Mutual Fund Stock Holdings and the Cross-Section of Option Returns*

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Abstract

This paper empirically studies whether mutual fund holdings in the underlying stock markets predict returns on equity options written on individual stocks. I find that fund holding concentrations in underlying stocks, measured as the Herfindahl-Hirschman Index, negatively predict the cross-section of corresponding option returns. This negative predictability is mainly driven by funds that use protective put strategy to hedge their stock positions and by those that overweight the underlying stocks relative to their benchmarks. It is stronger among options with higher unhedgeable risks. The findings are consistent with a hedging and demand pressure channel: For stocks with more concentrated ownership, some holders are more likely to overweight them and demand more of their options to hedge. To absorb the order imbalances, option market makers charge higher prices, leading to lower subsequent option returns.

Keywords: Demand-based option pricing; Variance risk premium; Mutual fund.
JEL Classification Codes: G13; G14; G23

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1 Introduction

Options are widely used for speculation and hedging purposes. Their embedded leverages make them appealing to speculators (Easley, O'hara, and Srinivas (1998)) and there is a large literature studying whether investors' option positions predict the underlying stock returns through an information channel. For example, Pan and Poteshman (2006) and Ge, Lin, and Pearson (2016) find that option trading volume contains private information and forecasts future stock returns.[1] The hedging role is well understood for the index option market, in which large net buying pressure from option end-users for out-of-the-money put options exists and contributes to the index-option expensiveness and negatively sloped implied volatility curve.[2] However, so far there is limited evidence about where hedging takes place in equity option markets, i.e. options written on individual stocks, and what the pricing implication is. This paper aims to fill this gap in the literature.

If we view investors' stock holdings as endowments, their stock positions should contain information on their hedging demands for equity options, which can be used to manage endowment risks. This paper looks at the stock holdings of institutional investors, who are major holders of the U.S. equity market. Combined with the fact that they are more sophisticated than individual investors, they are more likely to be end-users who use equity options for hedging. Koski and Pontiff (1999) find evidence consistent with the story that mutual funds use derivatives as a low cost way, due to embedded leverages, to achieve desired risk exposures. Cao, Ghysels, and Hatheway (2011) confirm the story using derivatives positions of mutual funds. Specifically, they find that mutual funds use derivatives to reduce risks following bad performance, which may cause outflows from funds and make portfolios riskier. Cici and Palacios (2015) examine

[1] Other related studies include Aragon and Martin (2012), Cao, Chen, and Griffin (2005), Hu (2014), Ni, Pan, and Poteshman (2008), and Roll, Schwartz, and Subrahmanyam (2010).

[2] See Bollen and Whaley (2004), Chen, Joslin, and Ni (2019), and Garleanu, Pedersen, and Poteshman (2008).

option holdings of mutual funds and find that funds use options to effectively lower risk with no evidence for aggressive risk-taking. Chen (2011) finds evidence that hedge funds use derivatives to reduce risk-taking. While the above papers associate derivative use with fund characteristics and examine how it would affect fund performance, this paper focuses on the pricing implication of institutional investors' hedging demands in equity option markets, that is, how they may affect cross-sectional option returns. Due to limited evidence associating derivative use with increased institutional risk-taking, this paper focuses on institutional hedging activities using equity options.[3]

I use the Herfindahl-Hirschman Index (HHI henceforth), constructed from institutional holdings on a firm's stock, as a firm-level proxy for stock holders' hedging demands for options written on the stock. HHI is a widely used concentration measure. High HHI indicates that a firm's stocks are concentrated among a few large holders, who are likely to place a large share of their wealth in this single firm. As a consequence, those holders may have high hedging demands for the firm's options. Imagine a case in which a mutual fund substantially overweights a stock relative to its benchmark based on some positive long-term information about the firm's fundamental. If the firm encounters uncertain events during the holding period, the fund may prefer to use the firm's options to hedge rather than liquidate part of their positions and buy back later, which can potentially incur large transaction costs and high taxes on short-term capital gains.

If investors have relatively higher hedging demands for some stocks' options, option market makers are expected to charge higher prices to absorb the order imbalances, which leads to lower subsequent returns on those options. Past literature documents the fact that options are non-redundant assets and the effect of demand imbalance on option pricing: Unlike in Black and Scholes (1973) model, option market makers cannot perfectly hedge their positions due to

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

market frictions (Figlewski (1989); Green and Figlewski (1999)). Bollen and Whaley (2004) find that changes in implied volatilities are related to option order flows. 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) (GPP hereafter) explicitly model demand pressure effects on option prices. In their model, the price impact of demand pressure is larger for options written on the stock with higher unhedgeable risks. However, their model treats demand imbalance in option markets as exogenous and is agnostic about the source of option end-users' demand.

This paper explores option demands from institutional investors in order to hedge against risks originated from their stock positions. I argue that HHI constructed from positions in the underlying stock is positively correlated with stock holders' hedging demand for options written on that stock, which should negatively predict option returns as suggested by the demand pressure channel. Empirically, I find that HHI negatively predicts cross-sectional option returns, consistent with the predicted sign. The negative predictability remains strong after controlling for a wide range of option return predictors and stock characteristics in Fama-MacBeth regressions.

I measure option returns across individual stocks using variance risk premium (VRP henceforth), following Heston and Li (2020). The VRP of a given stock is calculated as the held-to-maturity return of an option portfolio, consisting of out-of-the-money (OTM) options written on that stock, daily hedged with the underlying stock. I name that option portfolio VIX portfolio and name its return VIX return. These terms come from the CBOE VIX index, which is constructed from a portfolio of OTM options whose held-to-maturity payoff equals the future variance of the underlying stock return. For robustness, I also use the delta-hedged return of at-the-money (ATM) put (call) constructed by Bakshi and Kapadia (2003) as an alternative measure.[4] All measures above hedge away option exposure to the movement of underlying stock prices at daily frequency and yield the same negative option return predictability from HHI.[5]

I construct HHI using stock ownership data in the Thomson Reuters S12 and S34 databases, respectively. S12 records stock holdings of individual mutual funds. S34 aggregates holdings of funds under the same family and reports as a single entity. S34 also covers stock holdings of other 13f institutions, such as insurance companies and pension funds. Thus, S34 has broader coverage than S12 but less granularity. I find that both measures negatively predict cross-sectional option returns. In a horse race, the individual-fund-level HHI turns out to be a better option return predictor than the institution-level HHI. A possible explanation is that fund managers within the same family have incentives to compete with each other in a tournament for promotion and subsidization from the family (Gaspar, Massa, and Matos (2006) and Kempf and Ruenzi (2008)). Thus, when they make hedging decisions, they put more weights on the holdings of their own funds than on the net holdings of the whole family. In this case, the granularity of S12 outweighs the broad coverage of S34 and the individual-fund-level HHI is a better proxy for hedging demand. Therefore, this paper focuses on the fund-level measure.

The hedging and demand pressure channel consists of two necessary components: demand pressure (caused by stock holders' hedging demands for equity options) and price impact (originated from option market makers' inventory risks). I provide evidence consistent with this channel by showing that the option return predictability of HHI is positively related to each component.

First, I directly check the demand pressure component by identifying mutual funds that use equity options for hedging purpose. I construct HHI using a Morningstar dataset. This

[4] Bakshi and Kapadia (2003) find that delta-hedged option gain is closely related with volatility risk premium.

[5] In some exercises mentioned later, delta-hedged put returns show stronger negative relation with HHI than other measures do. This is consistent with the fact that put is a more natural instrument than call when investors want to hedge their long stock positions.

dataset records not only stock holdings for U.S. equity mutual funds, but also their equity option holdings, which are missing in S12. After classifying funds into different categories based on their long/short positions in puts/calls, I find that the negative predictability mainly comes from funds that long puts. To further tell whether funds long puts to hedge their stock positions or to speculate on downside information, I pair equity option positions with their underlying stock names and classify long put positions into protective put and naked put. I find that the main contributors for the negative effect of HHI are funds that use protective put strategy to hedge their long positions in underlying stocks, but not those that use naked put to circumvent short-sale constraints and speculate.

Second, I further check the demand pressure component by splitting mutual funds based on whether they overweight or underweight the stock, because funds are supposed to have more incentives to hedge their positions in a certain stock when they overweight, rather than underweight, the stock relative to their investment benchmarks. To test this conjecture, for a given stock every quarter, I split its fund holders by whether they overweight or underweight the stock based on their self-declared benchmarks. Then I construct HHI for the stock using the two groups of funds, respectively. I find that the option return predictability of HHI is entirely driven by funds that overweight the stock. This pattern is especially strong when I use delta-hedged put return as the dependent variable, consistent with the fact that put option is more commonly used for hedging than call.

Then I examine the price impact component. When price impacts are larger for some firms' options, HHI (if positively correlated with hedging demands) should be a stronger option return predictor among those firms, because a given level of option order imbalances would cause greater price movements for those options. I test this conjecture by testing model predictions in GPP, which show that price impact in option markets equals dealers' risk aversion times effective risk-free rate times option unhedgeable risks.[6] First, after splitting the sample into three sub-periods by TED spreads, I find that the negative effect of HHI is stronger during the sub-period in which intermediaries suffer tighter funding liquidity constraints and face greater effective risk-free rates. This is expected because intermediaries, as option market makers, charge higher compensation for bearing order imbalances when they are more constrained and risk averse. Second, I construct three empirical proxies for the three sources of option unhedgeable risks. At each month, I sort firms into terciles based on the three proxies, respectively, and then run Fama-MacBeth regressions within each tercile. I observe that HHI becomes a stronger predictor among firms whose options are more difficult to hedge and thus have higher price impacts.

A limitation of using HHI as a proxy for stock holders' hedging demands is that it fails to account for heterogeneous sizes of stock holders, which can break down the conjectured positive relation between HHI and investors' hedging motives. If a firm is held by a very large fund and several small funds, the large fund will largely drive the HHI. HHI would be high even if the large fund only invests a small portion of its portfolio in the stock. However, stock holders' hedging motives can be low in this case, especially for the large fund. To first verify this concern, I sort firms into terciles by the kurtosis of their fund holders' total net assets at the end of each quarter and run Fama-MacBeth regressions among each tercile. For a given firm, if the kurtosis of its fund holders' sizes is large, then HHI may not be a valid proxy for hedging demand and should be a weak option return predictor. Empirically, I find this to be true. To fix the problem, I construct a truncated HHI: Each quarter, I sort a given firm's fund holders into quintiles by their sizes and delete those in the highest quintile. Then I construct the firm's HHI using the fund holders that remain, whose sizes are less dispersed than before. In a horse race with the non-truncated HHI, the truncated measure is superior in predicting the return of put but not

[6] GPP investigate three sources of option unhedgeable risks: stochastic volatility risk, jump risk, and delta-hedging cost.

call. Since put is more commonly used for hedging, this is supporting evidence that HHI can be viewed as a hedging proxy and that accounting for heterogeneous sizes of stock holders can further improve the proxy.

I also explore and rule out three alternative stories in which HHI predict option returns through channels other than hedging. First, since firms with smaller sizes or lower share proportions held by mutual funds tend to be owned by fewer funds and thus have higher HHI, it is natural to ask whether the option return predictability of HHI comes from its correlation with size or share proportion. I use double sorts to control for firm size and share proportion, respectively, and I find that return spreads sorted by HHI remain highly significant with similar magnitudes for each size or share proportion quintile. Second, HHI may be related to stock holders' private information on firm fundamentals. Thus, it is possible that HHI predicts option returns through an information channel by predicting future return or variance of the underlying stock. However, I find evidence inconsistent with this story: In Fama-MacBeth regressions, HHI cannot predict cross-sectional stock returns and variances. Third, HHI may predict option returns through its relationship with short interest. When fewer funds own a firm, it has lower breadth of ownership and tends to have larger HHI. Chen, Hong, and Stein (2002) find that when breadth decreases, short-sale constraint becomes binding. This will push up demands and prices for puts and lead to low subsequent option returns. After I control for short interest and the change in breadth, HHI remains highly significant in predicting option returns.

An option strategy which sorts firms into quintiles by HHI and forms a long-short portfolio of their VIX returns generates a monthly Sharpe ratio of 0.4 and a risk-adjusted alpha of 6.87% per month. Option bid-ask spreads greatly reduce strategy profits. However, the impact can be reduced under reasonable transaction cost management, such as forming portfolios with more extreme HHI (deciles rather than quintiles) and discarding firms whose option bid-ask spreads are higher than the median of each month. After the two measures, return spread using delta-hedged put, to which HHI is the most strongly related, remains highly profitable even after considering full bid-ask spreads.

The rest of this paper is organized as follows. Section 2 describes data construction. Section 3 examines how HHI predicts cross-sectional option returns and proposes a hedging and demand pressure channel to explain the predictability. Section 4 validates the channel. Section 5 discusses the limitation of using HHI as a proxy for hedging demand, evaluates the performance of option strategies formed on HHI, and explores alternative explanations for the option return predictability. Section 6 concludes.

2 Data

This section presents the data steps to construct VIX portfolio and HHI. I obtain option data from the OptionMetrics Ivy DB database, which provides end-of-day bid-ask quotes on options traded on U.S. exchanges. The sample period is from January 1996 to December 2019. I use Thomson Reuters S12 and S34 databases, which include quarterly stock holdings of mutual funds and 13f institutions, to construct HHI. To extract the information needed later in this paper, I obtain information about stock returns and accounting data from CRSP and COMPUSTAT. The common risk factors and risk-free rates are taken from Kenneth French's website.

2.1 VIX portfolio

I construct the VIX portfolio following Heston and Li (2020). Its payoff closely approximates the realized variance of underlying stock return during the option holding period.[7] Therefore, the average return of VIX portfolio measures VRP.

[7] The detailed proof is in Appendix A. I define realized variance as the sum of squared daily stock returns.

The VIX portfolio of a stock is composed of two parts: a static position in a portfolio of OTM options written on the stock and a daily-hedged position in the underlying stock. I construct the option position following the CBOE White Paper[8]:

$$V(t,T) = 2\sum_i \frac{O(K_i,t,T)\Delta_i}{K_i^2}, \tag{1}$$

where: $V(t,T)$ is the time-t price of the option position maturing at T; $O(K,t,T)$ represents the time-t midpoint price of an OTM call or put with strike price K_i and expiration T; K_i are the available strikes of options written on the stock; Δ_i are the distances between adjacent strikes.

Since the weight of each option is proportional to the inverse of K_i^2, deeper OTM put will have a larger weight in the portfolio. Also, VIX portfolio includes options from all moneynesses.[9] Thus, regardless of the option moneyness institutional investors trade, their demand pressures will be directly reflected in the price of VIX portfolio. For example, a mutual fund could simply buy an OTM put on Apple to hedge its long position in Apple stocks. Its demand directly pushes up the price of put at that strike and therefore increases the price of Apple's VIX portfolio. An indirect channel, according to Garleanu, Pedersen, and Poteshman (2008), is that the demand for this OTM put can influence prices of options at all other strikes through correlated unhedgeable risks. In other words, investors do not need to trade the exact VIX portfolio to affect its price.

