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The Only Constant Is Change: Nonconstant Volatility and Implied Volatility Spreads

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Abstract

We examine the predictability of stock returns using implied volatility spreads (VS) from individual (nonindex) options. VS can occur under simple no-arbitrage conditions for American options when volatility is time-varying, suggesting that the VS-return predictability could be an artifact of firms' sensitivities to aggregate volatility. Examining this empirically, we find that the predictability changes systematically with aggregate volatility and is positively related to the firms' sensitivities to volatility risk. The alpha generated by VS hedge portfolios can be explained by aggregate volatility risk factors. Our results cannot be explained by firm-specific informed trading, transaction costs, or liquidity.

I. Introduction

An interesting feature of option pricing models is the ability to use an option's current market price to invert the model and calculate the option's implied volatility, or the volatility needed to generate the market price, as a measure of the market's estimate of the underlying asset's future volatility. Recent analysis suggests that implied volatilities may contain additional information about the underlying asset. Perhaps most interestingly, volatility spreads (VS) and smirks (differences between the implied volatilities of call and put options[1]) have been shown to

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[1]Volatility spreads are defined as the difference in implied volatility between a matched call and put option with the same underlying security, exercise price, and maturity. Volatility smirks are defined as the difference in implied volatility between an at-the-money call option and an out-of-the-money put option with the same underlying security and maturity.

predict the near-term returns to the underlying assets. For example, Cremers and Weinbaum (2010) show that VS positively predict individual stock returns over the following month.

Why do VS predict underlying stock returns? A popular explanation is that informed investors, attempting to exploit temporary inefficiencies or new firm-specific information, choose to trade first in option markets (Easley, O'Hara, and Srinivas (1998)) which creates demand pressure that temporarily moves option prices away from put-call parity and generates VS that predict stock returns (Amin and Lee (1997), Cao, Chen, and Griffin (2005), Pan and Poteshman (2006), Cremers and Weinbaum (2010), and Atilgan (2014)). Cremers and Weinbaum (2010) find that the VS-return predictability appears to decrease over time, consistent with the idea of informed investors taking advantage of temporary market inefficiencies. We offer an alternative explanation: VS proxy in part for aggregate volatility risk, which impacts the future returns to the underlying stocks and generates predictability.

We propose that the link between VS and aggregate volatility stems from a standard assumption used when calculating implied volatilities: constant volatility of the underlying asset's price process. For instance, a popular measure of implied volatilities comes from Option Metrics and is based on a Cox, Ross, and Rubinstein (1979) (CRR) binomial tree method to value American options. This is used in place of the Black and Scholes (BS) (1973) model to allow for an early exercise premium. Like the BS model, the CRR method assumes constant volatility throughout the option's life. If this is correct, VS should not exist in the absence of market frictions or a violation of put-call parity, consistent with the informed trading explanation suggested in prior works. On the other hand, we show that VS can exist under the simple no-arbitrage conditions of the CRR model when volatility is time-varying, despite the option prices remaining within the bounds of put-call parity.[2]

We compute prices of matched call and put options under no-arbitrage conditions in a simple 3-period framework, allowing the underlying stock's volatility to be dependent on the up or down move of the stock price. Confirming that the resulting options prices do not violate parity conditions, we take these as the true market prices and solve iteratively for the implied volatilities under the standard assumption of constant volatility. We find two interesting results. First, it can be optimal to exercise the put option under the constant volatility assumption when the option is held to maturity under time-varying volatility or vice versa. Second, differences in optimal early exercise between the constant and time-varying volatility cases and between the call and put options lead to a spread between the implied volatilities of the matched call and put. In other words, VS can exist without violating put-call parity, and the spreads are related to the time-varying nature of the underlying asset's volatility. To our knowledge, we are the first to document this result.

[2]Cremers and Weinbaum (2010) discuss the possibility of nonzero volatility spreads being driven by early exercise, but do not explore the implications of time-varying volatility. Instead, they explore how skewness in underlying returns might impact volatility spreads and control for the effects of skewness in their tests.

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Our option pricing examples focus on the underlying asset's total volatility and require no assumption for the source of the volatility. However, it is straightforward to argue that VS will be affected by aggregate volatility and the underlying stock's sensitivity to it. Consistent with this, prior evidence suggests that option prices and implied volatilities are partially driven by systematic risk (Bates (1991), Dennis, Mayhew, and Stivers (2006), and Xing, Zhang, and Zhao (2010)). Furthermore, aggregate volatility risk is priced in the cross section and relevant for explaining stock returns (Ang, Hodrick, Xing, and Zhang (2006b), Delisle, Doran, and Peterson (2011), and Barinov (2012), (2013)). We posit that the positive relation between VS and future returns could be driven by aggregate volatility risk that underlies both the VS and subsequent stock returns. Thus, sorting stocks based on VS could be, to an extent, sorting stocks based on sensitivity to aggregate volatility and thus expected returns, generating the observed predictability.

Motivated by this, we test whether aggregate volatility risk can explain the returns to VS hedge portfolios. We find that firms in the long (VS5) and short (VS1) portfolios have significantly different sensitivities to aggregate volatility risk, the difference in VS between the long and short portfolios closely tracks aggregate volatility, volatility spread hedge portfolio (VS5–VS1) returns are significantly correlated with aggregate volatility risk and firm sensitivities to it, and the abnormal returns to monthly-rebalanced hedge portfolios are small and insignificantly different from zero after accounting for volatility risk. Overall, our results suggest that a substantial portion of the VS-return predictability can be explained by aggregate volatility.

We first examine the VS-stock return relation over time in our sample period. We sort firms into quintiles each month based on the average implied VS for the firm's options and analyze the returns to the VS5 (top quintile) minus VS1 (bottom quintile) hedge portfolio over the subsequent month. We calculate the average monthly hedge portfolio returns for four subperiods within our sample. We find that the predictability is greatest during periods that include market downturns when aggregate volatility risk is likely to be high. In particular, the strongest predictability is from 2000 to 2003 and 2008 to 2012. Interestingly, this also suggests that the predictability has not decreased monotonically over time, as would be expected if it is driven primarily by market inefficiencies (Cremers and Weinbaum (2010)).

We continue by investigating the ability of aggregate volatility and economic state variables to predict the returns to the VS hedge portfolio. We follow Stivers and Sun (2010) by regressing the annualized hedge portfolio returns on measures of aggregate volatility calculated over the previous 3 months. We find that changes in the implied volatility of S&P 500 index options, cross-sectional return dispersion, the expected variance risk premium, and market variance positively predict, and the Chicago Fed National Activity Index negatively predicts, the subsequent returns to the VS hedge portfolio. This suggests that the profitability of the VS hedge portfolio is related to volatility risk and expected changes in the investment opportunity set. To further support this analysis, we show that the difference in VS between the long and short portfolios is highly correlated with the market's expectation for aggregate volatility and that VS and subsequent return predictability are correlated with the underlying firm's sensitivities to this risk. We also provide evidence of why firms may differ in their sensitivities to volatility risk. One such possibility is that the firms have different levels of assets-in-place versus growth options (Berk, Green, and Naik (1999), Zhang (2005), Barinov (2012), (2013), and Barinov and Wu (2013)). Consistent with this, we find that the VS are negatively correlated with the growth options of the underlying firms. These results suggest that VS captures both the market's expectations regarding aggregate volatility and the firm's sensitivity to this risk.

