volatility, rather than information or cash flow events.

The option momentum effect is correlated with previous anomalies. For example, it is well-known that option returns have a (negative) variance premium, and this variance premium extends to the cross-section. Specifically, Carr and Wu [2009] and Goyal and Saretto [2009] showed that stock options with high prices, relative to their historical volatility, have lower subsequent returns than options with low prices. In other words, there is a variance premium associated with option *value*, as measured by historical variance divided by current price. In contrast, option *momentum* is essentially a measure of historical variance divided by historical price. While returns to option momentum and option value are correlated, multivariate analysis shows that these two effects are distinct. In addition to being distinct from option value, the returns to historical option momentum also remain largely unexplained by risks and other option return predictors, do not lie within the bid-ask spread, and survive margin requirements.

Section 2 discusses the data used in our analysis. Section 3 explains how the theoretical link between variance swaps and option strategies inspires profitable momentum strategies. Section 4 controls for option value, risk, and a wide range of option return predictors. Section 5 examines the impact of option bid-ask spreads to the profitability of option momentum strategies, and a final section concludes.

2.2 Data and Methodologies

We begin by constructing option strategies across individual stocks, and later analyze the returns on these strategies. There are competing methodologies for accommodating options with different strike prices. Bakshi and Kapadia [2003a] use delta-hedged returns on selected option series, and Jones, Khorram, and Mo [2020] use delta-hedged straddle returns. The gains of their delta-hedged option portfolio qualitatively represent a volatility risk premium that depends on the options being used. In contrast, the most prominent published benchmarks for option prices are the Chicago Board of Options Exchange *VIX* index for *S&P* 500 options (CBOE, 2019[3]) and the corresponding equity-VIX indices for options on individual stocks. These indices are based on portfolios of options, weighted by the squared reciprocals of their strike prices. Carr and Wu [2009] interpolated option prices to measure an idealized continuous VIX portfolio, and then used a continuous-time variance swap approximation to the returns on their portfolio. Although it is not literally a tradable option strategy, the variance swap approach has an intuitive advantage of decomposing returns into risk-neutral variance and realized variance. We construct returns on a discrete daily-hedged analog of the continuous variance swap option strategy. This method provides a tradable strategy, while preserving the intuition of the variance swap decomposition.

The CBOE (2019) VIX index is based on the (interpolated) market value of a portfolio at time t comprising options expiring at time T.

$$V(t;T) = 2\sum_{i} \frac{O(K_i, t; T)\Delta_i}{K_i^2}, \tag{2.1}$$

where $O(K, t; T)$ represents time t price of an out-of-the-money call or put option with strike price K and expiration T, and Δ_i represents the gap between adjacent strike prices.[4] Importantly, VIX portfolios are "model-free" because their construction does not depend on any model parameters. Carr and Madan [2001] showed that

[3] CBOE White Paper used to construct the VIX index can be found at: https://www.cboe.com/micro/vix/vixwhite.pdf

[4] The sum uses out-of-the-money options with respect to the forward value of the strike price, $K(1 + r_f)^{T-t}$.

we can approximate the VIX price with a continuous integral over strike prices.[5]

$$\hat{V}(t;T) = 2\int_0^\infty \frac{O(K,t;T)}{K^2}dK. \tag{2.2}$$

Given the spot price $S(T)$ at expiration, the option payoff $O(K,T;T)$ equals $Max(S(T)-K,0)$ for a call option and $Max(K-S(T),0)$ for a put option. In the absence of intermediate dividends, integrating these option payoffs over strike prices (2.2) shows the terminal payoff of the idealized VIX portfolio.

$$\hat{V}(T;T) = -2\log(\frac{S(T)}{S(t)(1+r_f)^{T-t}}) + 2\left(\frac{S(T)}{S(t)(1+r_f)^{T-t}} - 1\right), \tag{2.3}$$

where r_f is the daily risk-free interest rate. The first term in the payoff (2.3) represents selling two units of the "log-portfolio". The second term represents a costless static hedge that leverages (the present value of) two dollars of stock at time t, and holds this hedge position constant until expiration at time T. The combined payoff is a U-shaped function of the stock price, resembling a squared stock return. Therefore, the price of this portfolio represents the approximate (risk-neutral) variance of return. Since the *S&P 500* VIX index and equity-VIX indices on individual stocks represent standard deviation, they are proportional to the square-root of the portfolio value $V(t;T)$.

Due to their U-shaped payoffs, the equity-VIX portfolios have (approximately)

[5] See also Demeterfi, Derman, Kamal, and Zou [1999], Britten-Jones and Neuberger [2000], and Jiang and Tian [2005] for various continuous-time derivations. Breeden and Litzenberger [1978] first expressed the risk-neutral density in terms of the second derivative of the option price with respect to the strike price. Carr and Madan [2001] then derived the formula (2.2) using integration by parts twice.

zero delta when they are constructed. In other words, they are locally insensitive to movements in the underlying stock price. But over time, the stock price will drift away from the center of the U-shaped payoff, and the equity-VIX portfolios will become sensitive to the stock price. Instead of using a fixed static hedge, we can further reduce risk of the VIX portfolios by dynamic hedging. This replaces the second term of (2.3) with delta-hedging of the log-portfolio. The elasticity of option value with respect to the stock price generally depends on a model. But due to the log-payoff (2.3), the delta of the idealized continuous-strike VIX portfolio does not. Instead, the delta-hedge of the log-portfolio buys $1/S(t)$ shares of stock for a price of $S(t)$, and rebalances to maintains a constant hedge exposure of one dollar. So, not only is the value of the VIX portfolio model-free, but its dynamic-hedge is also model-free. This dynamic hedge keeps the delta of the discrete equity-VIX approximately equal to zero, and reduces the volatility of returns (relative to using a fixed static hedge). The dynamically hedged payoff is

$$V_{hedged}(T;T) = -2\log(\frac{S(T)}{S(t)(1+r_f)^{T-t}}) + 2\sum_{u=t+1}^{T}(r_S(u) - r_f), \tag{2.4}$$

where $r_S(u)$ represents the stock return on day u. We can replace the stock price in equation (2.4) to express the $V_{hedged}(T;T)$ payoff in terms of a telescoping series of daily stock returns $r_S(u)$ at times u between t and T:

$$V_{hedged}(T;T) = -2\sum_{u=t+1}^{T}\log(\frac{1+r_S(u)}{1+r_f}) + 2\sum_{u=t+1}^{T}(r_S(u) - r_f). \tag{2.5}$$

When daily returns on the stock and risk-free rate are small, a second-order Taylor series expansion shows that the dynamically hedged option portfolio (2.5) approximates the payoff of variance swap contract in Carr and Wu [2009]:

$$V_{hedged}(T;T) \approx \sum_{u=t+1}^{T} (r_S(u) - r_f)^2. \tag{2.6}$$

The return on the unhedged VIX portfolio from equation (2.1) is simply the proportional change in its value

$$r_{unhedged}(t;T) = \frac{V(T;T) - V(t;T)}{V(t;T)}. \tag{2.7}$$

The return on the dynamically hedged VIX portfolio is adjusted by the difference between the static hedge term in (2.3) and the dynamic risk term in (2.4).

$$r_{hedged}(t;T) = \frac{V(T;T) - V(t;T) - 2\left(\frac{S(T)}{S(t)(1+r_f)^{T-t}} - 1 - \sum_{u=t+1}^{T}(r_S(u) - r_f)\right)}{V(t;T)}. \tag{2.8}$$

A comparison of the hedged return (2.8) with the Taylor Series approximation (2.6) shows that the dynamically hedged return on the VIX portfolio is approximately the realized variance relative to the VIX portfolio price.

$$r_{hedged}(t;T) \approx \frac{\sum_{u=t+1}^{T} (r_S(u) - r_f)^2}{V(t;T)} - 1. \tag{2.9}$$

Carr and Wu [2009] used the variance swap approximation to analyze variance premiums in the cross-section of option returns, and Bollerslev, Tauchen, and Zhou [2009] used it implicitly when forecasting returns variance premium. Giglio and Kelly [2018] later applied it to multiple asset classes. In unreported diagnostics, we found that the exact return on the underlying $S\&P$ 500 index VIX portfolio is 99% correlated with the variance swap approximation (2.6). In other words, the dynamically hedged payoff on the index VIX portfolio is very close to the realized variance over the month. But with individual stocks, the correlations of options returns with realized variance can be lower. Using returns on hedged option portfolios (2.8) is consistent with previous research that measured delta-hedged returns, while preserving compatibility with the variance swap literature (2.9).