To make the VIX index reflect the volatility for the next 30 days, CBOE implements interpolation using near- and next-term options. This paper does not follow this standard. Instead, I form the option position in VIX portfolio on the third Friday of each month (time t) and hold options to maturity, which is the third Friday of the subsequent month (time T). The return of VIX portfolio is calculated at monthly frequency.

[8] https://cdn.cboe.com/resources/vix/vixwhite.pdf.

[9] Prices of out-of-the-money puts are linked with those of in-the-money calls by the put-call parity.

By augmenting the static option position with a daily-hedged stock position, which requires investors to borrow \$1 at the risk-free rate and invest it in the stock for one day[10], I get the VIX portfolio whose return equals

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

where: $V(T,T)$ is the payoff of option position at expiration T; $S(t)$ 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. I call $r^{VIX}(t,T)$ VIX return.

In summary, to construct the VIX portfolio for a given firm, an investor needs to: 1. take a static option position formed at time t with price $V(t,T)$ and hold it until expiration T; 2. short a static hedged stock position with zero time-t price and a final payoff of $2(\frac{S(T)}{S(t)(1+r_f)^{T-t}} - 1)$ at time T; 3. take a daily-hedged stock position with zero time-t price and a payoff of $2(r(u) - r_f)$ on each day u during option holding period.

To construct VIX portfolios for all optionable firms in OptionMetrics, I apply the following filters: (1) to avoid extremely small and illiquid stocks, underlying stock prices should be at least \$5, (2) delete firm-month observations containing stock splits, (3) following Driessen, Maenhout, and Vilkov (2009), I discard options with missing implied volatilities or deltas (which occurs for options with nonstandard settlement or for options with intrinsic value above the current midpoint prices), (4) delete options whose ask prices are lower than bid prices, (5) remove options with zero open interest, in order to eliminate options with no liquidity, (6) filter options following the CBOE White Paper and get OTM puts and calls, (7) to further avoid microstructure-related bias, I follow Cao and Han (2013) and delete options with zero bid prices and require midpoint

[10]This is a model-free delta hedge because the option position delivers a log-payoff as shown in the appendix, whose delta is the inverse of stock price. This is equivalent to investing \$1 in the stock.

prices to be at least \$0.125, (8) delete options whose prices violate arbitrage bounds, (9) require at least two OTM puts and calls remaining on each side after applying the above filters, and (10) exclude a firm-month observation if the underlying stock pays a dividend during the remaining life of the option. Combined with the fact that I use short-term monthly options, early exercise premia are supposed to be very low.

Table 1 presents summary statistics. There are 288 months from 1996 to 2019. The final sample includes 199,648 firm-month observations and 6,413 unique stocks. To pass the above filters, those stocks tend to be relatively large and to have liquid option markets. On average, each month includes 693 stocks.[11] I construct VIX portfolios for both individual firms and the S&P 500 Index. I call them equity and index VIX portfolios, respectively. Index VIX return has a mean of -24.26% per month. The large negative average is consistent with the negative VRP embedded in index options documented by Carr and Wu (2009) and Driessen, Maenhout, and Vilkov (2009). The mean of equity VIX return is -8.24% per month. A more negative VIX return indicates more expensive option prices.

Since I only use discrete strikes available to form VIX portfolio in (1), the portfolio payoff only approximately equals realized variance.[12] To gauge the tracking error, I compare VIX return in (2) with variance swap return (VSR), defined following Carr and Wu (2009):

$$VSR(t,T) = \frac{\sum_{u=t+1}^{T} r(u)^2}{V(t,T)} - 1. \tag{3}$$

For the S&P 500 Index, the correlation between VIX return and VSR is 0.99. As indicated in Figure 1, index VIX return closely tracks VSR during the sample period. Both of them tend

[11]My sample gives a larger cross-section than previous studies on VRP: Carr and Wu (2009) use five stock indices and 35 individual stocks; Driessen, Maenhout, and Vilkov (2009) look at the VRP of the S&P 100 Index and its constituent firms; Duarte, Jones, and Wang (2019) use the S&P 500 Index and its constituent firms.

[12]On average, equity VIX portfolio consists of 7.97 strikes. For index VIX portfolio, the average number of strikes is 100.59.

to spike during market downturns, reflecting the fact that variance contracts are hedging assets with negative expected returns. Index VSR has an average of -24.73%, close to that of index VIX return. For each firm, I compute the correlation between its equity VIX return and VSR.[13] The median correlation equals 0.93. Therefore, VIX return closely approximates VSR even at the individual firm level, for which fewer strikes are available than for index. Individual-firm-level approximation errors could be further diversified away by forming portfolios: If I equally weight firms at each month, the time-series correlation between VIX return and VSR increases to 0.96. Since most stocks have the same discrete intervals across strikes, the errors may be differenced out if I form long-short portfolios. Overall, the evidence suggests that discrete strikes have limited impact on using VIX return to measure VRP.

2.2 Delta-hedged option returns

In addition to VIX return, I construct delta-hedged option returns following Bakshi and Kapadia (2003) as additional test assets. Specifically, I pick the put (or call) option[14] closest to the current stock price for each optionable stock on the third Friday of each month and hold it to expiration (third Friday of the next month). Then I evaluate the return of a portfolio that longs the put (or call), which is delta-hedged daily with the underlying stock using the delta computed by OptionMetrics.[15] By calculating delta-hedged returns for at-the-money (ATM) put and call separately, I can examine the relative effects HHI exert on the pricing of put and call in some sanity checks performed later. If HHI is correlated with investors' hedging demand for options, it should have a larger impact on put than on call, given that put is more commonly used for hedging.[16]

[13]To obtain accurate correlations, I require firms to have at least 30 observations in this exercise. There are 1,976 firms that meet this requirement.

[14]I require the put and call to have the same strike price.

[15]In some days, the delta is missing in the OptionMetrics. When this occurs, I impute a delta using the most recent non-missing implied volatility for the same option contract.

[16]HHI could still influence the price of call indirectly through the put-call parity.

To measure delta-hedged option returns, I first define delta-hedged gains for put and call over a period $[t, T]$ following Bakshi and Kapadia (2003) and Cao and Han (2013):

$$\Pi_P(t,T) = P_T - P_t - \sum_{n=0}^{N-1} \triangle_{P,t_n}[S(t_{n+1}) - S(t_n)] - \sum_{n=0}^{N-1} \frac{a_n r_{f,t_n}}{365}[P(t_n) - \triangle_{P,t_n} S(t_n)],$$

$$\Pi_C(t,T) = C_T - C_t - \sum_{n=0}^{N-1} \triangle_{C,t_n}[S(t_{n+1}) - S(t_n)] - \sum_{n=0}^{N-1} \frac{a_n r_{f,t_n}}{365}[C(t_n) - \triangle_{C,t_n} S(t_n)],$$

where: the hedge is rebalanced at each of the dates $t_n, n = 0, 1, ..., N-1$, with $t_0 = t, t_N = T$; $\triangle_{P,t_n}$ ($\triangle_{C,t_n}$) is the delta of the put (call) on date t_n; a_n is the number of calendar days between t_n and t_{n+1}. Bakshi and Kapadia (2003) show the close link between delta-hedged gains and volatility risk premium.

To compare across stocks, I scale $\Pi_P(t,T)$ and $\Pi_C(t,T)$ by the absolute value of portfolios, $P_t - \triangle_{P,t} S_t$ and $\triangle_{C,t} S_t - C_t$, respectively. The delta-hedged put (call) return for firm i is denoted as:

$$r_{i,t,T}^{Put} = \frac{\Pi_P(t,T)}{P_t - \triangle_{P,t} S_t},$$

$$r_{i,t,T}^{Call} = \frac{\Pi_C(t,T)}{\triangle_{C,t} S_t - C_t}.$$

I calculate delta-hedged option returns for firm-months with stock prices of at least \$5 and with no stock splits or dividend issues. There are 445,514 firm-month observations from January 1996 to December 2019. This is much larger than the number of VIX returns because I only require one liquid ATM option to calculate r^{Put} and r^{Call}. To avoid the complication from compounding different sample sizes with different ways to measure option returns, I restrict the sample to observations with r^{VIX}, r^{Put}, and r^{Call} available at the same time. The final sample includes 199,648 observations.

Table 1 presents statistics of delta-hedged option returns. r^{Put} (r^{Call}) has an average of -0.7% (-0.44%) per month, consistent with the negative variance risk premium documented by VIX return and previous studies. Due to different scalings, delta-hedged option return has a smaller mean and standard deviation than VIX return in absolute value. Therefore, when I use them as dependent variables in later sections, regression coefficients will have different magnitudes.

2.3 Herfindahl-Hirschman Index (HHI)

HHI is a widely used concentration measure in economics literature. Compared with the share proportion of a firm owned by institutional investors, HHI is a potentially better measure for hedging demand because it better captures how risks from the underlying stock are distributed among stock holders. Share proportion simply aggregates institutional holdings without considering the number of stock holders and relative sizes of their stock positions.

I first use the Thomson Reuters S12 database to construct an individual-mutual-fund-level HHI. S12 includes all registered domestic mutual funds filing with the SEC and records their equity holdings at quarterly frequency. Then I construct a more aggregate level HHI using the S34 database, which covers the quarterly equity holdings of entire investment companies, often called 13f institutions. S12 and S34 differ in their levels of granularity: S12 records stock holdings of individual mutual funds, while S34 aggregates holdings of funds under the same family and reports as a single entity. 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 S34. Fidelity also reports holdings of its individual funds, whose information is included in S12. In addition to mutual funds, S34 covers stock holdings of other 13f institutions, such as insurance companies, pension funds, endowments, and hedge funds. Therefore, S34 has a broader coverage but less granularity than S12. Neither S12 nor S34 records any short positions.

For a given firm at a certain quarter, I construct its mutual-fund-level HHI as follows: 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 total net assets; Third, calculate the firm's total number of shares owned by all mutual funds and use it to divide the share owned by each fund; Fourth, calculate the firm's HHI as the sum of squared share proportion owned by each fund n:

$$HHI\ Mutual\ Fund = \sum_{n}^{N} \left(\frac{Firm's\ Shares\ Owned\ by\ Fund\ n}{Firm's\ Total\ Shares\ Owned\ by\ Mutual\ Funds} \right)^2,$$

where N is the total number of funds that hold the firm's stock. The 13f-institution-level HHI can be calculated in the same method using S34. By construction, HHI takes value in $[\frac{1}{N}, 1]$: When it equals 1, the firm is owned by only one fund, which is the most concentrated ownership; When it equals $\frac{1}{N}$, each fund holder owns equal share of the firm, which is the least concentrated ownership.

Panel B in Table 1 reports summary statistics of HHI. For a given firm-month, I find its latest available HHI. The fund-level HHI has a mean of 0.154, higher than that of the institution-level HHI (0.067). It has a standard deviation of 0.22, more variable than that of the institution-level measure (0.081). In later sections, in order to further tell which types of mutual funds may use equity options for hedging purpose, I use different subsets of funds to construct HHI. The statistics for different versions of HHI are presented in Table A1.

3 HHI and the Cross-Section of Option Returns

This section examines how HHI predicts cross-sectional option returns, including equity VIX returns and delta-hedged put and call returns. I conjecture that HHI are positively correlated with stock holders' hedging demands for equity options and negatively predict option returns through a hedging and demand pressure channel as follows: For a firm with high HHI, its stocks are concentrated among a few large holders, who are likely to place a large share of their wealth in this single firm. Therefore, those holders tend to have high hedging demands for the firm's options. To absorb the order imbalances, option market markers charge higher prices, which lead to lower subsequent option returns.

3.1 Option return predictability of HHI

This section explores the cross-sectional option return predictability of both the mutual-fund-level and 13f-institution-level HHI. There is a trade-off between the granularity and coverage of the two measures: Since star fund tends to get the most subsidization allocated from the family (Gaspar, Massa, and Matos (2006)), fund managers within the same family compete with each other in a tournament (Kempf and Ruenzi (2008)). Therefore, when fund managers make hedging decisions, they have incentives to put more weights on their own fund holdings than on the net holdings of the family. In this sense, fund-level HHI is a better proxy for hedging demand than institution-level HHI. On the other hand, institution-level HHI has broader coverage in that it includes 13f institutions other than mutual funds, which can make it a better hedging proxy than fund-level HHI.

I run a monthly Fama and MacBeth (1973) regression,

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

to examine the predictability of HHI on one-month-ahead option returns. For robustness, I use three measures for the option return of firm i at month $t+1$: equity VIX return ($r_{i,t+1}^{VIX}$), delta-hedged put return ($r_{i,t+1}^{Put}$), and delta-hedged call return ($r_{i,t+1}^{Call}$).

Table 2 reports time-series averages of coefficients, together with their t-statistics corrected for heteroskedasticity and autocorrelation following Newey and West (1987) using three lags. Both fund-level and institution-level HHI negatively predict all three measures of option returns, regardless of whether they are used alone as a predictor or together. When fund-level HHI is used alone in Column (1), its average coefficient estimate is -0.156, with a t-statistic of -5.57. One standard deviation increase in HHI (0.22) decreases VIX return by 3.43% per month. The negative sign is consistent with the prediction from the hedging and demand-pressure story.

GPP document a net short position of end-users in equity option markets. Lakonishok, Lee, Pearson, and Poteshman (2007) find that directional hedging accounts for a small fraction of trading in equity option markets. Their results are documented on an aggregate level by pooling all firms together and suggest that hedging demand is not the key factor in determining the overall level of activity in equity option markets.[17] However, there may exist heterogeneities in hedging demands across firms, which can affect cross-sectional option returns.

The opaqueness of option end-users' positions in underlying stocks is a big obstacle to identifying option order flows submitted for hedging purposes. Intuitively, hedging demands for options should come from major holders of underlying stocks, who are financial institutions in the case of the U.S. equity market. Since U.S. registered investment companies are required to disclose their holdings every quarter and they are fairly sophisticated investors who may use options, I start from S12 and S34 databases. I conjecture that HHI constructed from institutional positions in underlying stocks are positively correlated with their hedging demands for equity options and use HHI as a hedging proxy.

[17]The following studies focus on how investor sentiment may affect option prices: Han (2008) examines how market sentiment affects index option expensiveness; Lemmon and Ni (2014) explore how individual investor sentiment affects demand and expensiveness for equity options on an aggregate level.

3.2 Robustness checks

This section checks whether the effect of HHI remains robust after controlling for other option return predictors and stock characteristics. I also explore the possibility that HHI predicts option returns through an information channel by predicting future returns or variances of the underlying stocks.

Control variables include option return predictors documented by previous studies.[18] Following Schürhoff and Ziegler (2011), I calculate holdings of mutual fund (institution) as the firm's total stock shares held by all mutual funds (institutions) divided by its total number of shares outstanding. This is essentially the share proportion of the firm held by mutual funds (institutions). I construct idiosyncratic volatility (IVOL) following Cao and Han (2013). 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 from all moneynesses, I modify their measure and replace ATM implied volatility with VIX. I call the measure $HV-VIX$. I follow Vasquez (2017) to construct the slope of implied volatility term structures (IV Term Spread). The risk-neutral skewness of stock return (RN Skew) is computed following Bakshi, Kapadia, and Madan (2003). It is a measure for jump risk and is closely related to the slope of the implied volatility curve. I use the percentage bid-ask spread of the option portfolio to measure option liquidity. In addition to these option return predictors, I also include well-known stock characteristics associated with underlying stock returns including beta, size (Ln(ME)), book-to-market (Ln(BM)), short-term stock return reversal ($RET_{t-1,t}$), stock return momentum ($RET_{t-12,t-1}$), and Amihud illiquidity measure (Amihud).