Next, we examine whether aggregate volatility risk factors can explain the returns to the VS hedge portfolio. Motivated by the results of Ang et al. (2006b), Delisle et al. (2011), and Cremers, Halling, and Weinbaum (2015), we augment the benchmark return model used by Cremers and Weinbaum (2010) (a standard Fama and French (1993) model plus Momentum and Coskewness) with factors intended to capture aggregate volatility risk. In particular, we include FVIX and CFVIX to capture the effect of this risk. FVIX is an aggregate volatility factor-mimicking portfolio following Ang et al. (2006b) and Delisle et al. (2011), and CFVIX is a conditional version of the FVIX factor designed to capture potential asymmetric effects of aggregate volatility risk when the risk unexpectedly increases or decreases.[3] We employ this conditional model rather than a linear model as the relation between aggregate volatility (FVIX specifically) and stock returns has been shown to be asymmetric, depending on whether volatility is unexpectedly high or low (Dennis et al. (2006), Delisle et al. (2011), and Arisoy (2014)), and our theoretical examples suggest a nonlinear relation between time-varying volatility and option implied VS.[4] This leads to two interesting results. First, we find that the VS hedge portfolio returns are significantly negatively related to FVIX and CFVIX, suggesting that the returns to the hedge portfolio are driven in part by aggregate volatility risk, with a larger impact when the FVIX factor returns are low. Second, the abnormal returns to the hedge portfolio are substantially reduced: from 51 basis points (bps) (t-stat. of 5.57) to a statistically insignificant 11 bps (t-stat. of 0.90) for the monthly rebalanced portfolio, while the model adjusted R^2 increases from 0.03 to 0.12.

We also perform a number of tests for robustness and to rule out alternative explanations. First, we note that our time-varying volatility option pricing results only predict that VS should exist when early exercise could occur. Supporting this, we document that European option VS are small and insignificant, and do not predict stock returns. Second, we analyze the ability of the aggregate volatility risk factors to explain the returns to hedge portfolios formed using volatility smirks (the difference in implied volatility between ATM calls and OTM puts), the difference in the changes in implied volatilities of calls and puts, and the combination of VS and changes in VS. We find that the abnormal returns to each hedge portfolio decrease after including the aggregate volatility factors, from an average of 42 bps per month

[3]CFVIX takes the value of the FVIX factor when FVIX is below the median, and 0 otherwise. This is similar to the conditional model used by Watanabe and Watanabe (2008) to examine potential nonlinear effects of liquidity. We consider a number of alternate specifications for the nonlinear model, such as splitting FVIX into high and low states or using the natural log of FVIX and find similar results.

[4]In some specifications, we also include the return to a gamma-neutral option straddle (VOL) and the return to a vega-neutral option straddle (JUMP) to further account for volatility and jump risks, following Cremers et al. (2015). We thank Martijn Cremers for providing the data for the JUMP and VOL factors.

(average *t*-stat. of 3.83) to 13 bps per month (average *t*-stat. of 1.13). This further supports that implied volatilities (spreads, smirks, changes) proxy in part for aggregate volatility risk. Third, we show that our results are not driven by deep OTM puts that would be more attractive to informed traders (Xing et al. (2010)) or by difficult-to-short stocks (Muravyev, Pearson, and Pollet (2018)). Finally, we note that PIN, analyst coverage, stock and option illiquidity, and stock and option volume cannot explain the VS-stock return relation in monthly Fama–MacBeth regressions. Taken together, our results support aggregate volatility risk as an explanation for a substantial portion of the predictability of stock returns using option-implied volatilities.

Our work makes a number of important contributions to the literature. First, we provide a theoretical link between option implied VS and time-varying volatility through the style of option exercise. To our knowledge, we are the first to document that VS can exist in a simple no-arbitrage framework without frictions when volatility is time-varying. This provides an important foundation for future works studying the links between VS and the characteristics of the underlying assets. Second, we show that the VS-stock return predictability is consistent with VS proxying for expectations regarding aggregate volatility and the firm's sensitivity to this risk. Our benchmark model incorporating aggregate volatility risk factors can explain the abnormal returns to the VS hedge portfolio even for subsets of stocks/options in which informed trading is more likely. Our results suggest that both risk and other drivers, such as informed trading or market frictions, may contribute to the abnormal performance of VS hedge portfolios for the 1-to-2-day period after formation.

The remainder of the article is structured as follows: Section II details our theoretical motivation and empirical predictions. Section III describes the data. Sections IV and V present our empirical results and robustness checks, respectively. Section VI concludes.

II. VS and Time-Varying Volatility

Several works have examined the implications on option prices when the underlying asset's return exhibits nonconstant volatility (Merton (1974), Cox and Ross (1976), Hull and White (1987), Wiggins (1987), Melino and Turnbull (1990), and Heston (1993a) (1993b)). For example, Heston (1993a) shows that the BS model will misprice options when volatility is stochastic and correlated with the underlying asset returns, with greater mispricing for options with a larger variance in the underlying volatility. Bakshi, Cao, and Chen (1997) and Pan (2002) find that a model assuming both stochastic volatility and jumps outperforms other S&P 500 option pricing models. Melino and Turnbull (1990) document that the BS model underprices currency options when volatility is stochastic, with greater mispricing of call options than put options, generating implied VS.

These works generally focus on variations of the BS model, in which options are all treated as having European-style exercise. However, a substantial portion of traded options use American-style exercise, and the price can include an early exercise premium. This leads to the question: What are the implications of time-varying volatility for American options?

A. Theoretical Motivation

In this section, we demonstrate that VS on American-style options can be informative about an underlying stock's time-varying volatility. Option VS, defined as the average difference between the implied volatility of otherwise identical calls and puts, have long been used to measure frictions in options markets. See, for example, Figlewski and Webb (1993), Amin, Coval, and Seyhun (2004), and Cremers and Weinbaum (2010).