An additional advantage of our benchmark approach is that it measures option portfolios with all available strike prices. These portfolios maintain consistent sensitivity to volatility because they always include at-the-money options. In a certain sense, a VIX portfolio is always at-the-money. In contrast, Bakshi and Kapadia [2003a] approach of delta-hedging a single option will generally lose vega sensitivity when the option drifts away from the money.

This paper uses data from the OptionMetrics Ivy DB database from January 1996 to December 2017. These data provide daily closing bid and ask quotes for U.S. equity options. We use the T-bill rate of appropriate maturity (interpolated when necessary) from OptionMetrics as the risk-free rate.[6] Finally, we obtain information about stock returns, dividends, and firm characteristics from CRSP and

[6]Since average interest rates over this period were less than 2% per year, they had little effect on our calculations with monthly returns.

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We apply a series of filters on the option data. First, we use only options on $S\&P$ 500 constituent stocks within the sample period. This leaves us with a total of 995 firms. Following Driessen, Maenhout, and Vilkov [2009], we remove all observations for which the option open interest is equal to zero, in order to eliminate options with no liquidity. We discard options with zero bid prices, and with missing implied volatility or delta (which occurs for options with nonstandard settlement or for options with intrinsic value above the current mid price). We delete all observations whose ask price is lower than the bid price, and eliminate options whose prices violate arbitrage bounds. We also require the mid-point bid-ask option quote to be at least \$0.125, and the underlying stock price to be at least \$5. We delete firm-month observations containing stock splits. Following Christoffersen, Fournier, and Jacobs [2018], we remove firm-month observations for which the present value of dividends before expiration is larger than 4% of the stock price. Following Conrad, Dittmar, and Ghysels [2013], we use an equal number of calls and puts to construct VIX portfolios, using the midpoint of bid-ask quotes. Our final sample includes 79,845 firm-month observations with 535,722 option contracts. On average, each equity VIX portfolio consists of 6.71 option contracts.

The official CBOE VIX methodology combines options with different expiration dates to achieve a 30-day weighted-average maturity. Our analysis uncovers temporal periodicity in option prices and returns. To measure returns accurately, we must calculate portfolio values without interpolating option prices across different maturities. Therefore, we establish option position in equity-VIX portfolios on a

Friday of each month, with exactly 28 days to expiration on the third Friday of the subsequent month.[7] This avoids interpolation by using exact option prices instead of 30-day weighted-averages used by the CBOE (2019) VIX methodology. We calculate returns to expiration on the underlying equity-VIX portfolio (2.1), hedged daily according to (2.8), without using any approximations nor interpolations. The resulting option portfolio *value* and its *returns* are model-free.

Panel A of Table 2.1 compares *exact* equity-VIX returns (2.8) with variance swap returns (2.9) at the individual firm level. The gross variance swap return is defined as the realized monthly variance of a stock return divided by the equity-VIX price. Options have a negative variance premium, with equity-VIX returns averaging a loss of 4.19% per month. While this seems large compared to average equity returns, equity-VIX portfolios are risky and highly levered. The standard deviation of return exceeds 85% per month. There is a particularly fat right tail, where returns exceed 115% on the upper 5% of observations. The variance swap return averages a loss of 2.64% per month. Overall, the two measures of return have similar distributions, but the average equity-VIX return is more negative than the average variance swap return.

Panel B shows the difference between cross-sectional average equity-VIX returns and variance swap returns in an equally weighted portfolio across all firms at each month. This is effectively a portfolio of option portfolios. By exploiting the benefit of a large cross section, this approach diversifies the approximation er-

[7] We usually establish the option positions on the third Friday of a month. In months with five Fridays, we postpone the portfolio formation by one week to keep a holding period of exactly 28 days. This procedure had little effect on our empirical results.

ror between equity-VIX returns and variance swap returns. The average difference between equally weighted variance swap returns and equally weighted equity-VIX returns is only 0.23% per month. Overall, equity-VIX returns are much less negative than index VIX returns, whose monthly average equals -23.24%. This is consistent with the findings in Carr and Wu [2009] and Driessen, Maenhout, and Vilkov [2009].

To reliably calculate correlations and risk-exposures, Panel C of Table 2.1 restricts the sample to 650 stocks which had data available to calculate equity-VIX prices for at least 30 monthly observations. Panel C shows that across these 650 stocks, the average within-firm correlation between equity-VIX return and variance swap return is 75%, and the median correlation is 87%. An equally weighted portfolio of all equity-VIX's as in Panel B gives an even higher correlation of 92%. By comparison, the $S\&P$ 500 Index VIX produced a 99% correlation between the variance swap return and the exact daily hedged VIX return. The variance swap methodology produces a higher correlation for the $S\&P$ 500 Index VIX returns because there are more strike prices available to construct the option portfolios. While the correlation between variance swap returns and equity-VIX returns is lower at the individual firm level than that at the index level, much of the discrepancy gets diversified away in large portfolios. It is reassuring to know that the two measures are similar enough to support comparison of our new results with previous research.

The last row of Table 2.1 Panel A shows the Black-Scholes deltas, i.e., elasticities with respect to the stock price. The deltas of the idealized continuous VIX portfolios (2.3) are exactly zero, and Table 2.1 shows that the deltas of the equity-VIX portfolios are nearly zero. Under the Black-Scholes assumptions, the equity-

VIX portfolios should be uncorrelated with stock returns. Panel C shows this is not the case. Equity-VIX returns have strong negative betas with respect to the stock return and even stronger negative betas with respect to $S\&P$ 500 returns. This is because of negative correlation between stock returns and innovations in variance. The final row of Panel C shows that equity-VIX returns have an average positive beta of 0.4 with respect to returns on $S\&P$ 500 index-VIX returns. In other words, equity-VIX returns share exposure to systematic market variance.

Options on individual equities have an additional American early exercise feature. While there are many numerical methods and approximations to the optimal exercise policy, a simple approximation is to exercise options early when their exercise value exceeds a certain threshold of the ask prices of options. Table A2.1 in the Appendix performs sensitivity analysis to show that the early exercise premium (0.36%) is small compared to the variance premiums in Table 2.1 and to the returns of our momentum strategies.[8] As an additional robustness check, we form option momentum strategy each month using only non-dividend paying firms and compare the result with that in Table 2.4. The monthly average return of momentum strategy only changes slightly from 16.13% with a t-statistics of 8.42 to 16.23% with a t-statistics of 8.14. Therefore, we ignore early exercise when computing returns in subsequent tables.