[18] Detailed constructions for all control variables used in this paper can be found in Appendix B. Summary statistics of control variables are in Table A1.

Table 3 reports results of Fama-MacBeth regressions:

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

In Columns (1) and (2), fund- and institution-level HHI both remain significant after controls. The coefficient and t-statistic of fund-level measure barely change after controlling for other predictors, but those of institution-level HHI almost halve. When I include both measures in Column (3), the coefficient of fund-level HHI remains highly significant with a t-statistic of -4.46. However, institution-level HHI becomes insignificant in predicting r^{VIX}. This pattern remains the same when I use HHI to predict r^{Call} in Column (5). When I use r^{Put} as the dependent variable in Column (4), institution-level HHI remains significant but its t-statistic is only half of that of the fund-level measure. The overall evidence suggests that fund-level HHI constructed from the more granular level ownership data in S12 is a better proxy than the institution-level measure. Therefore, the rest of this paper will only focus on the mutual-fund-level measure. Hereafter, I will call the fund-level HHI just HHI for simplicity.

Next, I explore the possibility that the option return predictability of HHI comes from its ability to predict the future return or variance of the underlying stock. In Column (6) and (7), I run Fama-MacBeth regressions and use one-month-ahead stock returns ($r^{Stock}_{i,t+1}$) and variances ($RV^{Stock}_{i,t+1}$) as dependent variables, respectively. The coefficients of HHI are close to zero and insignificant. Therefore, it is implausible that HHI contains information about future stock returns or variances.

4 Tests for the Hedging and Demand Pressure Channel

This section provides tests for the hedging and demand pressure channel in which HHI predicts option returns through its positive correlation with stock holders' hedging demands for equity options, which push up option prices and decrease returns on options. This channel consists of two necessary components: demand pressure and price impact in option market, which imply that the option return predictability of HHI should be positively related to each of them:

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

Section 4.1 and 4.2 below focus on the demand pressure component by identifying funds whose hedging demands may cause option order imbalances and by showing that they are the main contributors to the negative return predictability. Section 4.3 focuses on the price impact component by examining whether HHI becomes a stronger option return predictor when options become more costly to hedge and prices are more sensitive to order imbalances.

Nearly 80% of mutual funds have investment policies that allow the use of equity options (Deli and Varma (2002) and Deli, Hanouna, Stahel, Tang, and Yost (2015)). To identify mutual funds that actually trade equity options, I use a Morningstar dataset recording not only stock holdings for U.S. equity mutual funds but also derivatives holdings, which are missing in S12.[19] [20] This dataset ends in June 2015. In Section 4.1 and 4.2 below, I construct HHI using stock holdings in this dataset and match them with option returns whose formation dates end in September 2015, one quarter after the end of the dataset.

4.1 Funds that trade equity options for hedging

This section examines whether the option return predictability of HHI comes from mutual funds that trade equity options for hedging purposes. I identify those funds based on their equity option positions. I start the Morningstar dataset from January 1995, one year before the earliest

[19] I am indebted to David Hunter for sharing this dataset. It is used in his paper Hunter (2015): "Mind the Gap: The Portfolio Effects of 'Other' Holdings".

[20] The dataset also includes short stock positions of mutual funds, which only account for 0.24% of the total holdings observations. I delete them when constructing HHI.

available option returns, in order to construct the HHI matched with returns in the first quarter of year 1996. The dataset covers 4,387 funds during the period from January 1995 to June 2015.

An important advantage of the Morningstar dataset over S12 is that it records non-stock holdings, including options. Funds report the market value of option positions. A positive (negative) value means a long (short) position. This allows me to identify funds taking long or short positions on equity options. Combined with their positions in underlying stocks, I can explore whether they use options to hedge based on the nature of option strategies. However, a challenge is that funds report option holdings in a nonstandard way because of the lack of a standard requirement from SEC when it comes to the reporting of derivatives holdings: First, unlike stock holdings, most of option holdings reported do not have common identifiers like CUSIP, which makes it impossible to directly link option positions with their underlying stocks. Second, names of underlying firms are included in the security name item for option holdings. However, funds abbreviate underlying firms' names in an arbitrary way, and sometimes funds use tickers instead of names, which makes the matching with underlying firms more difficult. Lastly, funds usually do not report important characteristics of option contracts other than it is a call or put. Thus, it is impossible to tell the moneynesses and maturities of options. VIX portfolio consists of options from all moneynesses, which could partially alleviate this concern.

To extract option holdings, I follow procedures used in Cici and Palacios (2015): I begin by using the security names of fund holdings as the main input and identify observations that contain the "Call" or "Put" text strings in the names.[21] Next, I use visual inspection to remove misclassifications. Some observations contain the above text strings but are not option holdings, such as "Output", "Computer". To focus on options written on individual stocks, I exclude index

[21]Funds can be arbitrary in capitalizations and spelling: In addition to "Call", they can write "CALL", "call", "Calloption", etc. The same is true for put options. I also consider these variants in the search.

options. The final sample identifies 607 funds that utilized equity options at least once during the sample period. With a little abuse of terminology, I call them option funds.

Ideally, I would identify option funds at each month based on their option holdings during the past quarter. This would precisely identify which fund causes demand pressure in which firm's option market. However, the short-lived nature of options makes this difficult: Since fund holdings are observed at the end of each quarter, option holdings would be unobservable if they have short maturities such that they expire before the quarter end. Also, funds may deliberately liquidate their option positions before quarter-end reporting if they want to hide their strategies from competitors and investors or if they are concerned about the potential negative publicity associated with derivatives use. Therefore, I employ the above indicator variables to measure option use, following the standard in this literature.[22] However, both reasons can still lead to an underestimation on the number of option funds. Thus, the result in this section is a lower bound for the number of option funds.

Next, I split option funds into put fund, if a fund uses put during the sample period, and call fund, if a fund only uses call but never uses put. If a fund uses both put and call, it would be classified as a put fund. The union of put funds and call funds equals option funds. There are 343 put funds and 264 call funds.

I further split put funds into long put fund, if a fund takes any long position on put during the sample period, and short put fund, if a fund only takes short position on put but never takes any long position. There are 243 long put funds and 100 short put funds. I split call funds in the same way based on their long/short positions on call. There are 111 long call funds and 153 short call funds.

[22] See Koski and Pontiff (1999), Cici and Palacios (2015), Cao, Ghysels, and Hatheway (2011), Chen (2011), Deli and Varma (2002), and Almazan, Brown, Carlson, and Chapman (2004).

I construct different versions of HHI using funds in the above categories, respectively, and use them to predict cross-sectional r^{VIX}.[23] Table 4 reports the results. In Columns (1) and (2), HHI of option funds negatively predicts option returns and after controlling for it, HHI constructed from all Morningstar funds, including those which do not use equity options, becomes only marginally significant.[24] This is expected because option funds are the ones that cause demand pressures in option markets. Columns (3) and (4) suggest that among option funds, it is put funds that drive the negative option return predictability. They are more likely to use options for hedging than call funds. After controlling for HHI of put funds, HHI of option funds loses significance. HHI of call funds has a weakly positive relation with option returns. A possible explanation is that many call funds specialize in covered-call strategy, which sells calls, pushes down option prices, and leads to higher subsequent option returns. After I take into consideration the long/short positions on put and call in Column (5), it becomes clear that long put funds are the main driver for the negative return predictability. All the above results remain the same with similar magnitudes after I control for other option return predictors in Table A2.[25]

Funds may long put for speculation rather than hedging. Investors can use naked put strategy to bypass the short-sales constraint and speculate on negative news of a firm. Johnson and So (2012) argue that "the costs associated with short-selling make informed traders more likely to use options for bad signals than for good ones".[26] I take a further look at long put funds and examine whether they long put for hedging by combining their long positions on puts with those on the underlying stocks.

[23] For example, $HHI\ Put\ Fund = \sum_n^N \left(\frac{Firm's\ Shares\ Owned\ by\ Put\ Fund\ n}{Firm's\ Total\ Shares\ Owned\ by\ Put\ Funds}\right)^2$.

[24] HHI MStar becomes insignificant after I control for other option return predictors in Table A2.

[25] An exception is that the coefficient of the HHI for short put funds becomes significant. However, the result is not robust as the coefficient becomes insignificant again if I use r^{Put} and r^{Call} as dependent variables.

[26] Other related studies include Ofek, Richardson, and Whitelaw (2004), Evans, Geczy, Musto, and Reed (2009), Muravyev, Pearson, and Pollet (2018), Jones, Mo, and Wang (2018), and Khorram, Mo, and Sanger (2019).

First, I link equity option positions with the names of underlying firms. Due to the lack of common identifiers and arbitrary abbreviations of firm names discussed before, an easy and direct matching process is unavailable. I use a name-matching algorithm based on spelling distance to match security names with firm names. Then I use visual inspections to pick observations in which funds report tickers instead of firm names and match those security names with the firm tickers. In the last step, I do visual inspections again to filter out mismatches. After the above steps, 97% of equity option positions can be matched with the names and thus CUSIPs of their underlying firms.

Second, I identify the reason why funds long puts. If a fund takes a long position on the underlying stock at the same quarter, the long position on put is classified as protective put and the fund longs put for hedging in this case. If a fund does not take any position on the underlying stock at that quarter, the put position is classified as naked put. There are 135 (83) funds which used protective (naked) put strategy during the sample period. I construct HHI using the two groups of funds and use them to predict r^{VIX}.

Column (6) in Table 4 shows that funds that use protective put strategy for hedging purposes largely drive the negative return predictability. HHI of funds using naked put for speculation is not significant in predicting option returns. The pattern remains the same after I include other control variables in Table A2.

It is tempting to argue that a measure constructed directly from mutual fund option positions is more direct and superior in gauging option demands than the HHI formed from underlying stock positions. This is not necessarily true for two reasons. First, unlike stocks, options written on the same firm are heterogeneous assets in terms of moneynesses and expirations. Since mutual funds do not report those characteristics, it is impossible to construct a well-defined measure using homogeneous assets in option markets in the way that I construct HHI for a stock. Second, a measure constructed using only option positions without considering end-users' contemporaneous positions in the underlying stocks cannot differentiate hedging from speculating purpose.

The last part of this section examines how long the option return predictability of HHI persists. I use the n-month-lagged HHI of funds using protective put to predict r^{VIX} in a Fama-MacBeth regression, controlling for option return predictors used in Column (1) of Table 3. Specifically, I require that the formation date of the firm's VIX portfolio is at least n-month ahead of the construction date of the firm's HHI, with n taking values from 1 to 12.

Figure 2 plots the coefficient estimates of HHI (solid blue line) and their 95% confidence intervals (dashed yellow lines) with respect to month lags. The coefficients remain significant for up to three months. This means that the predictability persists no longer than two quarters: If we were to predict r^{VIX} formed on the third Friday of August, the 3-month-lagged HHI must be constructed no later than the end of May. In this example, the latest available HHI are those calculated in March, two quarters before August.

The coefficients of HHI become insignificant beyond three months but stay negative. This is different from the demand pressure effect in stock market, which is typically followed by a reversal of signs because of the reversal in demands. The reason is that after monthly options expire, there will be no reversal in their demands. Thus, the demand pressure effect in option markets does not switch signs in predicting option returns over different horizons.

To summarize, this section shows that the option return predictability of HHI comes from funds that long put for hedging purposes and that the effect persists no longer than two quarters.

4.2 Overweight vs. Underweight

When a mutual fund overweights a stock relative to its investment benchmark, the fund has more incentives to hedge its position on this stock than when it underweights the stock. The hedging motives may come from fund manager's career concern as 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. Also, the bad performance of the overweighted stock could lead to the under-performance of the fund relative to its benchmark or peers, which can cause outflows from the fund and decrease the manager's compensation. Therefore, for a given stock, the hedging demand for its options should mainly come from the subset of funds that overweight it. If HHI is a proxy for hedging demand, its option return predictability should come from funds that overweight the stock but not from those that underweight.

To test this conjecture, I construct two versions of HHI using two subsets of funds classified by whether they overweight or underweight the firm relative to their benchmarks. Then I use the two HHI to predict cross-sectional option returns.

I first download the self-declared benchmarks of mutual funds from the Morningstar Direct platform. I pick a total of 20 indices from two families: S&P/Barra and Russell. The S&P/Barra indices I pick are the S&P 500, S&P 500/Barra Growth, S&P500/BarraValue, S&PMidCap 400, and S&PSmallCap 600. The Russell indices I pick are the Russell 1000, Russell 2000, Russell 2500, Russell 3000, and Russell Midcap, plus their value and growth components. For benchmarks in the Russell family, I obtain their compositions and weights of stocks from Financial Times Stock Exchange (FTSE) Russell index holdings data, which is available in Wharton Research Data Services (WRDS). To proxy for the weights of constituent stocks in benchmarks from the S&P family, I use the portfolio holdings of iShares ETFs collected from S12.[27] Holdings data of iShares ETFs becomes available starting from December 31st, 2000. Due to this data availability, I look at option returns from January 2001 to September 2015 in this section. I can

[27]As of July 2020, S&P Dow Jones Indices constituent name data became licensed content and was removed from Compustat. This is why I use holdings of ETFs as proxies for the S&P family.

match 3,131 out of 4,365 funds covered during this sample period with benchmarks from the above 20 indices.

For a given firm at each quarter, I can then tell which funds overweight/underweight it. I construct a firm's HHI using only the holdings of funds which overweight (underweight) it and call it HHI Overweight (Underweight).[28] In addition, I use all funds in the Morningstar dataset to construct HHI and call it HHI MStar. The three versions of HHI are used to predict option returns in Fama-MacBeth regressions.

Table 5 reports results. HHI MStar negatively predicts cross-sectional option returns. After I split funds based on whether they overweight or underweight the stock, the negative predictability comes entirely from funds that overweight the stock.[29] This pattern is especially strong when I use r^{Put} as the dependent variable, which is consistent with the fact that put is more commonly used for hedging than call. After I control for other option return predictors in Table A3, all results above remain the same qualitatively.

Another possible candidate proxy for hedging demand is the share proportion of a firm overweighted by mutual funds.[30] To compare this measure with HHI, I construct it as follows: First, for stock i at month t, I calculate the dollar amount fund j invests in the stock in excess of its own benchmark:

$$AUM_{j,t} \times max(w_{i,j,t} - w_{i,t}^{Benchmark_j}, 0),$$

where: $AUM_{j,t}$ is the asset under management of fund j at month t; $w_{i,j,t}$ is the weight of stock i in fund j's portfolio at month t; $w_{i,t}^{Benchmark_j}$ is the weight of stock i in fund j's benchmark at month t. Second, I sum across funds holding stock i and scale the summation using the market

[28] $HHI\ Overweight = \sum_n^N \left(\frac{Firm's\ Shares\ Owned\ by\ Overweight\ Fund\ n}{Firm's\ Total\ Shares\ Owned\ by\ Overweight\ Funds}\right)^2$.