Less studied, however, is how nonzero implied VS can arise in the context of American options when the underlying asset's volatility is time-varying. Interestingly, these nonzero implied VS will arise in a standard no-arbitrage binomial option pricing model without the need for any market imperfections such as transaction costs or short-selling constraints. For simplicity, suppose that American calls and puts are traded on a non-dividend-paying stock with current price S_t.[5] Under mild no-arbitrage assumptions, it is never optimal to exercise an American call before expiration. However, it might be optimal to exercise an American put early. This leads to put-call parity between an American call with price C_t and an American put with price P_t being represented by the inequality

$$C_t + \mathrm{PV}(X) \leq S_t + P_t \leq C_t + X, \tag{1}$$

where X is the strike price and $\mathrm{PV}(X)$ is the present value of X dollars discounted from the options' common expiration date T to date t. Again, the put-call parity relationship given by equation (1) holds under mild no-arbitrage conditions without imposing strong distributional assumptions on the stock price S_t including any assumptions on the stock's volatility. For European options, the first inequality in equation (1) holds with equality.

A common way to measure put-call parity violations is to compute the difference in implied volatilities between otherwise identical calls and puts, a volatility "spread." However, nonzero VS need not imply put-call parity violations for American options. Instead, they can simply capture patterns in the time-varying volatility of the underlying as we demonstrate in a simple example using the binomial pricing framework of Cox et al. (1979).

Graph A of Figure 1 summarizes a 3-period option pricing problem for a non-dividend-paying stock with initial price $S_0 = 10$ where an otherwise identical American call and put are priced. These options have a strike price $X = 10$ and expire in 1 year (or 3 steps in the binomial tree). A riskless bond also exists with an annual interest rate with simple compounding of 5% to build the replication strategy to price options.

The stock exhibits time-varying volatility in that an up move has a different volatility than a down move. Here, the annual volatility of an up move is $\sigma_u = 25\%$ and of a down move is $\sigma_d = 45\%$. We assume that $\sigma_d > \sigma_u$ to capture that downside volatility is typically higher in equity markets.[6] Using the customary Cox et al. (1979)

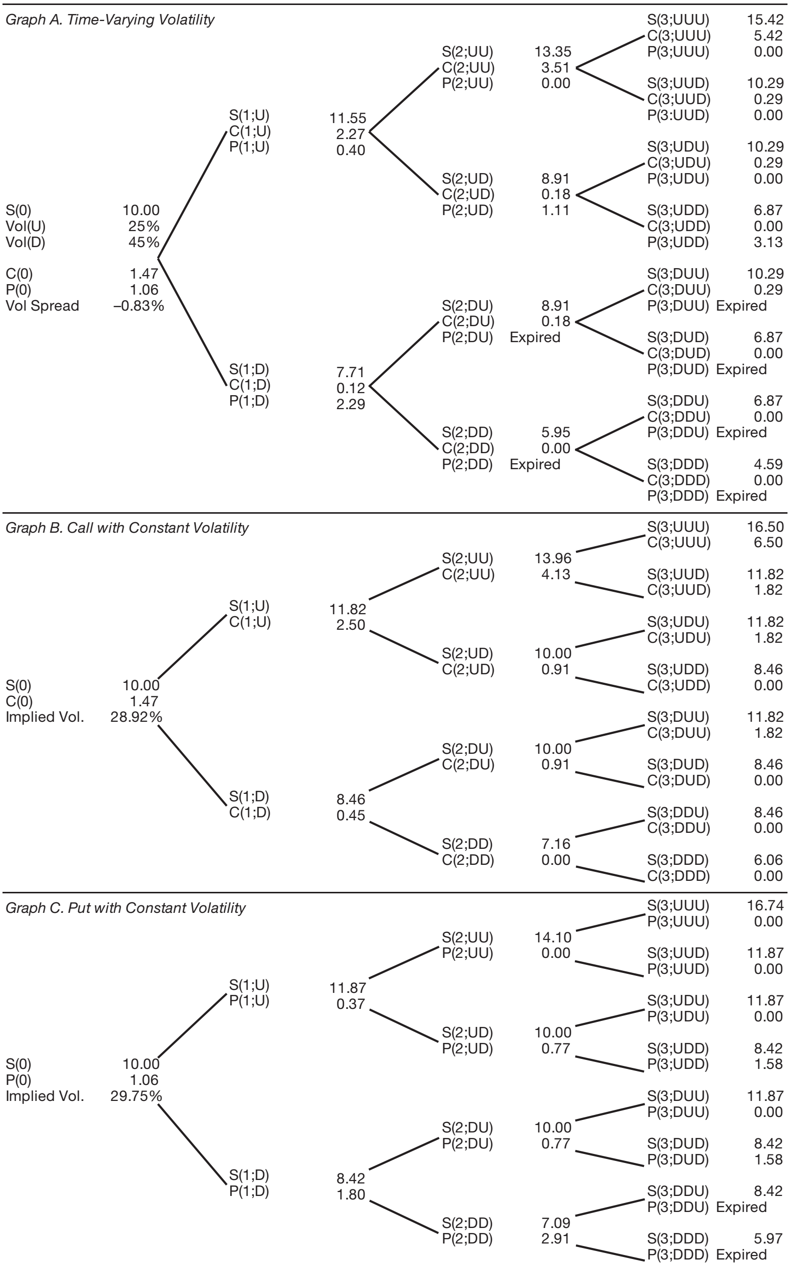
[5] Similar results can be obtained with dividend-paying stocks.

[6] The asymmetric volatility literature is voluminous. Some of the seminal works include Black (1976), Christie (1982), Campbell and Hentschel (1992), Duffee (1995), and Bekaert and Wu (2000).

FIGURE 1

Volatility Spread Example

Figure 1 presents a 3-period binomial option pricing model for a call and a put that expires in 1 year. In Graph A, the stock's volatility is time-varying with an annual volatility of 25% if the stock rises and an annual volatility of 45% if the stock falls. The initial stock price is $S(0) = 10$. Graphs B and C compute implied volatilities using the call's price and the put's price respectively from Graph A. A riskless bond also exists with an annual simple compounded interest rate of 5%. The strike price for the options is $X = 10$.



binomial tree parameterization, the stock price either increases to $11.55 = 10 \times \exp\left(0.25 \times \frac{1}{3}\right)$ or falls to $7.71 = 10 \times \exp\left(-0.45 \times \frac{1}{3}\right)$ after 1 step in the binomial tree. These different up and down volatilities are used throughout the binomial tree. While the stock's volatility is time-varying, we can still value options using the standard replication approach just by trading the stock and the bond. More sophisticated settings that incorporate features such as jumps or stochastic volatility would require additional assumptions on how to then price options in a potentially incomplete market. We focus on the complete markets case here for simplicity.