[8] By using a binomial tree method, Driessen, Maenhout, and Vilkov [2009] find that the early exercise premium is between 0.3% and 1.1% for the 1-month option price. Our result lies in this range.

2.3 Option Portfolio Strategies

The previous section described construction of returns on our monthly equity-VIX portfolios. We use returns to expiration on these discrete model-free option portfolios. In the rest of this paper, when we form momentum strategies each month, we only consider firms that were included in the $S\&P$ 500 Index at that month, so that our strategy does not have forward-looking bias. Bakshi, Kapadia, and Madan [2003] used 31 individual stocks, and Carr and Wu [2009] used 35 individual stocks. Our substantially larger cross-section allows exploration of many different investment strategies.

Jegadeesh and Titman [1993] developed the simplest benchmark for stock momentum strategies. Their "relative strength" strategies sort stocks based on historical return over 3-, 6-, 9-, or 12-month periods, and then hold the equally weighted top decile of winner stocks and short the bottom decile of loser stocks for subsequent 3-, 6-, 9, or 12-month periods. We measure the corresponding option strategy that buys the equally weighted top decile of equity-VIX option portfolios and shorts the equally weighted bottom decile of losers every month. Following Jegadeesh and Titman, we rebalance these portfolio each month to maintain equal weights.

Table 2.2 shows the results of simple decile spread strategies based on all combinations of 3-, 6-, 9-, and 12-month formation periods and 3-, 6-, 9-, or 12-month holding periods. The results are consistently profitable. Across all formation periods and all holding periods up to one year, the top decile of winners outperformed the bottom decile of losers. For example, with the 3-month-formation/3-month-hold strategies, the top decile of winners earned an average of 2.74% per month, while the bottom decile of losers lost 7.88% per month. This difference exceeds 10% per month. Across all strategies, the option decile spreads are economically large and statistically significant.

The strategies in Table 2.2 were not optimized for options. Table 2.2 merely represents an out-of-sample test of Jegadeesh and Titman's original strategies on an entirely new asset class. To understand why these strategies might be profitable, we decompose the option portfolio returns according to the variance swap approximation of the previous section.

Equation (2.9) shows that the gross return on an equity-VIX portfolio for the i^{th} stock over month t is approximately the realized variance, $RV_i(t)$, divided by the cost of the equity-VIX portfolio $VIX_i^2(t-1)$. In logarithms, this relationship is

$$log(1 + r_i(t)) \;\approx\; log(RV_i(t)) - log(VIX_i^2(t-1)). \tag{2.10}$$

This return decomposition shows that predictability in equity-VIX returns reflects predictability in realized variance relative to equity-VIX prices. To diagnose the sources of momentum profits, we run the cross-sectional regression

$$log(RV_i(t)) = \gamma_{0,t} + \gamma_{k,t} \cdot log(RV_i(t-k)) + \epsilon_i(t). \tag{2.11}$$

The coefficient estimate $\gamma_{k,t}$ shows the extent to which the cross-section of realized variance in one month is predicted by the previous cross-section lagged by k-months.

The average of $\gamma_{k,t}$ over all months t shows the average relationship. Figure 1 (a) shows that the cross-section of realized variance is persistent, with coefficients exceeding 0.6 for short monthly lags, and declining as lags grow to five years. Figure 1 (a) also displays the corresponding average coefficients for the analogous regression of the cross-section of logarithms of equity-VIX prices $log(VIX_i^2(t))$ on their own lags. Option prices are even more persistent than realized variance, with average coefficients exceeding 0.8 for short monthly lags, and remaining above 0.5 even for lags of five years. Across different lags, both the realized variance and VIX^2 coefficients exhibit a striking quarterly periodicity. It appears that variance has a quarterly seasonal pattern across stocks, and to a large extent, option prices anticipate the pattern in future variance.

To ascertain whether option prices properly anticipate the persistence and seasonality of realized variance, we run the cross-section regression using continuously compounded variance swap returns,

$$log(1 + \tilde{r}_i(t)) = \gamma_{0,t} + \gamma_{k,t} \cdot log(1 + \tilde{r}_i(t-k)) + \epsilon_i(t), \tag{2.12}$$

where $\tilde{r}_i(t)$ denotes the variance swap return. While compounded variance swap returns are not exactly equal to returns, they are a good approximation. Figure 1 (b) shows that the resulting pattern of average γ coefficients across different lags remains positive and visibly seasonal for at least five years. Figure 1 (b) suggests that option prices fail to properly anticipate the persistence and periodicity of realized variance.

Table 2.3 shows the coefficients of first year lags from Figure 1 (b). The univariate columns shows that coefficient estimates are all highly significant at all lags, with t-statistics ranging from 6 to 11. To measure the incremental statistical significance of individual lags, the multivariate column of Table 2.3 reports average (of time-series) coefficients from multivariate cross-sectional regression that includes a full year of monthly lags. The multivariate t-statistics are at least 3 at the quarterly lags of 3-, 6-, 9-, and 12-months. But they are mostly statistically insignificant at other lags. This indicates that persistence in the cross-section of option returns is primarily a quarterly seasonal phenomenon.

To recap, Table 2.2 provides simple and robust evidence that momentum strategies are profitable across options on different stocks. Figure 1 and Table 2.3 indicate this predictability has a quarterly pattern that lasts for up to five years. This suggests that we investigate strategies that exploit momentum and specifically quarterly momentum for various horizons up to five years.

Inspired by Table 2.3 and Figure 1, Table 2.4 reports returns on one-month equally weighted decile portfolios of equity-VIX option strategies ranked according to different historical measures of variance swap momentum. The Year 1 "All" deciles are sorted based on the geometric average of all 12 monthly variance swap returns over the past year; the Year 2 "All" deciles are sorted based on monthly lags 12-24, and so forth. The Year 1 quarterly decile portfolios are sorted only based on monthly lags 3, 6, 9, and 12. The Year 2 quarterly portfolio uses lags 15, 18, 21, and 24, and similarly for Years 3, 4, and 5. The nonquarterly decile portfolios are sorted on the monthly lags of a given year that are *not* quarterly, e.g., lags 1, 2, 4, 5, 7, 8, 10, and 11 for Year 1.

Table 2.4 shows that average monthly returns are nearly monotonic across momentum deciles sorted based on the past year of returns. Using all months in the past year, the lowest decile lost 13.47% per month, while the highest decile gained 2.65% per month. The difference exceeds 16% per month, and is highly statistically significant. Sorting deciles using only four lags of 3-, 6-, 9-, and 12-months is nearly as profitable, with a decile spread of 14.77%. The quarterly effect must be quite strong for a noisy momentum strategy using only 4 lagged months to be nearly as profitable as a strategy using all 12 lagged months within the past year. In fact, the t-statistic for this quarterly winner-loser strategy exceeds the t-statistic for the full-year strategy. The Year 1 Non-Quarterly strategy is also profitable; the corresponding 10-1 decile spread exceeds 11%. The Year 1 Quarterly decile spread outperforms the Non-Quarterly decile spread by 3.42% per month.

To examine the source of profits of momentum strategies, we report the risk-adjusted returns for the short- and long-leg in the portfolio Year 1 "All", controlling for the VIX returns of $S\&P$ 500 Index, five Fama and French [2015] factors, and stock momentum factor. Results are reported in Table 2.5. In terms of raw returns, the short leg (13.47%) contributes most to total profit (16.13%), as shown in the first row of Table 2.4. After adjusting for the risk exposure to index VIX returns, which is largely negative, the winner portfolio contributes 70.4% to total risk-adjusted profits (11.9% out of 16.9%). This resembles the pattern of stock market momentum in Jegadeesh and Titman [1993].