[29] Even though HHI Underweight is marginally significant in predicting r^{Put}, it becomes insignificant after I control for other option return predictors in Table A3.

[30] I thank Neil Pearson for suggesting this possibility.

cap of stock i at month t. I call this measure "Proportion Overweight" and use it to predict cross-sectional option returns.

Table A4 in the appendix presents regression results. Used alone as a predictor, Proportion Overweight positively predicts r^{Put} and r^{Call}. It loses significance after I control for HHI and other predictors, while the coefficient of HHI Overweight barely changes from Table A3. As mentioned before, HHI can be a better hedging proxy and thus a better option return predictor than share proportion, because it considers relative sizes of stock holders' positions and captures how risks from underlying stocks are distributed among them.

4.3 Price impact in option markets

Garleanu, Pedersen, and Poteshman (2008) (GPP) give an explicit characterization of the price impact in option markets:

$$\frac{\partial p}{\partial d} = \gamma(R_f - 1) \times Option\,Unhedgeable\,Risk,$$

where γ is option dealer's risk aversion and R_f is the risk-free rate. They consider three forms of option unhedgeable risks: stochastic volatility risk,[31] jump risk, and delta-hedging cost. If the hedging and demand pressure channel is accurate, HHI should be a stronger option return predictor when price impact is larger, because a given level of order imbalances could cause greater option price movements.

I test two hypotheses derived from the model in GPP: 1. The effect of HHI is stronger during periods in which TED spreads are higher. This is because TED spread is positively related to intermediaries' funding liquidity constraint. When TED spread increases, intermediaries as option market makers become more risk averse and face higher effective risk-free rate, which

[31] A large literature studies how stochastic volatility affects option pricing and explains the negatively sloped implied volatility curve. Some examples are Bakshi, Cao, and Chen (1997), Bates (2000), Heston (1993), and Heston and Nandi (2000)

leads to a larger price impact. 2. The predictability of HHI is stronger among stocks with higher stochastic volatility risk, jump risk, and delta-hedging cost. Since options written on those stocks are more difficult to hedge, price impacts are larger among those stocks.

To test Hypothesis 1, I split the sample into three sub-periods (Low, Medium, and High) based on the level of TED spread on the third Friday of each month.[32] I run Fama-MacBeth regressions, $r_{i,t+1} = \alpha_t + \gamma_t HHI_{i,t} + \theta_t Controls_{i,t} + \epsilon_{i,t+1}$, among each sub-period. For robustness, I use r^{VIX}, r^{Put}, and r^{Call} as the dependent variable, respectively. Controls include option return predictors in Column (1) of Table 3. In this section, I construct HHI using S12. I report the coefficients of HHI in the first row of Table 6. As TED spread increases, the coefficient becomes more negative and significant for all three measures of option returns. This pattern is consistent with Hypothesis 1.

To test Hypothesis 2, I sort firms into three subgroups (Low, Medium, and High) at each month by empirical proxies corresponding to the three forms of unhedgeable risks, respectively. Among each subgroup of firms, I then run the same Fama-MacBeth regressions as above and report the coefficients of HHI.

In order to find a proxy for stochastic volatility risk, I estimate the following EGARCH(1,1) model for each firm on the third Friday of each month using past-year daily stock returns:

$$r_t = \sigma_t z_t;\ ln\sigma_t^2 = \omega + \alpha r_{t-1}^2 + \beta ln\sigma_{t-1}^2 + \gamma[|z_{t-1}| - (\frac{2}{\pi})^{\frac{1}{2}}],$$

where r_t is the stock return, σ_t is the conditional volatility, and z_t is the innovation term. I set the maximum number of iterations as 500, and 97% of cases successfully converge. After I generate a series of time-varying volatility levels for each day in the estimation window, I calculate the volatility of those model-implied volatilities for each firm every month and use it as

[32] Data for TED spread is taken from the website of Federal Reserve Bank of St.Louis.

the proxy for stochastic volatility risk. Following Tian and Wu (2021), I use kurtosis to measure jump intensity. I estimate kurtosis on the third Friday of each month using rolling-one-year daily stock returns. To measure delta-hedging cost, I follow Tian and Wu (2021) and compute the ratio of the stock return variance ($\sigma_{i,t}^2$) uncorrelated with the market to the average daily dollar trading volume ($DV_{i,t}$, in millions) over the past year as follows:

$$\sigma_{i,t}^2(1-\rho_{i,t}^2)/DV_{i,t},$$

where $\rho_{i,t}$ is the correlation between returns of stock i and S&P 500 Index, calculated using past-year daily data. When the return of an individual stock is highly correlated with the market, dealers can use the highly liquid index futures to hedge the directional exposure. The idiosyncratic return variance is used to capture the portion of risk that needs to be hedged with the underlying stock.

Table 6 reports the coefficients of HHI for each subgroup sorted by the above three proxies, respectively. When the level of each unhedgeable risk in each row increases from Low to High, the coefficient becomes more negative and significant. This trend is especially strong when I use r^{Put} as the dependent variable, consistent with HHI being a proxy for hedging demands on put option. Overall, findings show that HHI is a stronger option return predictor when options become more costly to hedge, consistent with Hypothesis 2.

5 Limitation, Strategy Performance, and Alternative Stories

This section discusses the limitation of HHI as a hedging proxy, i.e. when its positive relationship with hedging demand may break down. I propose an improved version of HHI to address this limitation. I also examine the performance of option strategies formed by HHI and evaluate the impact of transaction cost such as option bid-ask spreads. Two alternative explanations for why HHI predicts option returns are also explored and ruled out.

5.1 Limitation: Heterogeneous sizes of stock holders

A limitation of using HHI as a proxy for hedging demand is that it fails to account for heterogeneous sizes of a firm's stock holders.[33] HHI can be easily driven by a very large fund into a direction that is irrelevant, or even negatively correlated, with hedging demand. Assume that in Scenario 1, a firm is held by two funds, one with \$100 million asset under management and one with \$10 billion. Each of these funds invest 1% of their wealth in the firm's stocks. In Scenario 2, the firm is held by two funds, both of which have \$5 billion asset under management and 1% of their wealth invested in the firm. HHI in Scenario 1 is larger than that in Scenario 2, but hedging demands in the two scenarios are not intuitively different. If the larger fund in Scenario 1 underweights the stock relative to its benchmark, HHI would be even negatively related to hedging demand.

If the hedging channel is correct, HHI should be a less valid hedging proxy and a weaker option return predictor among firms whose mutual fund holders are more dispersed in terms of asset sizes. To verify this conjecture, I construct HHI using S12, which records total net assets of mutual funds.[34] For a given firm at the end of the quarter, I calculate the kurtosis of fund holders' total net assets and use it to measure how dispersed fund holders' sizes are. To calculate kurtosis, I restrict the sample to firm-months with at least five holders. Then I sort firms into terciles (Low, Medium, High) by their latest available kurtosis and run the Fama-MacBeth regression, $r_{i,t+1} = \alpha_t + \gamma_t HHI_{i,t} + \theta_t Controls_{i,t} + \epsilon_{i,t+1}$, among each tercile. I use r^{VIX}, r^{Put}, and r^{Call} as the dependent variable, respectively.

[33] I thank Christopher Jones for raising this issue.
[34] Item "ASSETS" in S12.

Panel A of Table 7 reports the coefficient of HHI for each subgroup. The coefficients are similar across terciles when I use r^{VIX} as the dependent variable. When I use r^{Put} and r^{Call} as dependent variables, HHI does not significantly predict option returns among the group of firms with high kurtosis. This is consistent with the conjecture that HHI is not a valid hedging proxy when there are large dispersions among stock holders' sizes. When kurtosis decreases, the coefficient of HHI becomes more significant.

To alleviate the bias caused by large funds, I construct a truncated version of HHI:[35] For a given firm every quarter, I sort its fund holders into quintiles by their total net assets and delete those in the highest quintile. Then I construct HHI using funds left, whose sizes are less dispersed than before. I use both the non-truncated and truncated HHI to predict option returns with controls.[36]

Panel B of Table 7 reports regression results. When used alone, both HHI negatively predict option returns after controls. After I include both of them in one regression, the truncated HHI is superior in predicting r^{Put} in Column (6) with the coefficient estimate and t-statistic twice as much as those of the non-truncated measure. In contrast, when I use them to predict r^{Call} in Column (9), the truncated HHI becomes only weakly significant at the 10% level and the non-truncated measure remains highly significant. Again, given the popularity of put as a hedging instrument, this is supporting evidence that HHI can be viewed as a hedging proxy and that accounting for heterogeneous sizes of stock holders can further improve the proxy.

[35] I still focus on firms with at least five mutual fund holders.

[36] The non-truncated HHI is the one used in Panel A of Table 7.

5.2 Strategy performance and transaction cost

This section examines the performance of option strategies formed on HHI. Since bid-ask spreads are large in option markets, I also evaluate how transaction costs impact the profitabilities of these strategies.

At each month, I sort firms into quintiles by −HHI and equally weight them. I sort by negative HHI in order to generate an increasing pattern of returns only for illustration purposes. Portfolio returns are computed using r^{VIX}, r^{Put}, and r^{Call}, respectively. Alpha is controlled for Fama and French (2015) five factors, stock momentum, and S&P 500 Index VIX return in excess of risk-free rate.

Panel A in Table 8 presents average monthly returns. Quintile option return decreases as HHI increases. A long-short trading strategy using r^{VIX} generates a monthly return of 6.85%. After controlling for risk factors, the alpha, 6.87%, is similar to the raw return. The monthly Sharpe Ratio is 0.4. Patterns remain the same when I trade r^{Put} and r^{Call}. Sharpe ratio is especially large for r^{Put}, which is not surprising given that HHI is especially strong in predicting put returns.

Figure 3 plots the time-series of monthly returns for the above three strategies. The profits are especially high during the early sample period up until 2001, due to a combination of low option market liquidity and overall market uncertainties like the collapse of Long Term Capital Management and of the Dotcom Bubble. As option markets have become more liquid and market-making costs decrease over time, the overall magnitude of profits have become smaller than the early period. However, the returns remain positive most of the time, especially for r^{Put}.[37]

[37] When trading r^{VIX}, there is a large drawdown at early 2018 during the XIV Meltdown. This is likely due to the approximation error between r^{VIX} and r^{VSR}, because this drawdown disappears when investors trade r^{Put} and r^{Call}.

The above results assume that options can be bought and sold at the midpoint of bid and ask quotes. To evaluate how option bid-ask spreads could impact profits, I consider effective spreads equal to 25%, 50%, 75%, and 100% of the quoted spreads in Panel B. The effective spread is twice the difference between the trade price and midpoint. An effective-to-quoted spread ratio of 50% is equivalent to paying half of the quoted spread. The column "MidP" corresponds to zero effective spread, i.e., options are traded at midpoints. The column "100%" refers to the case in which traders buy options at ask and sell options at bid. De Fontnouvelle, Fishe, and Harris (2003) and Mayhew (2002) show that the typical spread ratio is less than 0.5. This measure assumes that the fair value equals midpoint and would overstate the true effective spread when fair value is closer to one side of the bid-ask quotes. Muravyev and Pearson (2020) show that option liquidity takers who time executions pay 20% of this conventional measure.[38] Traders who implement the long-short strategy tend to be liquidity providers, because they sell options written on firms with high HHI to hedgers. Thus, the fair value of options being sold tends to be above the midpoint and traders face low effective spreads. In addition to the relative magnitudes of fair value and midpoint, option traders commonly use limit orders, which are often filled inside the quotes set by market makers and could further reduce the effective spread.

I manage impacts of transaction costs in two ways. First, I implement strategies based on extreme deciles rather than quintiles because the higher average returns of decile-based strategies are more likely to survive transaction costs. Second, I reduce transaction costs by only focusing on firms whose percentage option bid-ask spreads are lower than the median of that month.

Panel B in Table 8 presents average monthly returns of long-short strategies under different spread ratios. I calculate returns in columns under "All" using all firms at that month. Returns

[38]This value follows from their finding that algorithmic traders pay an effective half-spread of \$0.026 on average when trading ATM options, while the average quoted half-spread is \$0.128.

in columns under "Low Bid-Ask Spread" are computed using firms whose option bid-ask spreads are lower than the median of that month.[39]

When I include all firms in the sample, the return using r^{VIX} becomes insignificant at the 25% spread ratio. This is not surprising given that VIX portfolio consists of OTM options whose bid-ask spreads are large. The return using r^{Call} turns negative at the 75% ratio. The strategy using r^{Put} is the most profitable: Its profit becomes insignificant and negative only when the full bid-ask spread is accounted for.

When I only focus on firms with lower-than-median bid-ask spreads, the return using r^{VIX} remains significantly positive at the 25% ratio with a t-statistic of 3.00. Therefore, the strategy would remain profitable if one were able to achieve the level of transaction costs that Muravyev and Pearson document for algorithmic traders. Both the returns using r^{Call} and r^{Put} remain positive and significant after the full bid-ask spread, especially for r^{Put}.

Overall, the evidence suggests that reducing trading costs is essential to maintain the profitability of option strategies formed by HHI. Trading put options delivers the best chance of making profits.

5.3 Firm size and share proportion owned by mutual funds

This section investigates whether firm size and share proportion of the firm owned by mutual funds can explain the relation between option returns and HHI. Smaller firms and firms with lower share proportions owned by mutual funds tend to be owned by fewer funds and thus have higher HHI, because the lower bound of HHI equals the reciprocal of the number of owners. Firm size (share proportion) and HHI have a negative correlation of -0.24 (-0.29).

[39] First, I exclude firms with higher-than-median spreads each month. Then I sort firms left into deciles by -HHI.

To control for the potential nonlinear pricing relations between HHI and the two variables, I implement a double-sort procedure: First, I sort firms into quintiles at each month by size or share proportion. Second, firms within each size or share proportion quintile are further sorted into quintiles by −HHI. I equally weight firms in the 5×5 subgroups. Table 9 presents the average r^{VIX} for each subgroup. Return spreads sorted by −HHI are highly significant in every size or share proportion quintile. Their magnitudes are similar to the 6.85% monthly profit implemented on the whole sample in Panel A of Table 8. Therefore, the option return predictability of HHI cannot be absorbed by size or share proportion.

5.4 Breadth of ownership and short interest

Chen, Hong, and Stein (2002) link the change in the breadth of mutual fund ownership with the short-sales constraint: When breadth decreases, i.e. fewer mutual funds long the firm's stock, short-sales constraint becomes more binding. Thus, a decrease in the breadth should forecast lower stock returns. It is possible that HHI predicts option returns through its relationship with the change in the breadth and short interest: When a firm's breadth decreases, it has higher short interest and tends to have larger HHI because the lower bound of HHI equals the reciprocal of the number of owners. Funds may demand more of the firm's put options to bypass the short-sales constraint, which pushes up prices of puts and leads to lower subsequent option returns.[40]

There are two reasons why a firm can have a higher HHI relative to other firms: First, its ownership is more concentrated among a few large stock holders; Second, it is owned by a smaller number of holders and thus has a larger lower bound for HHI than other firms. The hedging channel suggests that the first reason drives the option return predictability. To explore the possibility of the second, I control for the *level* of the breadth in addition to the *change*.