Graph A of Figure 1 shows the price path for the stock, call, and put under time-varying volatility. Prices labeled "Expired" denote nodes where the option was optimally exercised earlier. Here, the put is exercised early after one step in the binomial tree if the stock price falls. The initial no-arbitrage prices are 1.47 and 1.06 for the call and the put respectively which satisfies the put-call parity bound in equation (1). Graphs B and C compute the implied volatilities for the two options. Consistent with OptionMetrics, the implied volatilities are computed using a constant volatility binomial approach taking early exercise into account instead of a Black–Scholes–Merton approach. Here, the call option's implied volatility is 28.92%, while the put option's implied volatility is 29.75%. This implies a negative VS of −0.83%.

What drives this negative VS? First, from an inspection of Graphs B and C of Figure 1, the price paths of the stock and the options as well as the put's optimal exercise are impacted by imposing a constant volatility to compute the implied volatilities that match the option prices in Graph A. Given the time-varying volatility setting is one where $\sigma_u < \sigma_d$, the constant volatility binomial trees of Graphs B and C are such that they are tilted upward relative to Graph A's time-varying volatility setting. This leads to higher expiration date call cash flows under the constant volatility assumption in Graph B. In Graph C, put payoffs are generally lower with the early exercise region pushed back in time relative to Graph A. However, the early exercise of the put in Graph C under a constant volatility assumption is still strong enough to generate a negative VS as the put "appears" more expensive relative to the call.

To generate a nonzero VS, it is crucial that the put option is optimally early exercised in some future state. Otherwise, both the call and put will behave as if they are European options with put-call parity in equation (1) holding with equality. If we reduce the common strike price to 6.5 from 10 in Figure 1, the put option is never exercised early either in the time-varying volatility case or the constant volatility case when the implied volatility is computed.[7] So, the put's valuation collapses to a European put valuation. Subsequently, the VS between the call and the put collapses to 0.

For a low enough strike that still leads to the put's early exercise, it is possible to generate a positive VS. Figure 2 revisits the same example as in Figure 1 except with a strike price of $X = 8$. In contrast to when $X = 6.5$, the strike price is high enough to induce the put option to be early exercised after 2 steps in the binomial tree if the stock price makes two successive down moves (Graph A). However, due to the lower strike price, it is not optimal to early exercise the put option if the stock

[7]For completeness, this case is summarized in the Supplementary Material.

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price initially falls as in the put option with a strike of $X = 10$ of Graph A of Figure 1. Given the stock evolution in Graph A of Figure 2 is still driven by a setting where down moves have a higher volatility than up moves, the constant volatility binomial trees in Graphs B and C are tilted upward again. However, given the early exercise premium is lessened for this lower strike price example, the call option actually has a higher implied volatility of 39.79% than the put option of 39.28% under the assumption of a constant volatility binomial tree. This is enough to induce a slightly positive VS for these two options of 0.51%.

The previous examples demonstrate that nonzero VS are driven by the early exercise of puts with time-varying volatility and that both positive and negative VS can occur. To build a more complete picture of what information VS convey about time-varying volatility including how common positive and negative VS are, Figure 3 considers comparative statics where the stock's down volatility and the options' strike price are changed. A 5-period option pricing problem is studied to generate a rich set of early exercise regions. The non-dividend-paying stock's initial price is $S_0 = 10$ where identical American calls and puts are priced. These options expire in 1 year (or 5 steps in the binomial tree). A riskless bond also exists with an annual interest rate with simple compounding of 5%.

Three different strike prices are considered – $X = 9.5$ (Graph A of Figure 3), $X = 10$ (Graph B), and $X = 10.5$ (Graph C). The plots present the VS and the early exercise put premium. The early exercise put premium is computed as the fraction of the American put's price coming from the early exercise feature. Initially, the up and down annual stock volatilities are set equal to $\sigma_u = \sigma_d = 25\%$. In the x-axis of each plot labeled DOWN VOL Δ, the stock's annual down volatility is increased above its initial level of $\sigma_d = 25\%$. So, a DOWN VOL Δ of 10% implies an annual down stock volatility of 35%. Note that zero on the x-axis corresponds to the case when the stock's volatility is constant at 25% across the binomial tree. So, this captures the standard constant volatility case. Any other point captures a different time-varying volatility price system where $\sigma_d > \sigma_u$.

What do we learn from these comparative statics in Figure 3? First, not surprisingly, when there is no asymmetric volatility (DOWN VOL Δ = 0), the VS is 0 as all the options are priced under a constant volatility assumption. Second, VS are typically negative and only positive for lower strikes and smaller levels of asymmetric volatility. From the lowest strike in Graph A, a small level of asymmetric volatility can lead to a positive volatility spread. This is driven by the low level of the early exercise put premium induced by the put being exercised later in the binomial tree. In this region, call options under a constant volatility tree can have higher implied volatilities relative to puts. However, it is more common to see negative VS induced by higher early exercise put premiums as both when the down volatility increases or the option strike increases. Third, VS are the most negative when early exercise put premiums are maximized as can be seen in all graphs. At this point, early exercise for the put under asymmetric volatility occurs earliest in the tree driving the VS more negative. Finally, for larger amounts of asymmetric volatility, the negative VS moves back toward 0. As the down volatility grows, the early exercise premium for the American put shrinks as European put options are increasing in value in the down volatility. Putting this all together, the VS exhibits

FIGURE 2

Positive Volatility Spread Example

Figure 2 presents a 3-period binomial option pricing model for a call and a put that expires in 1 year. In Graph A, the stock's volatility is time-varying with an annual volatility of 25% if the stock rises and an annual volatility of 45% if the stock falls. The initial stock price is $S(0) = 10$. Graphs B and C compute implied volatilities using the call's price and the put's price respectively from Graph A. A riskless bond also exists with an annual simple compounded interest rate of 5%. The strike price for the options is $X = 8$.