The pattern of quarterly continuation in Table 2.4 relates to previous patterns of momentum in stock returns. Heston and Sadka [2008] found a quarterly pattern of continuation when using lagged stock returns less than one year. But beyond one year, this quarterly pattern disappeared. Instead, long-term stock returns exhibit long-term reversal (De Bondt and Thaler [1985, 1987]), with continuation at annual lags. The cross-section of option returns shares the quarterly pattern of continuation. While the quarterly pattern of options gets weaker and statistically less significant as the horizon recedes, it definitely does not turn into reversal within five years.

We have explored variables that might be related to the quarterly seasonality in option returns. These include firms' earnings months, ex-dividend months, calendar month, and length of trading-month. These variables are easy to diagnose by simply analyzing subsamples of monthly return observations. Unreported tables resemble full-sample results, and show that none of these variables explain the seasonal pattern in realized variance or in option returns. Jones, Khorram, and Mo [2020] find similar seasonal momentum effects in straddle returns, and conclude that these effects remain strong after controlling for characteristics and factor risk. A behavioral explanation is that markets fail to fully anticipate seasonality in volatility. This resembles the behavioral bias across expiration dates documented by Eisdorfer, Sadka, and Zhdanov [2017]. Alternatively, there might be a distinct risk premium associated with quarterly seasonal volatility. Similar patterns remain unexplained in the stock momentum literature, and present questions for future research.

2.4 Control for Risk and Option Return Predictors

If markets are efficient, then excess returns of options strategies should be compensation for systematic risk. While our equity-VIX portfolios are hedged to be insensitive to stock risk, they are constructed to be very sensitive to variance risk. Systematic market variance has a well-known negative risk premium (Bakshi and Kapadia [2003a]). The existence of a variance premium makes it plausible that past returns are correlated with exposure to variance. For example, stocks with high past variance swap returns might have high future comovement with systematic market variance.

Table 2.4 controls for risk by regressing the long-short momentum strategy returns on five Fama and French [2015] factors and the momentum factor of Carhart [1997]. It also includes the VIX returns of $S\&P$ 500 Index as an additional risk factor. The intercept "alpha" from this regression represent risk-adjusted average returns. These risk-adjusted means are generally close to the average decile spreads, and do not alter their statistical significance. There is little indication that momentum returns in the cross-section of options are related to stock factors (including momentum) or to covariance with systematic market volatility.

Given the profitability of momentum strategies in options, a concern is whether the momentum return effect is truly new, or just a disguised manifestation of existing anomalies. In particular, Goyal and Saretto [2009] and Carr and Wu [2009] documented a significant negative return premium on options with high implied variance, relative to their historical variances. We define option value as rolling

1-year historical variance divided by *current* equity-VIX price. Option momentum is similar to option *value*, because option momentum is historical realized variance divided by historical equity-VIX price.

Table 2.6 distinguishes option momentum from option value using a double-sort. The rows first sort stocks into equally weighted quintiles by 12-month option value. Then, the columns sorts by option momentum. The value effect is quite strong, and returns are almost monotonic in every column. But they are also almost monotonic in every row. The average excess return on the quintile spread of high momentum minus low momentum across all stocks exceeds 12% per month, and is largely unchanged when adjusted for risk factors. It appears that the effect of option momentum is distinct from previously documented profitability of option value.

While option momentum is not subsumed by option value, it may capture some effects overlapped with previously documented option return predictors. To control for these variables, we put them along with option momentum into a vector $Z_i(t-1)$, which is known at month $t-1$. We then run a cross-section regression

$$r_i(t) = \gamma_{0,t} + \gamma'_{k,t} Z_i(t-1) + \epsilon_i(t), \tag{2.13}$$

where: $r_i(t)$ is the excess return of equity-VIX portfolio over risk-free rate; the vector $\gamma'_{k,t}$ represents coefficients for the option return predictors. The controlled variables include HV-IV (volatility deviation in Goyal and Saretto [2009]), IVOL (idiosyncratic volatility in Cao and Han [2013]), Slope_VTS (slope of implied volatility term structures in Vasquez [2015]), VOV (volatility of volatility constructed using option implied volatilities in Cao, Vasquez, Xiao, and Zhan [2019]), RN_Skew (risk-neutral skewness in Bakshi, Kapadia, and Madan [2003]), Option Demand (option demand pressure calculated as the ratio of the average option open interest times $|\Delta|$ of option contracts over the past week to the total stock trading volume over the past week), Amihud (Amihud illiquidity measure (Amihud [2002])), and stock characteristics including firm size, book-to-market ratio, past one month stock return, stock return momentum, analyst forecast dispersion, cash holding, profitability, and stock issues constructed as Cao, Han, Tong, and Zhan [2017]. To check the robustness of results, we also use delta-hedged at-the-money (ATM) call and put returns (calculated as Bakshi and Kapadia [2003a]) as the dependent variable, respectively.

Table 2.7 reports the time-series averages of γ coefficients and their t-statistics, corrected for autocorrelation following Newey and West [1987] with three lags. Controlling for all of these option return predictors only moderately reduces the option momentum coefficient from 0.152 to 0.115. Results using delta-hedged call and put returns display very similar pattern. Option momentum remains highly profitable and statistically significant. We conclude that returns to option momentum are substantially independent of the option return predictors documented in previous literature.

2.5 Transaction Cost Analysis

Equity options have large trading costs. The median percentage bid-ask spread of our equity-VIX portfolios, defined as absolute bid-ask spread divided by the midpoint price of equity-VIX portfolio, is 14%. Such large trading costs might eliminate the profits on option strategies if mispricing lies entirely within the bid-ask spread. Margin requirements are another type of friction. Santa-Clara and Saretto [2009] show that margin requirements limit the notional amount of capital that can be invested in option strategies. Therefore, Table 2.8 evaluates the effect of these two trading frictions.

Table 2.8 uses the decile spread strategies from the first row of Table 2.4, forming monthly momentum portfolio based on "All" returns within the last year. The "0%" in the first column of Table 2.8 measures option prices at the mid-point of bid-ask quotes, just as in Table 2.4. The last column uses the full quoted bid-ask spreads. The intermediate columns use 50% and 75% of the quoted bid-ask spread around the mid-point prices.

Table 2.8, Panel A shows that the "All", "Quarterly", and "Non-Quarterly" strategies remain profitable for trading costs equal to 50% of the quoted bid-ask spread. When costs exceed 75% of the bid-ask spread, the "All" and "Quarterly" strategies earn insignificant profits, and the "Non-Quarterly" strategy loses insignificant money. When paying full bid-ask spreads, all the strategies lose money. Muravyev and Pearson [2019] show that the average effective bid-ask spread ratio for trades taking into account of high frequency trade timing ability is around 50%.

In the presence of bid-ask spreads, one could just trade the cheaper options. A simple strategy is to restrict trades to equity-VIX portfolio with percentage bid-ask spreads below the sample median of 14%. Panel B shows that this restriction hardly changes average profits when trading at the mid-point of the bid-ask spread. Indeed, this restriction insubstantially improves the mid-point profits from momentum based on "All" months from 16.1% to 17.0%. Using mid-point returns, restricting the sample increases the volatility and lowers the t-statistic due to a smaller sample of available firms. But it substantially improves profits when paying transactions costs. Even when paying the full bid-ask spread, the "All" strategy earns 9.1% per month, and the "Quarterly" strategy earns 7.1% per month. These post-trading-cost profits are positive at the 1% level of statistical significance. We conclude that with appropriate trade execution, the post-transactions cost momentum strategies preserve about half the mid-point trading profits.