[40] I thank Christopher Jones for raising this point.

In a cross-sectional regression, I control for the short interest and both the level and change in the breadth. I construct breadth following Chen, Hong, and Stein (2002) and define it as the ratio of the number of mutual funds that long the stock to the total number of mutual funds in that quarter. $\Delta Breadth$ is the change in the breadth from the previous quarter. Monthly short interest data is from Compustat. I scale a firm's number of stock shares that are held short by its total shares outstanding from CRSP.

Table 10 presents regression results after controlling for all other option return predictors used in Column (1) of Table 3. The variable "Breadth", which is the level of breadth, cannot predict option returns. This rules out the possibility that the option return predictability of HHI naively comes from the number of stock holders. $\Delta Breadth$ cannot predict r^{Put} and is only marginally significant in predicting r^{Call} at the 10% level. Short interest negatively predicts r^{Put} with a t-statistic of -4.59 but not r^{Call}, consistent with its positive correlation with investors' demand for put options. Even though the t-statistic of HHI decreases after controlling for Breadth, $\Delta Breadth$, and short interest, HHI remains highly significant. This echoes the result in Section 4.1 showing that funds that use naked put strategy to circumvent the short-sales constraint are not the main driver for the return predictability of HHI.

Overall, there is limited evidence supporting that the option return predictability of HHI comes from its correlation with the breadth of mutual fund ownership and short interest.

6 Conclusion

This paper documents that HHI constructed from mutual fund stock holdings negatively predicts cross-sectional equity option returns. The finding remains robust after controlling for a wide range of option return predictors and stock characteristics. The predictability is unrelated to firm size and share proportion of the firm owned by mutual funds. It also cannot be explained by the breadth of mutual fund ownership, whose change is correlated with short interest and demand for put options. Inconsistent with an information channel, HHI does not predict returns and variances of underlying stocks.

To explain the finding, I propose a hedging and demand pressure channel: HHI predicts option returns through its positive correlation with stock holders' hedging demand for equity options. To absorb the order imbalances and compensate for the inventory risk, option dealers charge higher prices, leading to lower subsequent option returns.

I provide the following evidence consistent with this channel: First, using option positions of U.S. equity mutual funds, I find that the negative option return predictability of HHI mainly comes from funds that trade equity options for hedging purposes. Second, the predictability comes entirely from funds that overweight the stock relative to their benchmark indices. Holdings of funds that underweight the stock cannot predict option returns. Third, HHI becomes a stronger option return predictor when price impact in option markets gets larger and option price movement becomes more sensitive to order imbalances.

Option strategies formed from the signal of HHI are profitable. The profits cannot be explained by conventional risk factors. Transaction costs like option bid-ask spreads may turn profits into losses. Therefore, reducing trading costs is essential to maintain the profitability of these strategies. Trading put options, whose prices are the most affected by hedging demands, offers the best chance of staying profitable.

A limitation of HHI as a hedging proxy is that HHI is sensitive to the holdings of large funds and can be driven into a direction that is unrelated, or even negatively correlated, with the hedging demand. Truncating mutual funds with extreme sizes in the construction of HHI can alleviate this problem. Future research may develop a measure accounting for heterogeneous sizes of stock holders and better reflecting their hedging demands. Also, it is possible that the positive relation between concentrations of marginal investors' positions in the underlying asset market and their hedging demands for the corresponding derivatives may continue to hold for other asset classes, such as corporate bonds and credit default swaps.

References

Almazan, A., K. C. Brown, M. Carlson, and D. A. Chapman, 2004, "Why constrain your mutual fund manager?," *Journal of Financial Economics*, 73(2), 289–321.

Amihud, Y., 2002, "Illiquidity and stock returns: cross-section and time-series effects," *Journal of Financial Markets*, 5(1), 31–56.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang, 2006, "The cross-section of volatility and expected returns," *The Journal of Finance*, 61(1), 259–299.

Aragon, G. O., and J. S. Martin, 2012, "A unique view of hedge fund derivatives usage: Safeguard or speculation?," *Journal of Financial Economics*, 105(2), 436–456.

Bakshi, G., C. Cao, and Z. Chen, 1997, "Empirical performance of alternative option pricing models," *The Journal of Finance*, 52(5), 2003–2049.

Bakshi, G., and N. Kapadia, 2003, "Delta-hedged gains and the negative market volatility risk premium," *The Review of Financial Studies*, 16(2), 527–566.

Bakshi, G., N. Kapadia, and D. Madan, 2003, "Stock return characteristics, skew laws, and the differential pricing of individual equity options," *The Review of Financial Studies*, 16(1), 101–143.

Bates, D. S., 2000, "Post-'87 crash fears in the S&P 500 futures option market," *Journal of Econometrics*, 94(1-2), 181–238.

Black, F., and M. Scholes, 1973, "The pricing of options and corporate liabilities," *Journal of Political Economy*, 81(3), 637–654.

Bollen, N. P., and R. E. Whaley, 2004, "Does net buying pressure affect the shape of implied volatility functions?," *The Journal of Finance*, 59(2), 711–753.

Cao, C., Z. Chen, and J. M. Griffin, 2005, "Informational content of option volume prior to takeovers," *The Journal of Business*, 78(3), 1073–1109.

Cao, C., E. Ghysels, and F. Hatheway, 2011, "Derivatives do affect mutual fund returns: Evidence from the financial crisis of 1998," *Journal of Futures Markets*, 31(7), 629–658.

Cao, J., and B. Han, 2013, "Cross section of option returns and idiosyncratic stock volatility," *Journal of Financial Economics*, 108(1), 231–249.

Carr, P., and L. Wu, 2009, "Variance risk premiums," *The Review of Financial Studies*, 22(3), 1311–1341.

Chen, H., S. Joslin, and S. X. Ni, 2019, "Demand for crash insurance, intermediary constraints, and risk premia in financial markets," *The Review of Financial Studies*, 32(1), 228–265.

Chen, J., H. Hong, and J. C. Stein, 2002, "Breadth of ownership and stock returns," *Journal of Financial Economics*, 66(2-3), 171–205.

Chen, Y., 2011, "Derivatives use and risk taking: Evidence from the hedge fund industry," *Journal of Financial and Quantitative Analysis*, pp. 1073–1106.

Cici, G., and L.-F. Palacios, 2015, "On the use of options by mutual funds: Do they know what they are doing?," *Journal of Banking & Finance*, 50, 157–168.

Cohen, R. B., C. Polk, and B. Silli, 2010, "Best ideas," *Available at SSRN 1364827*.

De Fontnouvelle, P., R. P. Fishe, and J. H. Harris, 2003, "The behavior of bid-ask spreads and volume in options markets during the competition for listings in 1999," *The Journal of Finance*, 58(6), 2437–2463.

Deli, D., P. Hanouna, C. W. Stahel, Y. Tang, and W. Yost, 2015, "Use of derivatives by registered investment companies," *SEC White Paper*.

Deli, D. N., and R. Varma, 2002, "Contracting in the investment management industry: evidence from mutual funds," *Journal of Financial Economics*, 63(1), 79–98.

Driessen, J., P. J. Maenhout, and G. Vilkov, 2009, "The price of correlation risk: Evidence from equity options," *The Journal of Finance*, 64(3), 1377–1406.

Duarte, J., C. S. Jones, and J. L. Wang, 2019, "Very noisy option prices and inferences regarding option returns," *Available at SSRN 3488738*.

Easley, D., M. O'hara, and P. S. Srinivas, 1998, "Option volume and stock prices: Evidence on where informed traders trade," *The Journal of Finance*, 53(2), 431–465.

Evans, R. B., C. C. Geczy, D. K. Musto, and A. V. Reed, 2009, "Failure is an option: Impediments to short selling and options prices," *The Review of Financial Studies*, 22(5), 1955–1980.

Fama, E. F., and K. R. French, 1992, "The cross-section of expected stock returns," *The Journal of Finance*, 47(2), 427–465.

——— , 2015, "A five-factor asset pricing model," *Journal of Financial Economics*, 116(1), 1–22.

Fama, E. F., and J. D. MacBeth, 1973, "Risk, return, and equilibrium: Empirical tests," *Journal of Political Economy*, 81(3), 607–636.

Figlewski, S., 1989, "Options arbitrage in imperfect markets," *The Journal of Finance*, 44(5), 1289–1311.

Garleanu, N., L. H. Pedersen, and A. M. Poteshman, 2008, "Demand-based option pricing," *The Review of Financial Studies*, 22(10), 4259–4299.

Gaspar, J.-M., M. Massa, and P. Matos, 2006, "Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization," *The Journal of Finance*, 61(1), 73–104.

Ge, L., T.-C. Lin, and N. D. Pearson, 2016, "Why does the option to stock volume ratio predict stock returns?," *Journal of Financial Economics*, 120(3), 601–622.

Goyal, A., and A. Saretto, 2009, "Cross-section of option returns and volatility," *Journal of Financial Economics*, 94(2), 310–326.

Green, T. C., and S. Figlewski, 1999, "Market risk and model risk for a financial institution writing options," *The Journal of Finance*, 54(4), 1465–1499.

Han, B., 2008, "Investor sentiment and option prices," *The Review of Financial Studies*, 21(1), 387–414.

Heston, S. L., 1993, "A closed-form solution for options with stochastic volatility with applications to bond and currency options," *The Review of Financial Studies*, 6(2), 327–343.

Heston, S. L., and S. Li, 2020, "Option Momentum," *Available at SSRN 3705573*.

Heston, S. L., and S. Nandi, 2000, "A closed-form GARCH option valuation model," *The Review of Financial Studies*, 13(3), 585–625.

Hu, J., 2014, "Does option trading convey stock price information?," *Journal of Financial Economics*, 111(3), 625–645.

Hunter, D. L., 2015, "Mind the Gap: The Portfolio Effects of 'Other' Holdings," *Asian Finance Association (AsianFA) 2015 Conference Paper, Available at SSRN: https://ssrn.com/abstract=2565274 or http://dx.doi.org/10.2139/ssrn.2565274*.

Jegadeesh, N., and S. Titman, 1993, "Returns to buying winners and selling losers: Implications for stock market efficiency," *The Journal of Finance*, 48(1), 65–91.

Johnson, T. L., and E. C. So, 2012, "The option to stock volume ratio and future returns," *Journal of Financial Economics*, 106(2), 262–286.

Jones, C. S., H. Mo, and T. Wang, 2018, "Do option prices forecast aggregate stock returns?," *Available at SSRN 3009490*.

Kempf, A., and S. Ruenzi, 2008, "Tournaments in mutual-fund families," *The Review of Financial Studies*, 21(2), 1013–1036.

Khorram, M., H. Mo, and G. C. Sanger, 2019, "Information flow and credit rating announcements," *Available at SSRN 3428816*.

Koski, J. L., and J. Pontiff, 1999, "How are derivatives used? Evidence from the mutual fund industry," *The Journal of Finance*, 54(2), 791–816.

Lakonishok, J., I. Lee, N. D. Pearson, and A. M. Poteshman, 2007, "Option market activity," *The Review of Financial Studies*, 20(3), 813–857.

Lemmon, M., and S. X. Ni, 2014, "Differences in trading and pricing between stock and index options," *Management Science*, 60(8), 1985–2001.

Levich, R. M., G. S. Hayt, and B. A. Ripston, 1999, "1998 survey of derivatives and risk management practices by US institutional investors," .

Mayhew, S., 2002, "Competition, market structure, and bid-ask spreads in stock option markets," *The Journal of Finance*, 57(2), 931–958.

Muravyev, D., 2016, "Order flow and expected option returns," *The Journal of Finance*, 71(2), 673–708.

Muravyev, D., and N. D. Pearson, 2020, "Options trading costs are lower than you think," *The Review of Financial Studies*, 33(11), 4973–5014.

Muravyev, D., N. D. Pearson, and J. M. Pollet, 2018, "Why Do Price and Volatility Information from the Options Market Predict Stock Returns?," *Available at SSRN 2851560*.

Newey, W. K., and K. D. West, 1987, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica: Journal of the Econometric Society*, pp. 703–708.

Ni, S. X., J. Pan, and A. M. Poteshman, 2008, "Volatility information trading in the option market," *The Journal of Finance*, 63(3), 1059–1091.

Ofek, E., M. Richardson, and R. F. Whitelaw, 2004, "Limited arbitrage and short sales restrictions: Evidence from the options markets," *Journal of Financial Economics*, 74(2), 305–342.

Pan, J., and A. M. Poteshman, 2006, "The information in option volume for future stock prices," *The Review of Financial Studies*, 19(3), 871–908.

Roll, R., E. Schwartz, and A. Subrahmanyam, 2010, "O/S: The relative trading activity in options and stock," *Journal of Financial Economics*, 96(1), 1–17.

Schürhoff, N., and A. Ziegler, 2011, "Variance risk, financial intermediation, and the cross-section of expected option returns," .

Tian, M., and L. Wu, 2021, "Limits of Arbitrage and Option Risk Premium," *Available at SSRN.*

Vasquez, A., 2017, "Equity volatility term structures and the cross section of option returns," *Journal of Financial and Quantitative Analysis*, 52(6), 2727–2754.

Figure 1: Index VIX Return and Variance Swap Return (VSR)

This figure plots the monthly index VIX return (blue solid line) and variance swap return (red dashed line). The sample period is from January 1996 to December 2019.

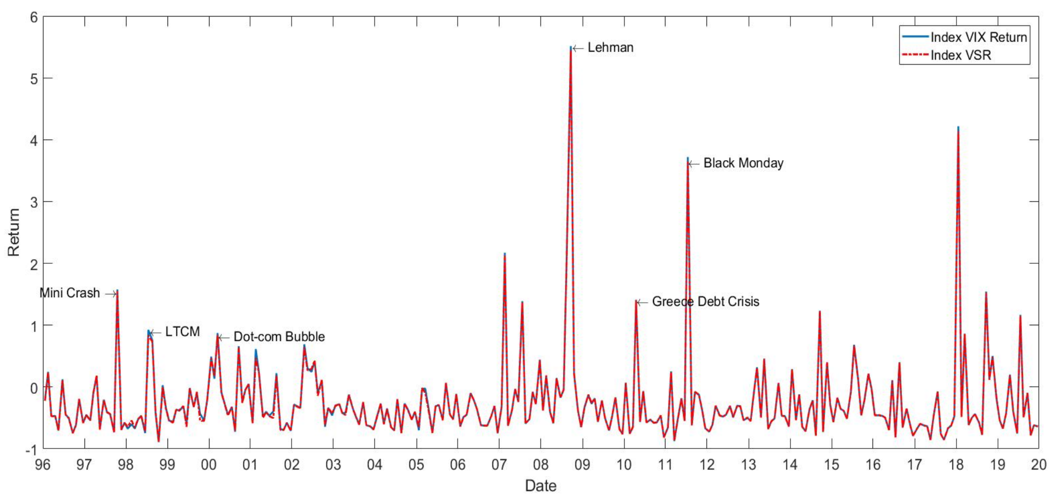


Figure 2: **Option Return Predictability of Lagged HHI**

This figure plots the coefficient estimates (solid blue line) of and the 95% confidence intervals (dashed yellow lines) of the n-month-lagged HHI Protective Put in the monthly Fama-MacBeth regression:

$$r_{i,t}^{VIX} = \alpha_{t,n} + \gamma_{t,n} HHI\ Protective\ Put_{i,t-n} + \theta_{t,n} Controls_{i,t-1} + \epsilon_{i,t}.$$

$r_{i,t}^{VIX}$ is firm i's equity VIX return in month t. HHI Protective Put is constructed using the stock holdings of mutual funds that used protective put strategy during the sample period. Control variables include those in Column (1) of Table 3. The sample period is from January 1996 to September 2015.