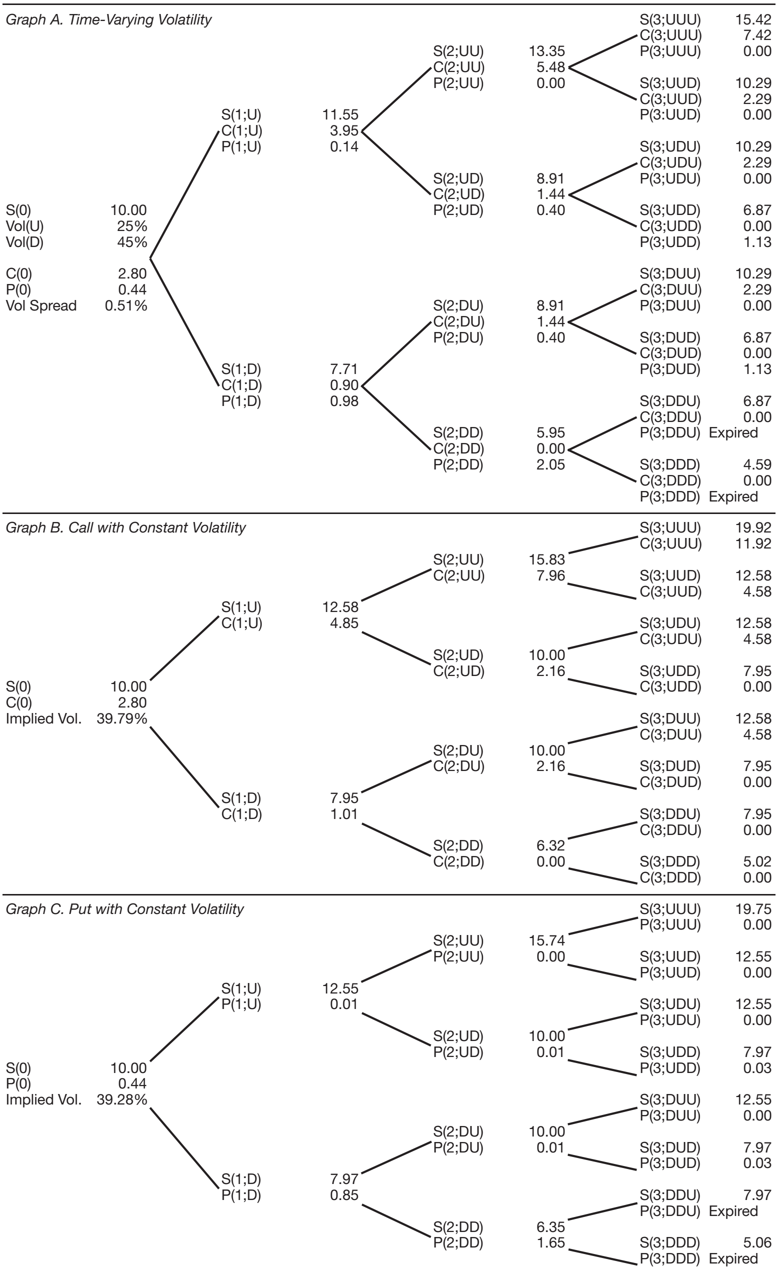
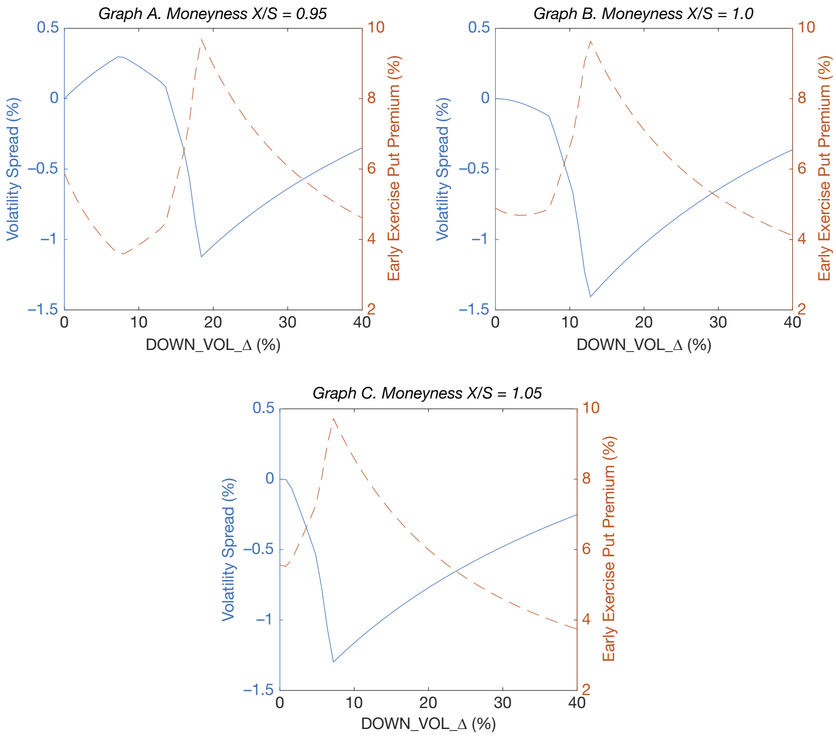


FIGURE 3

Volatility Spread Example Comparative Static

Figure 3 presents implied volatilities based on a call and a put and the resulting volatility spread for a 5-period binomial option pricing model that expires in 1 year. Three different strike prices are considered – X = 9.5 (Graph A), X = 10 (Graph B), and X = 10.5 (Graph C). The volatility structure imposed and other parameters are described in the text.



a v-shaped pattern as asymmetric down volatility is increased, and the VS is largely negative except for lower strikes and small amounts of asymmetric volatility.

Overall, VS is informative about time-varying volatility. Crafting a model that prices aggregate volatility risk and links aggregate volatility to individual stock volatility, and ultimately, VS is beyond the paper's scope. Doing so would require specifying both individual stock and aggregate volatility processes as well as a pricing kernel that prices aggregate volatility risk.[8] However, if a stock's volatility loads on aggregate volatility, it is natural to expect that VS should be informative about aggregate volatility risk which we now explore empirically.

B. Supporting Analysis

To support our theoretical intuition, we examine whether our basic predictions are consistent with patterns in the data. First, the impact of time-varying volatility

[8]One way to proceed is to incorporate individual stock volatility into the Bansal and Yaron (2004) setting described in Bollerslev, Tauchen, and Zhou (2009).

on VS is caused by early exercise in our model. In unreported theoretical results, we find that time-varying volatility does not lead to VS for European options. While we recognize that our framework does not account for all frictions that might impact VS, we would nonetheless expect smaller VS and would not predict VS to be informative about volatility risk among European options. To examine this, we calculate VS for the set of European options for which data is available. We find that VS are small in magnitude relative to American options (0.43 vs. −1.18 on average), do not significantly predict the returns to the underlying assets, and VS5-VS1 hedge portfolio returns are not significantly related to volatility risk factors or aggregate volatility (VIX).[9] This is consistent with early exercise generating the link between time-varying volatility and VS.

Finally, our theoretical results suggest that VS should generally become more negative as moneyness, defined as X/S, increases. As moneyness X/S increases, the maximum value of the early exercise put premium shifts toward lower levels of asymmetric volatility. This leads to negative VS over a larger range of asymmetric volatilities. To examine this empirically, we sort matched option pairs into deciles based on moneyness (X/S), and calculate the average VS across options within each moneyness decile. We find a nearly monotonically negative relation between moneyness and VS, such that VS has a slight negative value within the lowest moneyness decile and a large negative average value within the highest moneyness decile, consistent with our theoretical predictions. For brevity, the results are presented in Figure A1 in the Supplementary Material.[10] As discussed further in the Supplementary Material, we also find that VS decreases with underlying volatility, but at a decreasing rate, consistent with the v-shaped relation predicted by our theoretical results.