Since our option momentum strategy sells options in loser portfolios, we investigate the impact of margin requirements. We compute margins of the option positions in loser portfolios following the CME margin system, which is applied to institutional investors' margin accounts. Specifically, we implement the scenario analysis algorithm used in Goyal and Saretto [2009]. Each day, we use $\pm 15\%$ as the range for stock price movement, with progressive increments of 3%, and $\pm 10\%$ as the range for level of volatility. We then calculate option positions using the Black and Scholes [1973] model under each scenario, and determine the margin by the largest loss among those scenarios.

The initial margin haircut ratio is defined as $\frac{M_0 - V_0}{V_0}$, where M_0 is the initial margin of option positions in the firm's VIX portfolio when the trade is implemented, and V_0 equals the sum of option prices when the position is opened. Since additional margin calls may occur after the position is established, we also report the maximum haircut ratio during the holding month. Since the loser portfolio is equally weighted, we calculate the portfolio-level margin haircut by taking an equal-weighted average of the haircuts for individual firms.

Panel C reports the margin haircut ratio of shorting the loser portfolio in our "All" strategy. The initial haircut ratio has an average of 3.18 and maximum value of 6.64.[9] For each dollar of written options, investors need to borrow \$3.18, on average, to satisfy the initial margin requirement, which limits investors' option exposure to 31% of their capital. During the holding period after portfolio formation, the maximum haircut ratio has an average of 4.77 and maximum value of 8.94. To further explore the impact of margins on option momentum returns, we check the correlation between initial haircut and the momentum strategy return during the subsequent holding period. The two have a correlation of -0.27, which means initial haircuts tend to be high when the subsequent strategy returns are low. In this sense, the initial margins actually lower investors' exposure to potential negative momentum returns and alleviate the "momentum crashes" documented by Daniel and Moskowitz [2016].

To measure the joint impact of bid-ask spreads and margin requirements faced by institutional investors, we compute monthly returns from investing the inverse initial margin ratio, $\frac{V_0}{M_0 - V_0}$, in our 12-month option momentum strategy, and allocating the remainder to the risk-free asset. We also assume investors face 50% effective bid-ask spread. Panel C reports the results in the "Return (%)" column. The average monthly return equals 4.53% with a t-statistic of 4.59. The minimum return is

[9] As a benchmark, Santa-Clara and Saretto [2009] find that the initial margin of writing an ATM index put has an average of 2.6 and maximum value of 11.6.

-31.17%. The annual Sharpe Ratio is 1.00. Therefore, option momentum strategies are profitable after considering both margins and reasonable bid-ask spreads, with a mild monthly maximum loss.

2.6 Conclusions

This paper develops a new methodology to calculate exact returns on model-free VIX portfolios with a model-free dynamic hedge. This allows us to explore a large panel of option returns across different stocks. The new methodology preserves the intuition of continuous-time variance swaps; it decomposes returns into realized variance and implied variance. This enables a comparison of the dynamics of realized variance with the dynamics of implied variance.

We find that a variety of momentum strategies are profitable across options on individual stocks. Option momentum is a measure of historical option returns, i.e., realized variance relative to historical option prices. A related measure of option value is realized variance relative to current option prices. Returns to option momentum are distinct from returns to option value, and are not explained by standard risk factors, stock characteristics, or bid-ask spreads.

Option momentum has intriguing commonalities and contrasts with stock momentum. Momentum in options across $S\&P$ 500 firms displays a strong quarterly periodicity that matches the Heston and Sadka [2008] pattern of momentum within one year, but does not match the Heston and Sadka annual pattern for long-term momentum. Unlike stocks, options do not show long-term reversal of momentum profits. Instead, option momentum, particularly quarterly momentum, remains profitable for up to five years. It is tempting to speculate about risk factors or behavioral biases that might explain returns to option momentum. A successful theory would explain the quarterly pattern in options, and why the patterns of momentum profits are different in stocks and options.

Table 2.1: **Summary Statistics of Equity-VIX Returns**

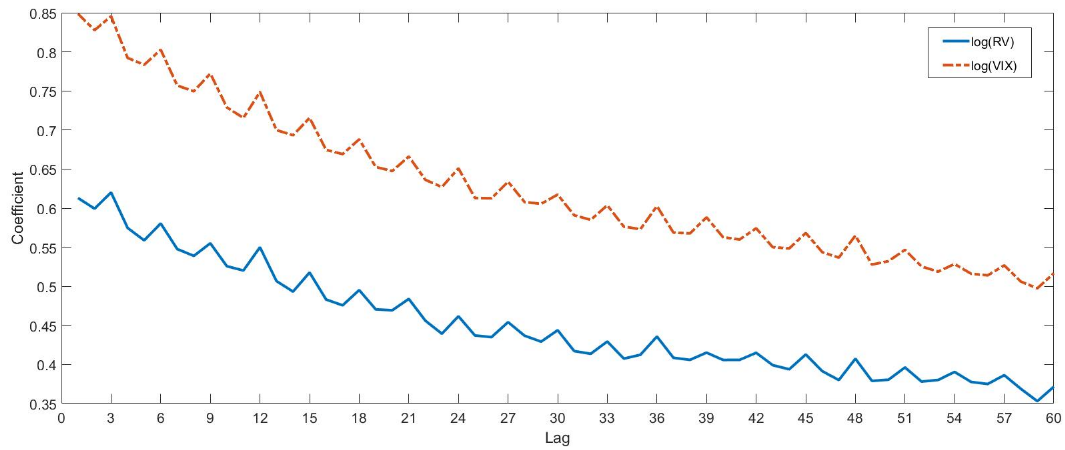
The sample data are from January 1996 to December 2017. We select firms that were included in the $S\&P$ 500 index during that period. There are 263 months of returns and 79,854 firm-month observations in total. Equity-VIX Return is the actual realized return of underlying equity-VIX portfolio, constructed as a static position in a basket of options plus a daily rebalanced position in the underlying stock. Variance Swap Return (VSR) is defined as the realized variance of the stock return divided by the price of the equity-VIX portfolio minus 1. Equity-VIX Return - VSR is the difference between equity-VIX return and variance swap return. Index-VIX Return is the VIX return of $S\&P$ 500 Index. EW Equity-VIX Return is the cross sectional average of equity-VIX returns each month. EW Variance Swap Return is the cross sectional average of firms' variance swap returns each month. Black-Scholes Delta Elasticity is the elasticity of equity-VIX portfolio with respect to the underlying stock price at the formation date. β_{Stock} is the exposure of the firm equity VIX return to its stock return; β_{SP500} is the exposure of firms' equity-VIX returns to the $S\&P$ 500 index return; $\beta_{MKT\,VIX}$ is the exposure of firm equity-VIX returns to the $S\&P$ 500 index VIX return. Correlation(Equity VIX Return,VSR) is the firm level time-series correlation between equity-VIX returns and variance swap returns. When calculating β_{Stock}, β_{SP500}, $\beta_{Mkt\,VIX}$ and Correlation(Equity-VIX Return, VSR), we require firms to have at least 30 observations. There are 650 firms meeting this requirement.