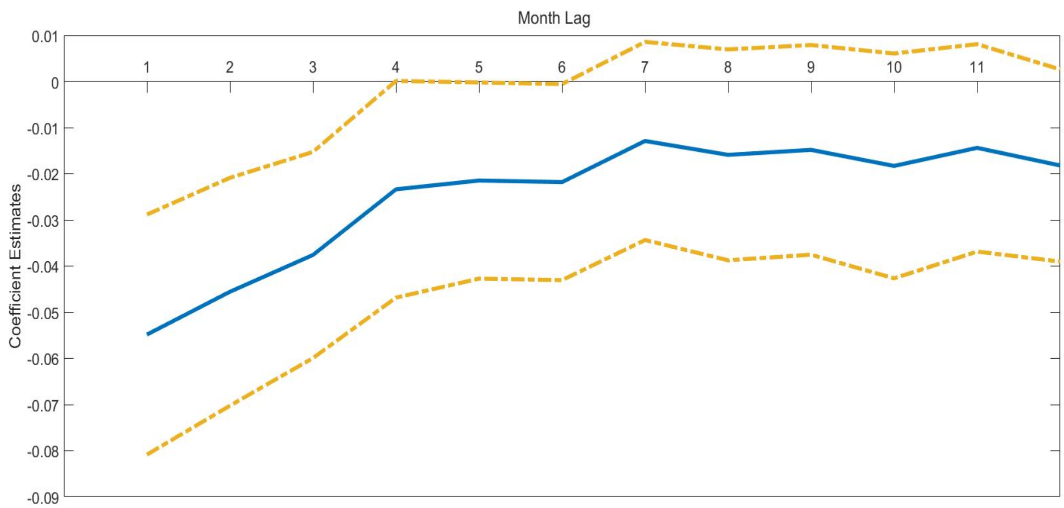
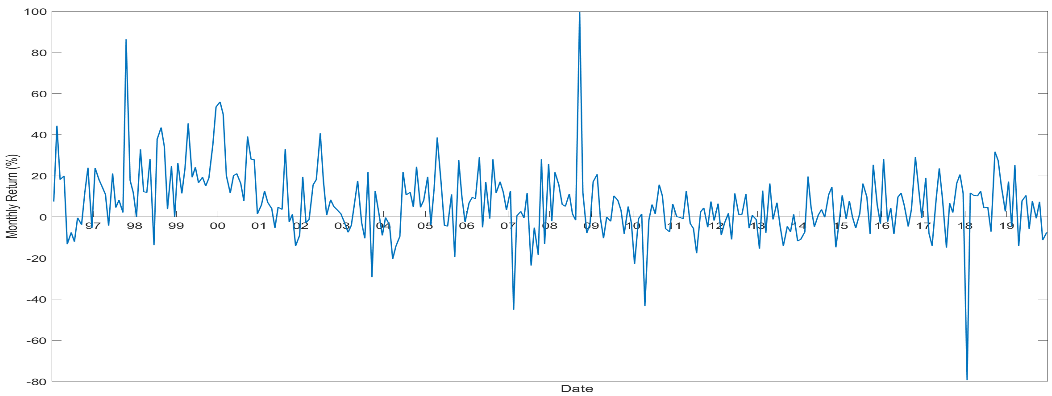
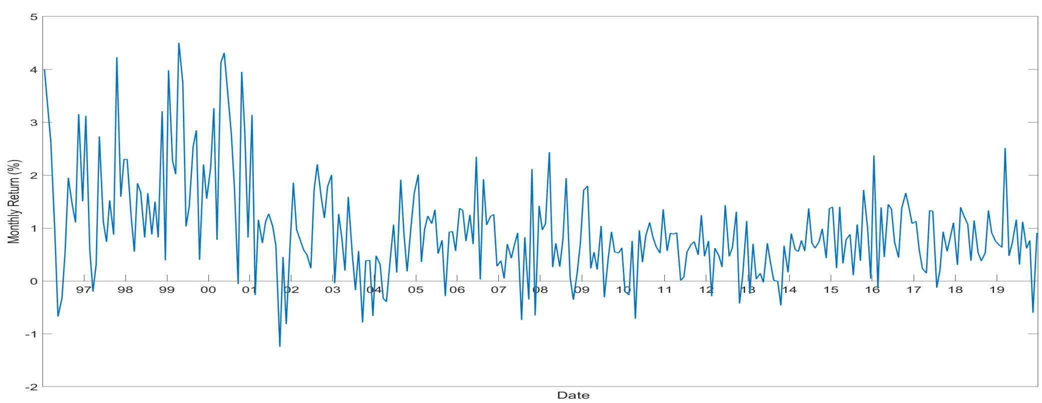


Figure 3: Time Series of Long-Short Strategies Sorted by $-HHI$

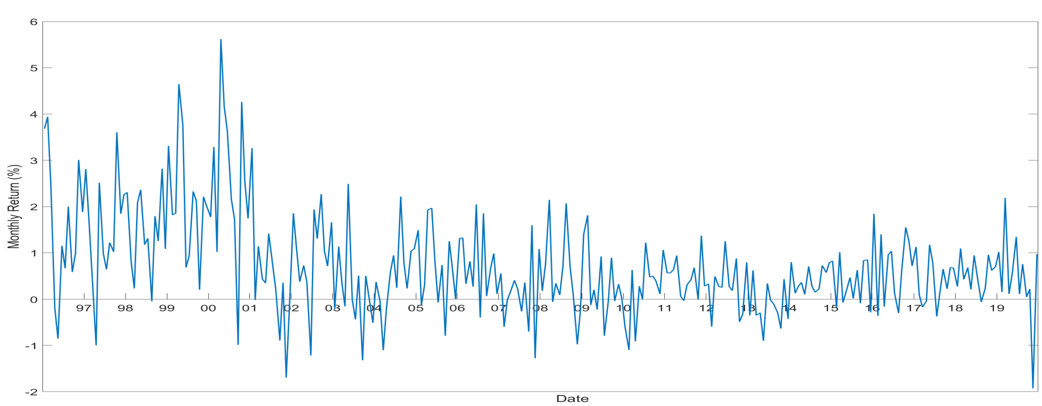
These figures plot monthly returns (in percentage) of long-short strategies sorted by $-HHI$ as in Panel A of Table 8. Panels (a), (b), and (c) correspond to the strategy returns of trading r^{VIX}, r^{Put} and r^{Call}, respectively.



(a) VIX Return



(b) Put Return



(c) Call Return

Table 1: Summary Statistics

This table reports summary statistics for main variables used in this paper. The sample period is from January 1996 to December 2019. Returns are reported on a monthly basis. (%) after a variable means that its statistics are reported in percent. Index (Equity) r^{VIX} is the return of index (equity) VIX portfolio. Index (Equity) r^{VSR} is defined as the realized variance of index (equity) return divided by the price of index (equity) VIX portfolio minus 1. Number of Strikes is the number of option contracts in an equity VIX portfolio. Correlation(r^{VIX}, r^{VSR}) is the firm-level time-series correlation between equity VIX returns and equity variance swap returns. To calculate the correlation, I require a firm to have at least 30 observations. r^{Call} is the delta-hedged gain of an ATM call until option maturity scaled by $(\Delta S - C)$, where Δ is the Black-Scholes option delta, S is the underlying stock price, and C is the price of call. r^{Put} is the delta-hedged gain of an ATM put until option maturity scaled by $(P - \Delta S)$, where P is the price of put. HHI Mutual Fund (Institution) is the Herfindahl-Hirschman Index of mutual fund (13f institution) ownership of the stock.

	Observation	Mean	Std	P10	Median	P90
Panel A: Option returns.						
Index r^{VIX}(%)	288	-24.26	68.34	-69.85	-43.48	28.90
Index r^{VSR}(%)	288	-24.73	67.40	-69.68	-43.98	28.16
Number of Firms Per Month	288	693	277	340	704	1057
Number of Strikes	199,648	7.97	6.30	4	6	13
Equity r^{VIX}(%)	199,648	-8.24	83.07	-62.60	-24.45	59.98
Equity r^{VSR}(%)	199,648	-8.80	100.55	-68.04	-30.57	61.58
Correlation(r^{VIX}, r^{VSR})	1,976	0.83	0.26	0.56	0.93	0.99
r^{Call}(%)	199,648	-0.44	5.18	-4.76	-0.64	3.62
r^{Put}(%)	199,648	-0.70	4.79	-5.01	-0.86	3.30
Panel B: HHI.						
HHI Mutual Fund	170,832	0.154	0.220	0.024	0.065	0.407
HHI Institution	177,831	0.067	0.081	0.027	0.045	0.113

Table 2: HHI and Cross-Sectional Option Returns

This table reports the results of monthly Fama-MacBeth regressions in which one-month-ahead option returns, including equity VIX returns and returns of delta-hedged put and call, are the dependent variables, respectively. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags. Average CS R^2 is the average adjusted R-squares in cross-sectional regressions. The sample period is from January 1996 to December 2019.

	$r_{i,t+1}^{VIX}$			$r_{i,t+1}^{Put}$			$r_{i,t+1}^{Call}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HHI Mutual Fund	-0.156		-0.145	-0.020		-0.016	-0.016		-0.013
	(-5.57)		(-4.60)	(-8.26)		(-6.51)	(-6.03)		(-4.87)
HHI Institution		-0.249	-0.125		-0.041	-0.028		-0.031	-0.019
		(-5.49)	(-2.72)		(-8.79)	(-7.55)		(-6.31)	(-4.62)
Intercept	-0.067	-0.071	-0.061	-0.005	-0.005	-0.004	-0.003	-0.003	-0.002
	(-3.62)	(-3.89)	(-3.26)	(-5.90)	(-6.31)	(-4.51)	(-3.09)	(-3.48)	(-2.18)
Observations	170,832	177,831	170,747	170,832	177,831	170,747	170,832	177,831	170,747
Average CS R^2	0.005	0.003	0.006	0.007	0.007	0.009	0.006	0.005	0.008

Table 3: Robustness Checks: Control for Option Return Predictors

This table reports the results of Fama-MacBeth regressions including controls. Holdings of Mutual Fund (Institution) is the share proportion of a firm owned by mutual funds (13f institutions). IVOL is the idiosyncratic volatility of stock return. HV-VIX is the difference between historical volatility and equity VIX. IV Term Spread is the difference between long- and short-term implied volatilities. RN Skew is the risk-neutral skewness of stock return, estimated from a portfolio of OTM options. Beta is the coefficient of regressing past year daily excess stock returns on excess market returns. Ln(ME) is the natural logarithm of the market equity of a firm. Ln(BM) is the natural logarithm of book-to-market ratio. $RET_{t-1,t}$ is the past-month return of the underlying stock. $RET_{t-12,t-1}$ is the return of the underlying stock during past 11 months ending at the previous month. Amihud is the Amihud illiquidity measure. Option Bid-Ask Spread is the percentage bid-ask spread of the option portfolio. To test the information channel, I use two additional dependent variables: $r^{Stock}_{i,t+1}$ is the one-month-ahead return of the underlying stock; $RV^{Stock}_{i,t+1}$ is the one-month-ahead realized variance of the underlying stock return. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags. The sample period is from January 1996 to December 2019.

		$r^{VIX}_{i,t+1}$		$r^{Put}_{i,t+1}$	$r^{Call}_{i,t+1}$	$r^{Stock}_{i,t+1}$	$RV^{Stock}_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HHI Mutual Fund	-0.157		-0.154	-0.015	-0.014	-0.004	0.000
	(-5.61)		(-4.46)	(-6.15)	(-5.59)	(-0.68)	(0.24)
HHI Institution		-0.138	-0.050	-0.013	-0.006	-0.019	-0.002
		(-2.89)	(-0.86)	(-3.30)	(-1.28)	(-1.73)	(-0.73)
Holdings of Mutual Fund	0.159		0.151	0.015	0.015	0.011	-0.004
	(2.40)		(1.97)	(3.25)	(3.24)	(0.97)	(-1.01)
Holdings of Institution		0.032	0.008	0.002	0.000	-0.002	-0.004
		(2.07)	(0.38)	(1.82)	(0.27)	(-0.41)	(-3.94)
IVOL	-1.929	-1.929	-1.961	-0.202	-0.179	-0.145	0.337
	(-5.53)	(-5.50)	(-5.52)	(-7.36)	(-6.42)	(-2.60)	(10.36)
HV-VIX	0.215	0.214	0.217	0.015	0.015	-0.005	-0.002
	(8.47)	(8.38)	(8.53)	(8.63)	(8.74)	(-1.36)	(-2.09)
IV Term Spread	0.231	0.239	0.226	0.053	0.060	0.007	-0.094
	(3.68)	(3.84)	(3.58)	(10.29)	(9.03)	(0.62)	(-9.96)
RN Skew	0.039	0.038	0.039	0.002	-0.002	0.005	0.001
	(4.07)	(3.93)	(4.03)	(3.49)	(-3.29)	(3.94)	(3.05)
Beta	0.028	0.031	0.029	0.001	0.001	-0.001	0.010
	(2.94)	(3.33)	(3.04)	(1.47)	(1.18)	(-0.39)	(9.79)
Ln(ME)	-0.004	-0.002	-0.005	0.001	0.000	-0.000	-0.003
	(-0.87)	(-0.50)	(-1.05)	(2.30)	(0.74)	(-0.59)	(-11.35)
Ln(BM)	0.004	0.003	0.003	0.001	0.001	0.000	-0.002
	(1.37)	(0.83)	(1.00)	(3.69)	(3.50)	(0.08)	(-9.44)
$RET_{t-1,t}$	-0.085	-0.086	-0.086	-0.008	-0.004	-0.004	-0.013
	(-2.49)	(-2.46)	(-2.47)	(-2.76)	(-1.28)	(-0.51)	(-4.39)
$RET_{t-12,t-1}$	0.021	0.021	0.019	0.001	0.000	0.007	-0.000
	(1.77)	(1.81)	(1.65)	(1.55)	(0.47)	(2.35)	(-0.27)
Amihud	-1.809	-2.589	-1.885	-0.487	-0.361	-0.610	0.553
	(-1.20)	(-1.87)	(-1.28)	(-3.58)	(-2.69)	(-2.31)	(4.53)
Option Bid-Ask Spread	-0.021	-0.023	-0.027	-0.001	0.000	0.005	-0.006
	(-0.62)	(-0.71)	(-0.81)	(-0.33)	(0.16)	(0.95)	(-5.63)
Intercept	-0.000	-0.049	0.014	-0.011	-0.005	0.020	0.040
	(-0.00)	(-0.64)	(0.18)	(-2.59)	(-1.01)	(1.66)	(9.33)
Observations	150,062	151,853	150,013	150,013	150,013	150,013	150,013
Average CS R^2	0.046	0.046	0.046	0.086	0.090	0.109	0.305

Table 4: HHI: Funds with Different Option Positions

This table reports the results of Fama-MacBeth regressions in which I use HHI to predict one-month-ahead r^{VIX}. I construct HHI using stock holdings of funds under different categories, classified by their option holdings, in the Morningstar dataset. HHI MStar is constructed using all U.S. equity funds in the Morningstar dataset. HHI Option Fund is constructed using only funds that used equity options during the sample period. HHI Put Fund is constructed using funds that used puts. HHI Call Fund is constructed using funds that only used calls and never used 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. HHI Protective Put is constructed using funds that used protective put strategy during the sample period. HHI Naked Put is constructed using funds that used naked put strategy during the sample period. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags. The sample period is from January 1996 to September 2015.