C. Empirical Predictions

Our theoretical examples and supporting empirical results suggest that VS proxies for changes in early exercise premia that are driven by time-varying volatility. In other words, while VS may appear to represent a violation of put-call parity, this need not be true when options have American-style exercise and volatility is time-varying. What implications does this have for our understanding of the usefulness of the information contained in VS? A number of related works have documented a significant relation between VS (or similar proxies for possible violations of parity) and future returns to the underlying asset (Bates (1991), Xing et al. (2010), and Atilgan (2014)). A popular explanation is that investors with new firm-specific information or informed investors attempting to exploit temporary inefficiencies choose to trade first in option markets (Easley et al. (1998)), creating demand pressure that temporarily moves option prices away from put-call parity, generating implied volatilities spreads that predict stock returns. For example, Cremers and Weinbaum (2010) show that VS can be used to predict the underlying

[9]We do find that these returns are significantly related to jump risk, which could be consistent with Broadie, Chernov, and Johannes (2007) who find that jump risk is an important consideration for understanding option returns.

[10]Available on the Cambridge website, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4384496, or https://drive.google.com/file/d/1s7p5Qi7uZvOP9NvXaTEAmvLGCv-zTRZ7/view.

stock returns in general throughout their sample period, but this predictability declines between 1996 and 2006, consistent with temporary inefficiency.

A separate stream of research documents the impact of aggregate volatility risk on stock returns, both theoretically (Campbell (1993), (1996)) and empirically (Ang et al. (2006b), Dennis et al. (2006), Delisle et al. (2011), Arisoy (2014), and Cremers et al. (2015)). Priced aggregate volatility risk offers an interesting potential explanation for the VS-return predictability in light of our theoretical findings. Our theoretical motivation demonstrates that VS captures characteristics of firm-level volatility and thus could capture aggregate volatility risk through firm-level sensitivity to this risk. Combined with extant findings that aggregate volatility risk impacts stock returns, our work offers an alternative explanation for the observed VS-return predictability. We posit that VS predicts future stock returns as each is driven in part by aggregate volatility risk.

If our intuition is correct, firms with greater volatility and greater sensitivity to aggregate volatility should be at greater risk of large shifts in volatility over the life of the option, and these firms should be more likely to have large-magnitude VS. As noted above, we find theoretically and empirically that VS becomes more negative, with greater potential for large negative spreads, as baseline firm volatility increases. We note that we do not model other potential drivers of VS. However, this suggests that all else equal, the portion of VS that is explained by nonconstant volatility should increase as firm-level volatility increases. That is, VS should offer a cleaner signal of underlying firm-level volatility, and thus aggregate volatility, when firm-level volatility is high, generating the strongest stock return predictability. Further, the VS-return predictability should not decrease monotonically over time, as would be expected if it were driven by temporary market inefficiencies. In contrast, we would expect the predictability to vary throughout time with aggregate volatility. Finally, we posit that aggregate volatility risk may also account for stock return predictability using alternate measures of the difference in implied volatilities between call and put options. While our main focus is on VS, a more general statement is that our theoretical intuition suggests that the combination of early exercise and time-varying volatility can lead to asymmetric errors in the measurement of call and put implied volatilities. This suggests that other measures, such as volatility skews or the difference in the changes in call and put implied volatilities, may also capture aggregate volatility risk and predict stock returns.

To summarize, we test the following empirical predictions. First, we examine whether the VS-stock return predictability increases with firm volatility and whether this effect is stronger when VS is more likely to capture aggregate volatility (i.e., in periods when aggregate volatility is high). Second, we test the prediction that the returns to VS trading strategies do not disappear over time, but are time-varying and countercyclical, as aggregate volatility is negatively correlated with the state of the economy (Barinov (2012)). As a part of this analysis, we examine whether the hedge portfolio returns can be predicted by measures of expected aggregate volatility or expected economic downturns. Third, we test whether VS hedge portfolio returns can be explained by benchmark return models that account for this aggregate volatility risk. Finally, we investigate the ability of aggregate volatility risk to explain related option implied volatility-based stock return anomalies. We detail the sample and measurement of VS and hedge portfolio in Section III.

III. Data and Variable Measurement

A. Data and Sample

Our sample consists of firms with stock option data available from OptionMetrics, which contains end-of-day information on equity put and call options from all exchanges in the U.S. OptionMetrics uses the closing transaction price on the underlying to estimate option implied volatility using a Cox et al. (1979) binomial approach that allows for early exercise.[11] Our option sample includes all available American-style individual stock options with positive open interest and implied volatility.

We obtain stock return data from CRSP and firm-level variables from Compustat. To be included in the sample, a stock must have option data in OptionMetrics and have pricing information in CRSP. We also exclude all stocks with a price below $5 (Barinov (2013)). We then follow Cremers and Weinbaum (2010) and compute VS using daily data from all valid option pairs and aggregate daily ratios to a monthly level. Fama–French and momentum factors are from the data library on Kenneth French's website, and the coskewness factor is calculated following Harvey and Siddique (2000). Using these data sources, we construct a sample of monthly stock returns used for tests of the general VS-stock return predictability. Our final sample covers the period from Jan. 1996 to Dec. 2017 and includes 603,601 stock-month observations across 7,461 individual stocks.

B. Volatility Spread Measurement

Our primary variable of interest is the spread between the implied volatilities of matched call and put options written on individual stocks. We follow Cremers and Weinbaum (2010) and calculate the difference in implied volatilities between call and put options for the same underlying stock, strike price, and expiration date. We then calculate the stock's VS as the weighted average of the individual VS for each matched pair of put and call options written on the stock, weighted by the average open interest for the put and call options used in the matched pair. Each firm's VS is calculated on a daily basis. Formally,

$$\text{(2)} \qquad \mathrm{VS}_{i,t} = \sum_{k=1}^{n_{i,t}} w_{k,t} \left(\mathrm{IV}_{k,t}^{\mathrm{call}_i} - \mathrm{IV}_{k,t}^{\mathrm{put}_i} \right),$$

where $\mathrm{VS}_{i,t}$ is the volatility spread between the call and put options for the same stock, $w_{k,t}$ is an average weight based on open interest (meaning that both the put and call options should have positive open interest), and $\mathrm{IV}_{k,t}^{\mathrm{call}_i}$ and $\mathrm{IV}_{k,t}^{\mathrm{put}_i}$ are the implied volatilities of the put and call options, respectively. Each stock has only one

[11] The use of closing transaction prices introduces a potentially severe nonsynchronicity issue, which we address in our empirical tests as detailed below.