	Mean	Std	5%	25%	50%	75%	95%
Panel A: Individual firms.							
Number of Firms Each Month	304	111	147	203	293	411	468
Number of Strikes	6.71	4.90	4.00	4.00	6.00	8.00	14.00
Equity-VIX Return (%)	-4.19	85.52	-69.18	-42.78	-19.49	14.73	115.1
Variance Swap Return (VSR) (%)	-2.64	101.9	-71.66	-48.74	-24.73	11.73	126.3
Black-Scholes Delta Elasticity	-0.05	0.09	-0.17	-0.07	-0.04	-0.02	0.00
Panel B: Time series of $S\&P$ 500 Index and equally weighted (EW) portfolio.							
Index-VIX Return(%)	-23.24	72.66	-73.10	-56.43	-37.18	-13.80	65.52
Index Variance Swap Return(%)	-24.35	74.19	-74.72	-58.32	-38.75	-13.11	60.02
EW Equity-VIX Return (%)	-3.46	32.85	-38.03	-22.88	-9.87	6.64	56.13
EW Variance Swap Return (%)	-3.23	44.19	-39.80	-26.13	-12.02	5.66	67.08
Panel C							
Correlation(Equity-VIX Return, VSR)	0.75	0.31	0.13	0.69	0.87	0.95	0.99
β_{Stock}	-2.24	2.55	-6.37	-3.36	-2.07	-0.98	1.06
β_{SP500}	-4.02	3.50	-9.75	-5.98	-3.82	-1.96	1.18
$\beta_{Mkt\,VIX}$	0.40	0.31	-0.06	0.24	0.38	0.55	0.85

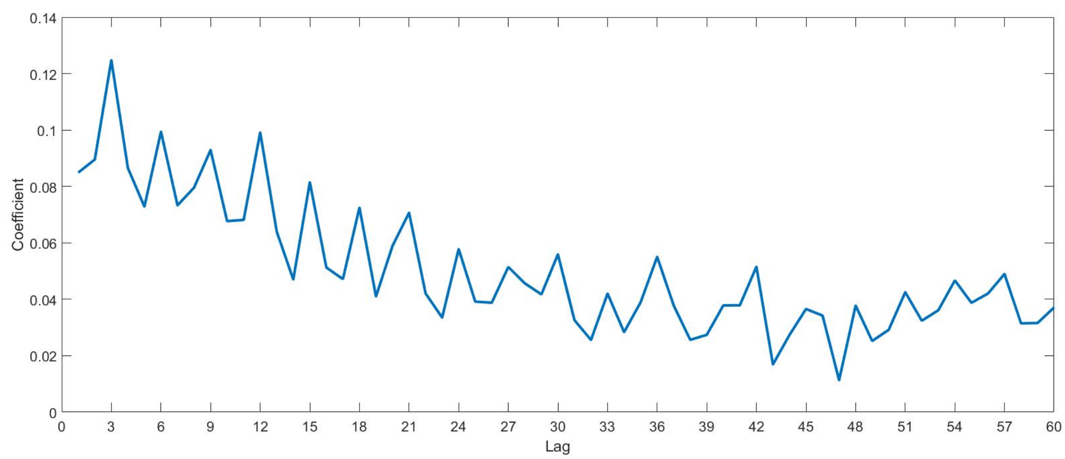
Table 2.2: **Option Momentum Strategy Returns**

The momentum portfolios are formed based on J-month lagged equity-VIX returns and held for K months as in Jegadeesh and Titman (1993). In addition, we require the firms to have non-missing equity-VIX returns for at least $\frac{2}{3}J$ past months. The values of J and K for the different strategies are indicated in the first column and row, respectively. To avoid forward-looking bias, we only include firms that are included in the $S\&P$ 500 index when we form the portfolio. The portfolios are equally weighted. The average monthly returns of these portfolios are presented in this table. The t-statistics are reported in parentheses. Portfolio returns are expressed in percent. The sample period is from January 1996 to December 2017.

J	$K=$	3	6	9	12
3 Loser		-7.88	-6.81	-6.41	-6.42
		(-3.53)	(-3.09)	(-2.95)	(-2.94)
3 Winner		2.74	0.52	-0.93	-1.46
		(1.00)	(0.21)	(-0.39)	(-0.62)
3 Winner-Loser		10.63	7.32	5.49	4.96
		(5.90)	(5.44)	(4.67)	(4.43)
6 Loser		-8.15	-7.69	-7.03	-7.10
		(-3.48)	(-3.36)	(-3.08)	(-3.15)
6 Winner		1.93	0.37	-0.74	-1.02
		(0.69)	(0.14)	(-0.30)	(-0.41)
6 Winner-Loser		10.08	8.05	6.29	6.08
		(5.09)	(4.93)	(4.06)	(4.22)
9 Loser		-7.89	-7.61	-7.65	-7.17
		(-3.07)	(-3.16)	(-3.27)	(-3.09)
9 Winner		1.63	1.05	-0.01	-0.31
		(0.60)	(0.40)	(-0.00)	(-0.12)
9 Winner-Loser		9.52	8.67	7.64	6.86
		(4.67)	(4.82)	(4.34)	(4.19)
12 Loser		-5.60	-7.18	-6.91	-7.15
		(-2.22)	(-2.91)	(-2.83)	(-3.02)
12 Winner		1.21	0.40	-0.17	-0.91
		(0.43)	(0.15)	(-0.07)	(-0.36)
12 Winner-Loser		7.21	7.58	6.74	6.24
		(3.27)	(3.95)	(3.68)	(3.57)



(a) Coefficients of $log(RV_{i,t-k})$ and $log(VIX^2_{i,t-k})$



(b) Coefficients of $log(1 + VSR_{i,t-k})$

Figure 1. Monthly univariate cross-sectional regression of the form $x_{i,t} = \alpha_{k,t} + \gamma_{k,t} \cdot x_{i,t-k} + \varepsilon_{i,t}$, are calculated for each month t and lag k, where $x_{i,t}$ is either the logarithm of realized variance (RV), logarithm of the price of equity-VIX portfolio, or the logarithm of the variance swap return (VSR) of firm i in month t. The regression is calculated for every month t from January 1996 through December 2017 and for lag k values of 1 through 60. Figures (a) and (b) plot the time-series averages of $\gamma_{k,t}$.

Table 2.3: **Univariate and Multivariate Cross-sectional Regressions of Variance Swap Returns**

Monthly univariate cross-sectional regression of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} \cdot r_{i,t-k} + \varepsilon_{i,t}$, are calculated for each month t and lag k, where $r_{i,t}$ is the continuously compounded variance swap return of firm i in month t. The regression is calculated for every month t from January 1996 through December 2017 and for lag k values 1 through 12. Monthly multivariate cross-sectional regression takes the form: $r_{i,t} = \alpha_{k,t} + \sum_{k=1}^{12} \gamma_{k,t} \cdot r_{i,t-k} + \varepsilon_{i,t}$. To avoid forward-looking bias, we only include firms that are included in the *S&P 500* index when we form the portfolio. The time-series averages of $\gamma_{k,t}$ along with their t-statistics, are reported in the table.