	(1)	(2)	(3)	(4)	(5)	(6)
HHI MStar		-0.055				
		(-2.02)				
HHI Option Fund	-0.069	-0.052	0.019	-0.099		
	(-3.54)	(-3.10)	(0.87)	(-5.78)		
HHI Put Fund			-0.098			
			(-5.25)			
HHI Call Fund				0.027		
				(1.79)		
HHI Put Long					-0.082	
					(-5.42)	
HHI Put Short					-0.014	
					(-0.89)	
HHI Call Long					-0.003	
					(-0.28)	
HHI Call Short					0.014	
					(1.04)	
HHI Protective Put						-0.066
						(-4.59)
HHI Naked Put						-0.018
						(-1.39)
Intercept	-0.060	-0.058	-0.044	-0.060	-0.029	-0.028
	(-2.74)	(-2.63)	(-1.83)	(-2.66)	(-0.91)	(-0.92)
Observations	123,258	123,017	121,540	119,397	97,410	107,546
Average CS R^2	0.005	0.006	0.006	0.005	0.008	0.006

Table 5: Over- v.s. Under-weighted HHI

This table reports the results of Fama-MacBeth regressions in which I use HHI, constructed using stock holdings of funds in the Morningstar dataset, to predict one-month-ahead option returns. HHI Overweight (Underweight) is constructed using the holdings of funds that overweight (underweight) the firm relative to their self-declared benchmarks. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags. The sample period is from January 1996 to September 2015.

	$r^{VIX}_{i,t+1}$		$r^{Put}_{i,t+1}$		$r^{Call}_{i,t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
HHI MStar	-0.099		-0.013		-0.010	
	(-3.59)		(-6.10)		(-4.60)	
HHI Overweight		-0.268		-0.036		-0.027
		(-4.73)		(-9.69)		(-5.80)
HHI Underweight		0.002		-0.003		-0.002
		(0.07)		(-2.01)		(-1.06)
Intercept	-0.068	-0.087	-0.007	-0.004	-0.004	-0.003
	(-3.28)	(-3.36)	(-6.90)	(-3.54)	(-3.93)	(-2.63)
Observations	126,558	75,803	126,558	75,803	126,558	75,803
Average CS R^2	0.006	0.006	0.007	0.013	0.006	0.012

Table 6: Option Price Impact

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

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

$r_{i,t+1}$ is firm i's one-month-ahead option return. I use S12 database to construct HHI. Control variables include those in Column (1) of Table 3. The first row reports the coefficients of HHI among three sub-periods ranked by TED spread. In the next three rows, I sort firms by three stock characteristics associated with option unhedgeable risks: To proxy for stochastic volatility, I estimate the EGARCH(1,1) model for stock return and calculate the volatility of fitted volatilities; I use the kurtosis of underlying stock returns to proxy for jump risk; to measure delta hedging cost, I use the ratio of the stock return variance uncorrelated with the market to the average dollar trading volume. All three variables are estimated using past-one-year daily stock returns on the third Friday of each month. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags. The sample period is from January 1996 to December 2019.

	$r^{VIX}_{i,t+1}$			$r^{Put}_{i,t+1}$			$r^{Call}_{i,t+1}$		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
TED spread	-0.080	-0.167	-0.222	-0.010	-0.019	-0.026	-0.007	-0.015	-0.018
	(-2.16)	(-3.01)	(-4.62)	(-4.04)	(-5.17)	(-6.18)	(-2.66)	(-4.44)	(-4.24)
Stochastic Volatility	-0.132	-0.211	-0.134	-0.006	-0.016	-0.020	-0.002	-0.015	-0.014
	(-1.84)	(-3.03)	(-3.16)	(-1.80)	(-4.21)	(-6.09)	(-0.57)	(-3.91)	(-3.94)
Jump Risk	-0.063	-0.170	-0.246	-0.008	-0.019	-0.027	-0.006	-0.010	-0.023
	(-1.19)	(-2.57)	(-4.72)	(-1.95)	(-4.87)	(-6.04)	(-1.53)	(-2.23)	(-5.27)
Delta Hedging Cost	-0.100	-0.165	-0.133	-0.003	-0.011	-0.020	-0.001	-0.007	-0.015
	(-0.88)	(-2.75)	(-3.46)	(-0.65)	(-3.27)	(-6.26)	(-0.10)	(-2.16)	(-4.74)

Table 7: Dispersion of Fund Sizes

This table examines how the dispersion of sizes among mutual funds that hold the firm could affect the option return predictability of HHI. I restrict the sample to firms held by at least five mutual funds in a quarter and use S12 to construct HHI. In Panel A, I first sort firms into three subgroups each month by the kurtosis of their fund holders' total net assets. Then I run the Fama-MacBeth regression, $r_{i,t+1} = \alpha_t + \gamma_t HHI_{i,t} + \theta_t Controls_{i,t} + \epsilon_{i,t+1}$, among each subgroup and report the coefficient of HHI. In Panel B, I run the same Fama-MacBeth regression using the whole sample of firms, controlling for option return predictors in Column (1) of Table 3. To construct *HHI Truncated* for a firm, I delete the highest quintile of its fund holders ranked by their asset sizes. *T*-statistics, in parentheses, are computed using Newey-West standard errors with three lags. The sample period is from January 1996 to December 2019.

Panel A: Sort by kurtosis of fund sizes.

	Low	Medium	High
$r^{VIX}_{i,t+1}$	-0.107	-0.303	-0.384
	(-2.41)	(-2.61)	(-2.34)
$r^{Put}_{i,t+1}$	-0.016	-0.020	-0.009
	(-4.98)	(-2.53)	(-1.12)
$r^{Call}_{i,t+1}$	-0.010	-0.016	-0.005
	(-3.37)	(-2.15)	(-0.58)

Panel B: Truncated HHI.

	$r^{VIX}_{i,t+1}$			$r^{Put}_{i,t+1}$			$r^{Call}_{i,t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HHI Non-Truncated	-0.144		-0.044	-0.018		-0.007	-0.012		-0.008
	(-4.17)		(-1.09)	(-7.79)		(-2.42)	(-5.43)		(-2.55)
HHI Truncated		-0.144	-0.134		-0.020	-0.016		-0.011	-0.006
		(-3.08)	(-2.62)		(-6.93)	(-4.73)		(-4.26)	(-1.65)
Intercept	-0.002	-0.062	-0.049	-0.012	-0.015	-0.013	-0.006	-0.010	-0.008
	(-0.03)	(-0.73)	(-0.56)	(-2.67)	(-3.07)	(-2.59)	(-1.40)	(-2.02)	(-1.49)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	149,663	149,663	149,663	149,663	149,663	149,663	149,663	149,663	149,663
Average CS R^2	0.046	0.047	0.047	0.085	0.086	0.087	0.088	0.089	0.090

Table 8: Strategy Performance

This table reports monthly average returns (in percentage) of long-short strategies sorted by −HHI and also examines the impact of option bid-ask spreads. In Panel A, I sort firms into quintiles based on −HHI Mutual Fund on every third Friday and equally weight firms within each quintile. Alpha is the risk-adjusted return of the long-short strategy. It is adjusted for Fama and French five factors, stock momentum, and the S&P 500 Index VIX return in excess of risk-free rate. Monthly Sharpe Ratio is also reported. In Panel B, I examine the impact of option bid-ask spreads by comparing the long-short strategy returns computed from the midpoint price (MidP) with those computed from the effective bid-ask spread (ESPR), estimated to be 25%, 50%, 75%, and 100% of the quoted spread (QSPR). I use more extreme deciles rather than quintiles sort in this panel. I calculate returns in "Low Bid-Ask Spread" columns using firms with percentage bid-ask spreads lower than the median of that month. I calculate returns in "All" columns using all firms in that month. T-statistics are in parentheses. The sample period is from January 1996 to December 2019.

Panel A: Quintile sort by $-HHI$.

	1	2	3	4	5	5-1	Alpha	Sharpe Ratio
r^{VIX}	-12.60	-9.78	-8.04	-7.34	-5.74	6.85	6.87	0.40
						(6.83)	(6.40)	
r^{Put}	-1.36	-0.94	-0.69	-0.55	-0.39	0.97	0.92	1.00
						(16.93)	(14.79)	
r^{Call}	-0.92	-0.65	-0.43	-0.33	-0.19	0.73	0.69	0.67
						(11.38)	(9.82)	

Panel B: Decile sort after bid-ask spreads

	All					Low Bid-Ask Spread				
		ESPR/QSPR					ESPR/QSPR			
	MidP	25%	50%	75%	100%	MidP	25%	50%	75%	100%
r^{VIX}	7.67	2.12	-3.83	-10.43	-18.52	7.23	4.14	1.04	-2.10	-5.27
	(5.35)	(1.44)	(-2.49)	(-6.29)	(-9.86)	(5.17)	(3.00)	(0.76)	(-1.54)	(-3.87)
r^{Put}	1.11	0.82	0.52	0.23	-0.07	1.11	0.96	0.81	0.66	0.52
	(14.48)	(10.88)	(7.06)	(3.07)	(-1.02)	(11.81)	(10.38)	(8.90)	(7.37)	(5.79)
r^{Call}	0.82	0.51	0.20	-0.11	-0.41	0.85	0.68	0.52	0.36	0.19
	(9.87)	(6.28)	(2.53)	(-1.34)	(-5.25)	(8.36)	(6.84)	(5.28)	(3.66)	(2.01)

Table 9: Double Sort: Firm Size and Share Proportion

This table reports monthly return means (in percentage) and t-statistics from sequential double sorts on r^{VIX}. In Panel A (B), I first sort firms into quintiles based on firm size (share proportion of the firm held by mutual funds), and then further sort each quintile by −HHI Mutual Fund. Firms are equally weighted. The sample period is from January 1996 to December 2019.

Panel A: Control for firm size.

	$-HHI$						
Size	1(Low)	2	3	4	5(High)	5-1	t-statistics
Low	-14.98	-14.37	-10.97	-8.51	-5.92	9.06	(4.85)
2	-12.10	-9.72	-8.02	-7.18	-5.27	6.83	(3.99)
3	-12.14	-10.47	-8.43	-7.80	-6.60	5.54	(3.33)
4	-9.74	-9.62	-8.92	-7.90	-5.28	4.46	(3.29)
High	-9.63	-6.91	-5.38	-7.78	-3.96	5.67	(3.61)

Panel B: Control for share proportion.

	$-HHI$						
Holdings of Mutual Fund	1(Low)	2	3	4	5(High)	5-1	t-statistics
Low	-14.77	-12.46	-10.53	-8.84	-8.63	6.14	(3.67)
2	-11.96	-9.46	-8.64	-10.66	-5.81	6.15	(3.74)
3	-12.51	-10.46	-9.12	-7.10	-6.43	6.08	(3.53)
4	-10.35	-9.11	-6.92	-5.35	-3.06	7.29	(4.34)
High	-11.18	-6.79	-7.65	-4.03	-6.72	4.46	(3.45)

Table 10: Breadth of Ownership and Short Interest

This table reports the results from monthly Fama-MacBeth regressions in which I control for short interest and the level and change of breadth of mutual fund ownership, together with other controls. Breadth is the breadth of mutual fund ownership as in Chen, Hong, and Stein (2002). $\Delta Breadth$ is the change in breadth. Short Interest is a firm's number of stock shares that are held short, normalized by its total shares outstanding. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags. The sample period is from January 1996 to December 2019.

	$r_{i,t+1}^{VIX}$		$r_{i,t+1}^{Put}$		$r_{i,t+1}^{Call}$	
	(1)	(2)	(3)	(4)	(5)	(6)
HHI Mutual Fund	-0.157	-0.155	-0.018	-0.017	-0.013	-0.012
	(-5.61)	(-3.60)	(-8.45)	(-7.27)	(-6.49)	(-5.41)
Breadth		0.162		-0.006		-0.015
		(0.90)		(-0.63)		(-1.53)
$\Delta Breadth$		3.134		0.101		0.120
		(2.40)		(1.55)		(1.83)
Short Interest		-0.060		-0.021		0.000
		(-0.87)		(-4.59)		(0.07)
Holdings of Mutual Fund	0.159	0.188	0.019	0.019	0.014	0.013
	(2.40)	(2.02)	(4.93)	(4.08)	(3.83)	(2.56)
IVOL	-1.929	-1.482	-0.206	-0.184	-0.180	-0.183
	(-5.53)	(-3.12)	(-7.59)	(-5.88)	(-6.53)	(-6.21)
HV-VIX	0.215	0.223	0.015	0.014	0.015	0.014
	(8.47)	(8.67)	(8.69)	(8.47)	(8.89)	(8.37)
IV Term Spread	0.231	0.264	0.052	0.050	0.059	0.059
	(3.68)	(3.72)	(10.23)	(9.02)	(9.02)	(8.52)
RN Skew	0.039	0.035	0.002	0.002	-0.002	-0.001
	(4.07)	(3.07)	(3.53)	(3.36)	(-3.32)	(-2.07)
Beta	0.028	0.027	0.001	0.001	0.001	0.001
	(2.94)	(2.34)	(1.36)	(0.77)	(1.09)	(0.80)
Ln(ME)	-0.004	-0.008	0.001	0.000	0.000	0.001
	(-0.87)	(-0.94)	(2.29)	(0.59)	(0.97)	(1.52)
Ln(BM)	0.004	0.002	0.001	0.001	0.001	0.001
	(1.37)	(0.41)	(3.40)	(3.72)	(3.66)	(3.17)
$RET_{t-1,t}$	-0.085	-0.089	-0.008	-0.009	-0.004	-0.005
	(-2.49)	(-2.36)	(-2.78)	(-3.19)	(-1.29)	(-1.78)
$RET_{t-1,t}$	0.021	0.006	0.001	-0.000	0.000	-0.000
	(1.77)	(0.46)	(1.58)	(-0.03)	(0.48)	(-0.30)
Amihud	-1.809	-1.627	-0.516	-0.679	-0.356	-0.328
	(-1.20)	(-0.96)	(-3.79)	(-4.76)	(-2.65)	(-2.18)
Option Bid-Ask Spread	-0.021	-0.041	-0.000	-0.004	0.001	-0.001
	(-0.62)	(-0.97)	(-0.16)	(-1.62)	(0.29)	(-0.29)
Intercept	-0.000	0.034	-0.011	-0.004	-0.006	-0.010
	(-0.00)	(0.28)	(-2.51)	(-0.78)	(-1.27)	(-1.75)
Observations	150,062	132,008	150,062	132,008	150,062	132,008
Average CS R^2	0.046	0.057	0.085	0.103	0.089	0.111

Appendices

A VIX Portfolio

This section follows Heston and Li (2020) and proves that the payoff of VIX portfolio approximates the realized variance of the underlying stock return.