TABLE 1
Summary Statistics

Table 1 presents descriptive statistics for average monthly individual stock volatility spreads (VS) over the sample period. Volatility spreads are calculated as the difference in implied volatilities for each firm's matched call and put options, averaged over the month as follows:

$$\mathrm{VS}_{i,t} = \sum_{k=1}^{n_{i,t}} w_{k,t}\left(\mathrm{IV}_{k,t}^{\mathrm{call}_i} - \mathrm{IV}_{k,t}^{\mathrm{put}_i}\right),$$

where $\mathrm{VS}_{i,t}$ is a volatility spread between the call and put options for the same stock, $w_{k,t}$ is an average weight based on open interest (meaning that both the put and call options should have positive open interest), and $\mathrm{IV}_{k,t}^{\mathrm{call}_i}$ and $\mathrm{IV}_{k,t}^{\mathrm{put}_i}$ are the implied volatilities of the put and call options, respectively. The mean, median, 25th percentile, 75th percentile, and standard deviation values are reported in the corresponding rows. VS statistics are reported over our the entire sample period (Total) and 5 sample subperiods: i) 1996–1999, ii) 2000–2003, iii) 2004–2007, iv) 2008–2012, and v) 2013–2017. The sample period is from Jan. 1996 to Dec. 2017.

	1996–1999	2000–2003	2004–2007	2008–2012	2013–2017	Total
Mean	−1.00	−1.11	−1.18	−1.65	−1.02	−1.18
Median	−0.88	−0.80	−0.70	−0.93	−0.50	−0.74
P25	−2.58	−2.01	−1.42	−2.16	−2.06	−2.04
P75	0.71	0.16	−0.22	−0.11	0.61	0.27
Std. Dev.	5.27	4.13	3.25	5.67	5.95	4.96

VS at every point in time. We then calculate monthly VS as the average of daily VS throughout the month.

We sort stocks into equally-weighted quintile portfolios based on their average VS at month $t-1$ and measure the returns to each portfolio as well as the VS5–VS1 hedge portfolio over the month following portfolio formation.[12] Additionally, we sort stocks into quintile portfolios based on their daily VS at day $t-1$ and measure the returns to each portfolio over the following day and week to establish returns for daily and weekly rebalancing. We follow Cremers and Weinbaum (2010) and sort stocks into portfolios based on daily VS on Wednesdays to obtain weekly portfolios.

To avoid nonsynchronicity between the closing of the option and equity markets (Battalio and Schultz (2006)), we drop the daily VS measure on the last day prior to our return measurement window for our tests using monthly-rebalanced hedge portfolios and use open-to-close returns for the first day following portfolio formation for our tests using weekly- and daily-rebalanced hedge portfolios. Our tests focus on the returns to the hedge portfolio based on taking a long position in stocks with the highest VS (top quintile) and a short position in stocks with the lowest VS (bottom quintile).

Table 1 presents the summary statistics for VS. We present summary statistics for the entire sample and for 5 subperiods within the sample: i) 1996–1999, ii) 2000–2003, iii) 2004–2007, iv) 2008–2012, and v) 2013–2017. Similarly to Cremers and Weinbaum (2010), we document that VS are negative on average. However, from 2008 to 2012, VS values appear to become more negative on average, and this is accompanied by an increase in the standard deviation of VS. This shift may relate to the market downturn in 2008.

[12]For robustness, we also consider value-weighted portfolios using NYSE breakpoints and value-weighted portfolios based on the natural log of the market value of equity. Each alternative leads to similar results.

IV. Empirical Tests and Results

Using the VS hedge portfolios described above, we first examine whether VS captures aspects of the underlying asset's volatility, with particular emphasis on aggregate volatility risk. We analyze the relation between the monthly returns to the hedge portfolio and differences in risk between the long and short portfolios. We predict that the hedge returns will be countercyclical and predictable, that they will be correlated with the market's expectation for aggregate volatility and the sensitivity of the underlying stocks to market volatility risk, and that they will be better explained by benchmark returns models that account for this risk.

A. VS-Return Predictability and Underlying Asset Volatility

We posit that VS will capture aggregate volatility risk through the link between firm-level and aggregate volatility. As noted above, this leads to a number of testable empirical predictions. First, to the extent that firm-level volatility is driven by aggregate volatility and aggregate volatility risk is priced, firms with greater volatility should exhibit greater VS-return predictability, particularly when aggregate volatility is high. To examine this, we perform a conditional double-sorting procedure. Every month we first sort stocks in quintiles based on their firm-level volatility and then on VS. We then report next month's average benchmark-

TABLE 2

Sensitivity to Firm-Level and Aggregate Volatility

Table 2 presents the abnormal performance (Daniel, Hirshleifer, and Subrahmanyam (1998)) for the implied volatility spreads (VS) portfolios formed within quintiles of stocks sorted on idiosyncratic volatility. Panel A presents the results of a dependent double-sorting procedure with stocks sorted first on idiosyncratic volatility and then implied volatility spreads. The benchmark-adjusted returns to each of the five VS portfolios as well as the hedge portfolio (High–Low) are presented for firms within each quintile of firm volatility. Panel B presents the results of a triple-sorting procedure that first sorts the sample into high and low VIX periods, and then repeats the double-sorting procedure from Panel A within high and low VIX periods. For brevity, we restrict the presentation to the VS hedge portfolio returns (High–Low) for this triple-sort. Also included are the hedge portfolio (High–Low) performance formed within high and low VIX periods, respectively, but unconditional on firm volatility (All). *t*-statistics are in parentheses below. The sample period is from Jan. 1996 to Dec. 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Volatility Spread Premium Conditional on Idiosyncratic Volatility

Idiosyncratic Volatility Rank	Low VS	2	3	4	High VS	High–Low
Low	−0.05	0.12	0.08	0.23**	0.22*	0.27**
	(−0.39)	(1.04)	(0.76)	(2.14)	(1.92)	(2.59)
2	−0.09	0.14	0.25***	0.11	0.35***	0.44***
	(−0.81)	(1.46)	(2.72)	(1.11)	(3.38)	(3.83)
3	0.08	0.21**	0.23**	0.19**	0.45***	0.37**
	(0.74)	(2.32)	(2.58)	(1.99)	(4.26)	(2.59)
4	0.00	0.13	0.17	0.41***	0.48***	0.48***
	(0.04)	(0.93)	(1.50)	(3.18)	(3.42)	(2.81)
High	0.14	0.40*	0.12	0.29	0.99***	0.85***
	(0.55)	(1.87)	(0.60)	(1.46)	(4.64)	(4.25)

Panel B. Volatility Spread Premium Conditional on Aggregate-Level Volatility

VIX	All	Low IV	2	3	3	High IV	High–Low
Low VIX	0.04	0.11	0.27**	−0.05	0.03	0.43*	0.33
	(0.52)	(0.83)	(2.03)	(−0.36)	(0.16)	(1.96)	(1.21)
High VIX	0.76***	0.41**	0.59***	0.72***	0.84***	1.21***	0.79**
	(5.62)	(2.57)	(3.26)	(3.14)	(3.24)	(3.80)	(2.10)

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adjusted portfolio returns (Daniel, Grinblatt, Titman, and Wermers (1997)). Panels A and B of Table 2 present the results of this analysis.