	Univariate		Multivariate	
Lag	Coefficient	t-statistic	Coefficient	t-statistic
1	0.085	7.85	0.043	2.24
2	0.089	9.65	0.026	1.93
3	0.125	11.26	0.053	3.10
4	0.087	8.74	0.049	2.34
5	0.073	6.93	0.030	2.21
6	0.099	9.83	0.046	2.95
7	0.073	9.24	0.013	0.51
8	0.080	9.35	0.023	1.05
9	0.092	10.46	0.078	3.93
10	0.068	6.93	0.027	1.42
11	0.068	7.51	0.019	1.49
12	0.099	11.30	0.050	3.73

Table 2.4: **Returns of Strategies Based on Past Variance Swap Returns**

Every month firms are grouped into ten portfolios according to various categories based on the geometric average of past variance swap returns. To avoid forward-looking bias, we only include firms that are included in the $S\&P$ 500 index when we form the portfolio. For example, the trading strategy that is formed based on past quarterly returns during Year 2 ranks firms according to their average log variance swap returns over historical monthly lags 15, 18, 21, and 24. The trading strategy "All" in a given year is formed based on each firm's average log variance swap return over that lagged year. The equity-VIX's in each portfolio are equally weighted across firms, and portfolios are rebalanced monthly. To calculate alpha, we control for the VIX return of the $S\&P$ 500 index, five Fama and French (2015) risk factors, and the Carhart (1997) stock momentum factor. The average monthly returns of these portfolios are presented in percent, with t-statistics reported in parentheses. The sample period is from January 1996 through December 2017.

	Strategy	1	2	3	4	5	6	7	8	9	10	10-1	Alpha
Year 1	All	-13.47	-7.82	-4.82	-3.56	-4.86	-1.58	-1.77	0.00	1.44	2.65	16.13	16.92
												(8.42)	(8.21)
	Quarterly	-12.56	-6.97	-5.62	-2.26	-3.23	-2.47	0.72	-0.10	-0.67	2.21	14.77	15.39
												(8.75)	(8.71)
	Non-Quarterly	-11.51	-6.57	-5.56	-2.73	-2.61	-1.31	-2.17	-0.84	0.71	0.13	11.64	11.52
												(6.49)	(5.99)
Year 2	All	-9.10	-4.24	-5.13	-3.45	-2.32	-3.78	-3.97	-2.96	-1.75	-1.20	7.90	5.75
												(3.98)	(2.74)
	Quarterly	-7.26	-6.95	-2.98	-4.23	-4.62	-2.94	-1.23	-1.09	-3.85	0.54	7.80	8.27
												(4.21)	(4.15)
	Non-Quarterly	-5.92	-5.09	-6.36	-2.31	-3.52	-3.25	-1.17	-3.51	-3.50	-2.63	3.29	1.34
												(1.48)	(0.57)
Year 3	All	-7.72	-5.87	-5.67	-3.70	-6.22	-4.87	-2.65	-5.45	-3.66	-3.63	4.09	2.01
												(2.03)	(0.94)
	Quarterly	-7.05	-7.91	-6.08	-6.67	-5.44	-4.10	-2.16	-2.38	-2.56	-3.84	3.21	2.88
												(1.83)	(1.52)
	Non-Quarterly	-6.95	-4.60	-4.26	-4.58	-4.37	-5.44	-4.30	-3.79	-4.47	-5.21	1.73	0.06
												(0.97)	(0.03)
Year 4	All	-7.15	-5.63	-5.42	-4.95	-4.61	-4.76	-5.33	-4.81	-6.36	-4.21	2.94	3.11
												(1.68)	(1.65)
	Quarterly	-7.12	-5.41	-4.02	-5.71	-4.85	-5.78	-7.31	-5.47	-3.75	-1.81	5.31	4.85
												(2.96)	(2.50)
	Non-Quarterly	-6.11	-6.13	-4.35	-4.85	-4.46	-7.06	-4.64	-4.56	-5.45	-5.84	0.26	-0.67
												(0.15)	(-0.34)
Year 5	All	-6.54	-7.66	-8.57	-8.07	-5.62	-7.73	-6.14	-6.84	-5.25	-3.55	2.99	0.18
												(1.26)	(0.07)
	Quarterly	-9.89	-8.51	-6.82	-5.93	-7.63	-5.58	-7.55	-5.78	-5.99	-3.89	6.00	5.39
												(3.46)	(2.86)
	Non-Quarterly	-6.24	-6.42	-6.60	-10.19	-8.13	-6.51	-7.45	-5.39	-3.91	-4.90	1.34	-0.94
												(0.65)	(-0.343)

Table 2.5: **Risk-adjusted Option Momentum Returns**

Option momentum portfolios are formed by sorting firms' geometric average of all 12 monthly variance swap returns over the past year, the same as the first row in Table 2.4. The table presents results from the following time-series regression: $r_{p,t} = \alpha_p + \beta_p \cdot F_t + \varepsilon_{p,t}$, where $r_{p,t}$ is the monthly excess return of loser, winner, and long-short portfolio, respectively. F_t is a vector of risk factors including: the return of S&P 500 Index VIX portfolio in excess of the risk-free rate, the Fama and French (2015) five factors (MKT-Rf, SMB, HML, RMW, and CMA), and the Carhart (1997) momentum factor (Stock MOM). Coefficient estimates are reported with the associated t-statistics in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Loser	Winner	W-L
Alpha	-0.051***	0.119***	0.169***
	(-3.63)	(5.99)	(8.21)
Index VIX Ret-Rf	0.345***	0.395***	0.050
	(15.85)	(12.81)	(1.56)
MKT-Rf	-0.397	-0.002	0.395
	(-1.05)	(-0.00)	(0.71)
SMB	-0.962*	-1.237	-0.275
	(-1.82)	(-1.65)	(-0.35)
HML	-0.653	0.141	0.794
	(-1.34)	(0.20)	(1.10)
RMW	-0.096	0.543	0.639
	(-0.15)	(0.61)	(0.69)
CMA	-0.049	-1.231	-1.182
	(-0.06)	(-1.04)	(-0.95)
Stock MOM	0.022	-0.047	-0.069
	(0.11)	(-0.17)	(-0.24)
Adj.R^2	0.637	0.517	-0.004

Table 2.6: **Average Monthly Returns on Equity-VIX Portfolios Sorted on Value and then Momentum**

Each month, we first sort firms into quintiles based on option value, defined as $log(\frac{RV_{i,t-12,t}}{VIX_{i,t}^2})$, where $log(RV_{i,t-12,t})$ is the geometric average of firm i's realized variance over the past 12 months. Then, within each quintile, we sort firms based on option momentum, which is the compound variance swap return over the past 12 months. The "All" row shows statistics for portfolios sorted by momentum only, without controlling for value. Portfolios are equally weighted. Portfolio 1 has the lowest value or momentum. To avoid forward-looking bias, we only include firms in the $S\&P$ 500 index when we form the portfolio. To compute the alpha of portfolio returns, we control for the Fama and French (2015) five factors, the Carhart (1997) momentum factor, and the VIX return of the $S\&P$ 500 index. Returns are expressed in percent, with t-statistics in parentheses.

	Momentum						
Value	1 (Low)	2	3	4	5 (High)	5-1	Alpha
1 (Low)	-19.98	-13.66	-12.55	-9.63	-5.84	14.13	15.46
						(5.21)	(5.48)
2	-9.50	-8.14	-4.14	-5.83	-2.85	6.64	10.15
						(2.95)	(4.35)
3	-4.41	-4.40	-5.58	-2.90	1.07	5.48	2.99
						(2.18)	(1.13)
4	-3.23	0.19	0.89	-0.19	2.70	5.93	7.56
						(2.04)	(2.42)
5 (High)	-1.07	5.23	5.39	3.03	7.42	8.49	9.56
						(3.00)	(3.11)
All	-10.62	-4.20	-3.22	-0.87	2.04	12.67	12.69
						(8.48)	(7.93)

Table 2.7: **Option Momentum Controlling for Other Predictors**

We estimate the cross-sectional regression: $r_{i,t} = \alpha_t + \gamma_t \cdot Z_{i,t-1} + \varepsilon_{i,t}$, where $r_{i,t}$ is the monthly equity-VIX returns in excess of risk-free rate, and $Z's$ are option return predictors including Option MOM (continuously compounded variance swap return over the past 12 months), HV-IV (volatility deviation in Goyal and Saretto (2009)), IVOL (idiosyncratic volatility in Cao and Han (2013)), Slope_VTS (slope of implied volatility term structures in Vasquez (2017)), VOV (volatility of volatility in Cao et al. (2020)), RN_Skew (risk-neutral skewness in Bakshi et al. (2003)), Option Demand (option demand pressure), Amihud (Amihud illiquidity measure over the previous month), and stock characteristics in Cao et al. (2017). Results using delta-hedged ATM call and put returns calculated as Bakshi and Kapadia (2003) are also reported. The associated t-statistics using Newey and West (1987) with three lags are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The sample period is from January 1997 to December 2017.