Equation (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 the realized variance 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, the terminal payoff of this idealized 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 rate 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 the 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 the stock return.

We can further reduce risk of the idealized VIX portfolio by using a daily hedge instead of the static hedge just at time t. We replace the second term of (A2) with a daily delta hedge of the log-portfolio. Due to the special case of log-payoff, its delta is model-free and equals $\frac{1}{S(t)}$.

Thus, to delta hedge the log-portfolio at daily frequency, investors only need to buy $\frac{1}{S(t)}$ shares of the stock, i.e. invest \$1 in the stock, and rebalance the hedging position each day. The payoff of this daily-hedged idealized VIX portfolio equals

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

We can further rewrite (A3) to express the log-payoff in terms of a telescoping series of daily stock returns 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 return and risk-free rate 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 the stock return over time t to T defined as the sum of squared daily returns:

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

Since r_f is very small, the last approximation holds tightly. Combine Equation (A2) and (A5), it is obvious that the numerator in Equation (2) approximates the realized variance.

B Variable Construction

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

- Holdings of Mutual Fund: The share proportion of a firm owned by mutual funds, calculated using the S12 database.

- Holdings of Institution: The share proportion of a firm owned by 13f institutions, calculated using the S34 database.
- IVOL: Idiosyncratic volatility of the stock return, estimated from Fama-French 3 factors using rolling one-month daily returns, following Ang, Hodrick, Xing, and Zhang (2006).
- HV-VIX: The difference between historical volatility, estimated using rolling one-year daily stock returns, and equity VIX. It is similar to the volatility deviation measure in Goyal and Saretto (2009).
- IV Term Spread: The difference between long- and short-term implied volatilities. Following Vasquez (2017), I use the average of ATM put- and call-implied volatilities. I use the options with the maturity closest to 30 days for short-term and those with the longest maturity and the same strike for long-term.
- RN Skew: Risk-neutral skewness of the stock return, estimated from a portfolio of OTM options following Bakshi, Kapadia, and Madan (2003).
- Beta: The coefficient of regressing past year daily excess stock returns on excess market returns.
- Ln(ME): Firm size, measured as the natural logarithm of the market equity for June of year t following Fama and French (1992).
- Ln(BM): Value, measured as the natural logarithm of book equity for the fiscal year-end of a calendar year divided by market equity at the end of December of that year, as in Fama and French (1992).
- $RET_{t-1,t}$: Short-term stock return reversal, calculated as the cumulative stock return from the start of a month to the third Friday of the same month.

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

- Amihud: Amihud illiquidity measure (Amihud (2002)), calculated using the past 30-days daily data and multiplied by 10^6 to adjust the scale.

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

- Breadth: The breadth of mutual fund ownership in Chen, Hong, and Stein (2002). It is the ratio of the number of mutual funds that long the stock to the total number of mutual funds in that quarter.

- $\Delta Breadth$: Change in the breadth of mutual fund ownership from the previous quarter.

- Short Interest: The firm's number of stock shares that are held short, normalized by its shares outstanding.

Table A1: Complementary Summary Statistics

This table presents complementary summary statistics for variables used in this paper. Panel A reports the statistics for all control variables. Panel B presents the statistics for HHI constructed using different subsets of mutual funds.

	Observation	Mean	Std.	P10	Median	P90
Panel A: Control Variables.						
Holdings of Mutual Fund	170,728	0.088	0.098	0.001	0.042	0.237
Holdings of Institution	177,726	0.691	0.271	0.242	0.766	0.995
IVOL	199,648	0.021	0.017	0.007	0.016	0.039
HV-VIX	199,648	0.125	0.272	-0.199	0.130	0.442
IV Term Spread	199,648	-0.025	0.093	-0.122	-0.008	0.056
RN Skew	196,849	-0.522	0.329	-0.937	-0.504	-0.130
Beta	199,648	1.218	0.655	0.622	1.158	1.946
Ln(ME)	196,631	15.065	1.631	13.061	15.019	17.193
Ln(BM)	174,028	-1.160	1.150	-2.459	-1.135	0.013
$RET_{t-1,t}$	199,648	0.014	0.114	-0.104	0.015	0.130
$RET_{t-12,t-1}$	199,393	0.127	0.474	-0.405	0.128	0.642
Amihud	199,648	0.002	0.014	0.000	0.000	0.004
Option Bid-Ask Spread	199,648	0.270	0.194	0.085	0.226	0.497
Call Bid-Ask Spread	199,648	0.131	0.126	0.033	0.100	0.250
Put Bid-Ask Spread	199,648	0.151	0.154	0.035	0.111	0.295
Breadth	169,566	0.027	0.030	0.004	0.016	0.060
$\Delta Breadth$	169,566	0.001	0.004	-0.002	0.000	0.003
Short Interest	174,561	0.075	0.097	0.010	0.043	0.173
Panel B: HHI Different Versions.						
HHI MStar	126,558	0.144	0.208	0.030	0.066	0.343
HHI Overweight	101,427	0.162	0.214	0.037	0.083	0.381
HHI Underweight	75,822	0.195	0.122	0.102	0.172	0.285
HHI Option Fund	123,258	0.297	0.253	0.084	0.201	0.699
HHI Put Fund	121,860	0.428	0.284	0.131	0.339	0.986
HHI Call Fund	119,910	0.400	0.281	0.122	0.303	0.957
HHI Put Long	121,131	0.462	0.291	0.145	0.376	1.000
HHI Put Short	102,394	0.778	0.256	0.383	0.921	1.000
HHI Call Long	116,754	0.593	0.265	0.266	0.538	1.000
HHI Call Short	116,481	0.460	0.310	0.138	0.355	1.000
HHI Protective Put	115,767	0.566	0.313	0.187	0.502	1.000
HHI Naked Put	111,644	0.771	0.257	0.381	0.900	1.000
HHI Non-Truncated	168,459	0.121	0.144	0.024	0.064	0.301
HHI Truncated	168,459	0.108	0.152	0.013	0.049	0.284

Table A2: HHI of Different Fund Categories with Controls

This table provides robustness checks for the results in Table 4 by including a list of controls.

	(1)	(2)	(3)	(4)	(5)	(6)
HHI MStar		-0.021				
		(-0.72)				
HHI Option Fund	-0.059	-0.059	-0.003	-0.083		
	(-3.60)	(-3.36)	(-0.17)	(-4.28)		
HHI Put Fund			-0.069			
			(-4.03)			
HHI Call Fund				0.017		
				(1.14)		
HHI Put Long					-0.069	
					(-4.71)	
HHI Put Short					-0.042	
					(-3.00)	
HHI Call Long					-0.021	
					(-1.43)	
HHI Call Short					0.011	
					(0.91)	
HHI Protective Put						-0.054
						(-3.94)
HHI Naked Put						0.002
						(0.16)
Holdings of Mutual Fund	0.130	0.133	0.119	0.126	0.080	0.120
	(1.89)	(1.97)	(1.74)	(1.82)	(1.11)	(1.84)
IVOL	-1.691	-1.638	-1.657	-1.729	-1.624	-1.841
	(-4.34)	(-4.23)	(-4.14)	(-4.40)	(-3.62)	(-4.54)
HV-VIX	0.230	0.231	0.232	0.226	0.258	0.232
	(7.60)	(7.64)	(7.54)	(7.31)	(7.23)	(7.68)
IV Term Spread	0.291	0.296	0.293	0.325	0.347	0.290
	(4.06)	(4.14)	(4.04)	(4.60)	(3.83)	(3.70)
RN Skew	0.039	0.040	0.038	0.038	0.045	0.037
	(3.51)	(3.55)	(3.35)	(3.35)	(3.95)	(3.26)
Beta	0.034	0.035	0.034	0.036	0.034	0.036
	(3.20)	(3.24)	(3.15)	(3.32)	(2.68)	(3.12)
Ln(ME)	-0.001	-0.002	-0.003	-0.003	-0.012	-0.004
	(-0.20)	(-0.26)	(-0.56)	(-0.54)	(-1.78)	(-0.54)
Ln(BM)	0.005	0.005	0.006	0.003	0.001	0.004
	(1.30)	(1.38)	(1.69)	(0.70)	(0.27)	(1.12)
$RET_{t-1,t}$	-0.082	-0.086	-0.085	-0.096	-0.085	-0.074
	(-2.14)	(-2.20)	(-2.15)	(-2.45)	(-1.90)	(-1.89)
$RET_{t-12,t-1}$	0.040	0.040	0.039	0.041	0.043	0.043
	(3.47)	(3.47)	(3.44)	(3.48)	(3.16)	(3.33)
Amihud	-2.581	-2.481	-1.601	-2.127	-0.114	-2.222
	(-1.40)	(-1.31)	(-0.85)	(-1.20)	(-0.05)	(-1.15)
Option Bid-Ask Spread	0.033	0.031	0.034	0.029	0.035	0.023
	(0.88)	(0.83)	(0.88)	(0.76)	(0.76)	(0.60)
Intercept	-0.074	-0.065	-0.027	-0.045	0.151	-0.023
	(-0.80)	(-0.70)	(-0.28)	(-0.48)	(1.31)	(-0.22)
Observations	107,643	107,607	106,889	106,138	89,681	97,107
Average CS R^2	0.050	0.050	0.050	0.051	0.058	0.052

Table A3: **Over- v.s. Under-weighted HHI with Controls**

This table provides robustness checks for the results in Table 5 by including a list of controls.

	$r_{i,t+1}^{VIX}$		$r_{i,t+1}^{Put}$		$r_{i,t+1}^{Call}$	
	(1)	(2)	(3)	(4)	(5)	(6)
HHI MStar	-0.074		-0.010		-0.008	
	(-2.91)		(-5.91)		(-4.37)	
HHI Overweight		-0.202		-0.018		-0.013
		(-3.22)		(-4.32)		(-2.87)
HHI Underweight		-0.012		0.000		0.001
		(-0.38)		(0.02)		(0.55)
Holdings of Mutual Fund	0.157	-0.345	0.016	-0.019	0.013	0.014
	(2.33)	(-0.58)	(4.12)	(-0.49)	(3.09)	(0.59)
IVOL	-1.629	-2.068	-0.184	-0.201	-0.157	-0.185
	(-4.20)	(-4.09)	(-5.85)	(-6.53)	(-4.91)	(-5.29)
HV-VIX	0.229	0.117	0.017	0.010	0.017	0.010
	(7.59)	(4.47)	(8.50)	(4.97)	(8.33)	(4.85)
IV Term Spread	0.300	0.319	0.056	0.048	0.063	0.052
	(4.21)	(3.15)	(9.86)	(6.72)	(9.20)	(5.72)
RN Skew	0.039	0.039	0.002	0.001	-0.002	-0.001
	(3.46)	(3.11)	(2.94)	(1.13)	(-2.72)	(-1.56)
Beta	0.036	0.046	0.001	0.001	0.001	0.001
	(3.36)	(3.72)	(1.75)	(1.66)	(1.37)	(1.29)
Ln(ME)	0.001	-0.004	0.001	0.000	0.001	0.000
	(0.17)	(-0.49)	(3.37)	(1.37)	(2.15)	(0.64)
Ln(BM)	0.006	0.001	0.001	0.001	0.001	0.001
	(1.62)	(0.27)	(3.54)	(1.55)	(3.78)	(1.53)
$RET_{t-1,t}$	-0.081	-0.085	-0.008	-0.008	-0.003	-0.006
	(-2.10)	(-1.63)	(-2.32)	(-2.31)	(-0.93)	(-1.40)
$RET_{t-12,t-1}$	0.041	0.031	0.002	0.002	0.001	0.001
	(3.53)	(2.17)	(2.40)	(1.81)	(1.41)	(0.53)
Amihud	-2.718	2.990	-0.525	-0.222	-0.382	-0.073
	(-1.52)	(0.93)	(-3.34)	(-0.88)	(-2.51)	(-0.29)
Option Bid-Ask Spread	0.032	-0.009	0.002	-0.002	0.004	-0.002
	(0.86)	(-0.20)	(0.66)	(-0.69)	(1.27)	(-0.51)
Intercept	-0.117	-0.039	-0.020	-0.011	-0.014	-0.007
	(-1.29)	(-0.31)	(-3.83)	(-1.69)	(-2.57)	(-1.05)
Observations	108,181	71,645	108,181	71,645	108,181	71,645
Average CS R^2	0.051	0.048	0.089	0.089	0.091	0.096

Table A4: Share Proportion Overweighted by Mutual Funds

This table checks the option return predictability for the share proportion of a firm overweighted by its mutual fund holders relative to their benchmarks. I calculate the variable "Proportion Overweight" as follows: For a given stock, I calculate the dollar amount each fund holder invests in the stock in excess of its own benchmark. Then I sum across funds and scale the summation by the market cap of the stock.

	$r^{VIX}_{i,t+1}$		$r^{Put}_{i,t+1}$		$r^{Call}_{i,t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Proportion Overweight	0.068	0.082	0.011	0.004	0.007	0.006
	(0.82)	(1.02)	(3.90)	(0.80)	(2.63)	(1.21)
HHI Overweight		-0.200		-0.019		-0.015
		(-3.23)		(-4.43)		(-3.38)
HHI Underweight		-0.026		-0.001		0.000
		(-0.71)		(-0.37)		(0.11)
Holdings of Mutual Fund		-0.163		-0.020		0.013
		(-0.43)		(-0.64)		(0.58)
IVOL		-1.745		-0.190		-0.166
		(-3.12)		(-5.95)		(-4.56)
HV-VIX		0.135		0.010		0.010
		(5.24)		(4.91)		(4.66)
IV Term Spread		0.298		0.046		0.051
		(2.81)		(5.93)		(5.42)
RN Skew		0.041		0.001		-0.001
		(3.05)		(0.94)		(-1.55)
Beta		0.040		0.001		0.001
		(3.22)		(1.31)		(0.99)
Ln(ME)		-0.001		0.001		0.000
		(-0.10)		(1.75)		(1.06)
Ln(BM)		0.000		0.000		0.000
		(0.05)		(1.37)		(1.16)
$RET_{t-1,t}$		-0.109		-0.009		-0.007
		(-2.00)		(-2.43)		(-1.60)
$RET_{t-12,t-1}$		0.031		0.002		0.000
		(2.02)		(1.69)		(0.36)
Amihud		4.409		-0.234		-0.062
		(1.43)		(-0.92)		(-0.23)
Option Bid-Ask Spread		-0.019		-0.002		-0.003
		(-0.44)		(-0.43		(-0.81)
Intercept	-0.114	-0.088	-0.010	-0.014	-0.007	-0.009
	(-3.50)	(-0.74)	(-8.48)	(-1.99)	(-6.01)	(-1.38)
Observations	90,556	63,339	90,556	63,339	90,556	63,339
Average CS R^2	0.007	0.054	0.004	0.098	0.004	0.104