	Equity-VIX Return		Delta-hedged Call		Delta-hedged Put	
	(1)	(2)	(3)	(4)	(5)	(6)
Option MOM	0.152***	0.115***	0.007***	0.005***	0.007***	0.005***
	(7.18)	(5.75)	(5.52)	(6.23)	(6.37)	(6.13)
HV-IV		0.113**		0.009***		0.009***
		(2.26)		(3.67)		(3.74)
IVOL		-2.629***		-0.171***		-0.120***
		(-2.67)		(-4.02)		(-2.77)
Slope_VTS		0.640***		0.046***		0.048***
		(4.23)		(6.93)		(7.33)
VOV		-0.664***		-0.012		-0.028***
		(-3.03)		(-1.11)		(-2.87)
RN_Skew		0.017		-0.001**		0.002***
		(1.18)		(-2.50)		(3.23)
Option Demand		-0.005***		-0.000***		-0.000**
		(-3.72)		(-2.89)		(-1.98)
Amihud		88.835		1.960		3.350
		(1.45)		(0.82)		(1.29)
Size		0.003		-0.000		-0.000
		(0.34)		(-0.23)		(-0.19)
Book-to-Market		0.001		0.000		-0.000
		(0.18)		(0.62)		(-0.74)
$RET_{t-1,t}$		-0.171**		-0.009***		-0.012***
		(-2.48)		(-2.75)		(-4.27)
$RET_{t-12,t-1}$		0.019		-0.002*		-0.001
		(0.72)		(-1.90)		(-1.27)
Analyst Dispersion		-0.052		0.002		0.002
		(-0.83)		(0.69)		(0.77)
Cash Holding		0.029		-0.000		0.002*
		(1.08)		(-0.26)		(1.92)
Profitability		-0.016		0.001*		0.001
		(-0.80)		(1.81)		(0.70)
Issue		0.082		0.005*		0.005**
		(1.62)		(1.95)		(2.35)
Intercept	-0.003	0.012	0.001	0.004	-0.003***	0.000
	(-0.12)	(0.08)	(0.63)	(0.79)	(-3.14)	(0.07)
adj. R^2	0.016	0.072	0.017	0.109	0.019	0.106

Table 2.8: **Impact of Transaction Costs**

Option momentum portfolios are formed as in Table 2.4. The portfolio returns are computed from the mid-point price and from the effective bid-ask spread, estimated to be equal to 50%, 75%, and 100% of the quoted spread. In panel B, if the percentage bid-ask spread of VIX portfolio price of a firm is larger than the sample median, we don't trade the firm that month. All returns are expressed in percent, with t-statistics in parentheses. Panel C reports the margin haircut ratio of shorting loser portfolios. The initial margin haircut is defined as $(M_0 - V_0)/V_0$, where M_0 is the initial margin of option positions in equity-VIX portfolios when the trade is implemented, and V_0 equals the sum of option prices when the position is opened. Max haircut is the maximum haircut ratio during the month. Correlation between initial haircut ratio and the subsequent option momentum strategy return of the month is also reported. The column "Return (%)" in Panel C reports the monthly return of momentum strategy "All" with 50% effective spreads combined with initial margin requirements. The t-statistics are reported in parenthesis.

Panel A: Option momentum returns

	Percentage of Quoted Bid-Ask Spread			
	0%	50%	75%	100%
All	16.13	6.74	1.86	-3.22
	(8.42)	(3.62)	(1.00)	(-1.69)
Quarterly	14.77	5.85	1.24	-3.53
	(8.75)	(3.55)	(0.75)	(-2.08)
Non-Quarterly	11.64	2.52	-2.31	-7.46
	(6.49)	(1.44)	(-1.30)	(-4.08)

Panel B: Percentage bid-ask spread lower than median.

	0%	50%	75%	100%
All	17.05	13.25	11.17	9.08
	(5.66)	(4.48)	(3.78)	(3.08)
Quarterly	13.91	11.53	9.35	7.17
	(5.52)	(4.08)	(3.31)	(2.53)
Non-Quarterly	11.95	8.13	6.03	3.93
	(4.90)	(3.43)	(2.54)	(1.65)

Panel C: Margin haircut ratio of loser portfolio.

	Initial haircut	Max haircut	Correlation	Return (%)
Mean	3.18	4.77	-0.27	4.53 (4.59)
Std	1.29	1.59		15.64
Min	0.68	1.23		-31.17
Max	6.64	8.94		

2.7 Appendix

Table A2.1: **Early Exercise Premium**

This table examines the difference between the European option return-to-expiration and the American early exercise return of our equity-VIX portfolios. We consider approximate policies that exercise options at end of each day if the exercise value is higher than 95%, 96%, 97%, 98% and 99% of the ask price of the option. Using these policies, there are up to 17,000 firm-month observations with early exercise. To calculate the early-exercise payoff of a call option, we borrow the strike price at risk-free rate and hold the stock position to option maturity; to calculate the early exercised payoff of a put option, we short-sell the stock and reinvest the payoff to maturity at risk-free rate. All dividends are reinvested to maturity at the risk-free rate.
The Mean calculates the monthly average error between the European return and the American return. All returns are expressed in percent. The standard error (Std) calculates the standard deviation of the error. The mean absolute error (MAE) calculates the monthly average absolute error. Correlation reports the correlation between European return and American return. Panel B shows that the maximum American exercise premium of .355% is achieved with an early-exercise threshold of 96%. This is smaller, by an order of magnitude, than the average European return-to-expiration of -4.19% in the first row of Table 1 Panel A. We conclude that early exercise is not quantitatively important to our analysis.

Panel A: Summary Statistics of European Return and American Return

	Mean	Std	5%	25%	50%	75%	95%
European	-4.195	85.52	-69.18	-42.78	-19.49	14.73	115.10
American 99%	-3.970	85.59	-69.06	-42.56	-19.22	15.01	115.45
American 98%	-3.895	85.58	-69.01	-42.49	-19.12	15.11	115.53
American 97%	-3.849	85.51	-69.02	-42.42	-19.04	15.19	115.47
American 96%	-3.839	85.47	-69.00	-42.38	-19.02	15.20	115.38
American 95%	-3.854	85.43	-69.02	-42.38	-19.02	15.19	115.43

Panel B: Early Exercise Premium

	Mean	Std	MAE	t-statistic	Correlation
99%	0.225	4.35	0.627	14.59	0.999
98%	0.299	5.00	0.782	16.91	0.998
97%	0.346	5.77	0.959	16.93	0.998
96%	0.355	6.40	1.099	15.68	0.997
95%	0.341	6.89	1.237	13.98	0.997

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