We start by examining the VS-return predictability within each level of firm volatility quintiles. As shown in Panel A of Table 2, we find that VS-return predictability increases nearly monotonically with firm-level volatility, with the VS hedge portfolio generating 27 bps per month among low-volatility firms, increasing to 85 bps per month among high-volatility firms. To further investigate the link between firm-level volatility, aggregate volatility, and VS, we perform a triple-sort, first sorting periods into high or low aggregate volatility based on sample median aggregate volatility, and then repeating the double-sort on firm-level volatility and VS. We also construct a VS hedge portfolio within high/low aggregate volatility periods that is unconditional on firm-level volatility. In Panel B, we find that the VS-return predictability and the positive relation between firm-level volatility and VS-return predictability are almost entirely driven by portfolios formed during high aggregate volatility periods. During low aggregate volatility periods, there is no VS-return predictability on average (4 bps, *t*-stat. of 0.52), the VS hedge portfolio generates no more than 43 bps per month within any firm-level volatility quintile (among the highest volatility stocks), and there is no significant difference between high and low-volatility stocks. On the other hand, during high aggregate volatility periods, the "unconditional" VS hedge portfolio generates 76 bps (*t*-stat. of 5.62), VS-return predictability increases monotonically with firm-level volatility from 41 to 121 bps, and the difference between high and low volatility firms is statistically significant (*t*-stat. of 2.10).[13] Consistent with our theoretical predictions, this analysis suggests that there is greater VS-return predictability among volatile firms and that the predictability primarily occurs during periods of high aggregate volatility.

We further examine the relation between the VS hedge portfolio and aggregate volatility, comparing the difference between the spreads of firms in VS5 and VS1 varies with aggregate volatility risk. We graph the difference in spreads for VS5 and VS1 and VIX over time in our sample and present the results in Graph A of Figure 4. We find that the difference in VS tracks closely the overall volatility of the market, with a correlation of 58%.[14] Taken together, this evidence suggests that VS captures aggregate volatility risk and firm-level sensitivity to this risk.

B. Hedge Portfolio Performance over Time

Our second prediction is that the VS-return predictability will not decrease monotonically over time, but will be time-varying and countercyclical. We first test this prediction by sorting the sample into 5 subperiods: i) 1996–1999, ii) 2000–2003, iii) 2004–2007, iv) 2008–2012, and v) 2013–2017. We then calculate the average performance of each VS quintile portfolio and the hedge portfolio within each subperiod. The results of this test are presented in Table 3.

[13]We find nearly identical results if we instead consider the 5-factor model (Fama–French plus Momentum and Coskewness) alphas rather than benchmark-adjusted or raw returns.

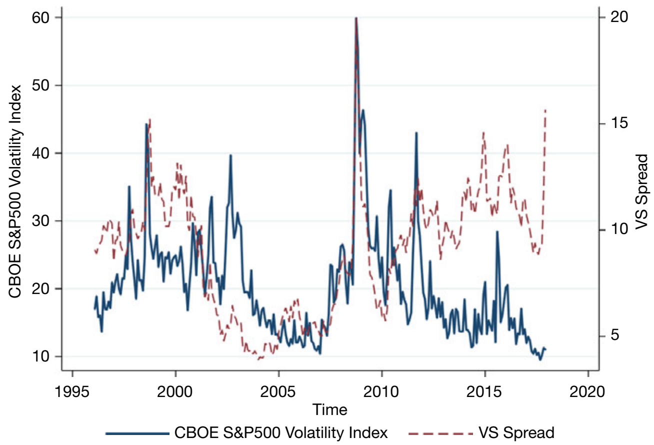
[14]Consistent with this effect being driven primarily by early exercise, we find a correlation with VIX of −6% when VS is measured for European options.

FIGURE 4

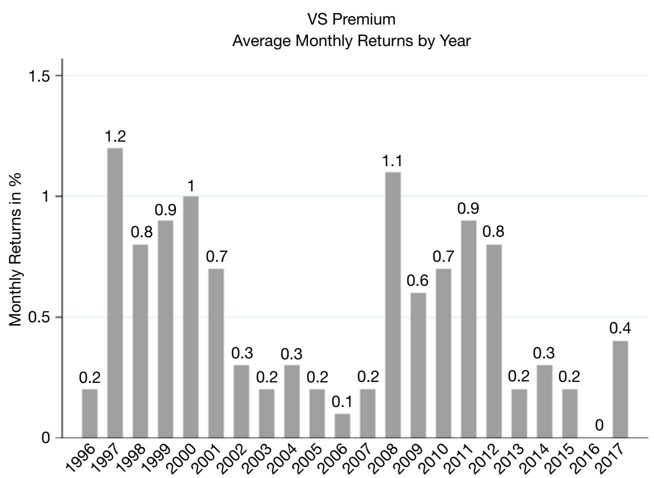
VS Spreads and Payoffs over Time

Figure 4 presents the difference in volatility spreads for VS5 and VS1 compared with VIX, the level of aggregate volatility (Graph A), and the returns to the VS5–VS1 hedge portfolio for each year within our sample period (Graph B). The volatility spread is calculated as the difference in implied volatilities for each firm's matched call and put options, averaged over the month. We then calculate the average returns over the following month for the hedge portfolio. Presented are the monthly hedge portfolio returns averaged over the calendar year.

Graph A. VIX and VS 'Spread'



Graph B. VS Payoff by Year



This table documents three interesting results. First, we find that the VS-stock return predictability decreases over the sample period from 1996 to 2007, from a statistically significant 77 bps per month (t-stat. of 2.69) in the 1996–1999 subperiod to an insignificant 20 bps per month (t-stat. of 1.60) in the 2004–2007 subperiod. This is consistent with the results of Cremers and Weinbaum (2010). Second, we also find that this pattern did not continue through the end of our sample period, with the VS hedge portfolio generating a statistically significant 80 bps per month (t-stat. of 3.62) during 2008–2012 and 29 bps per month (t-stat. of 2.71) and

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TABLE 3

Sorting Results

Table 3 presents the next periods performance to the five monthly-rebalanced volatility spread quintile portfolios and the hedge portfolio (High–Low) for the full sample and 5 sample subperiods: i) 1996–1999, ii) 2000–2003, iii) 2004–2007, iv) 2008–2012, and v) 2013–2017. The implied volatility spread is calculated as the difference in implied volatilities for each firm's matched call and put options, averaged over the month. We then calculate the raw (Panel A) and abnormal Daniel et al. (1998) (Panel B) returns over the following month for each quintile portfolio sorted on the volatility spread. *t*-statistics are in parentheses below. The sample period is from Jan. 1996 to Dec. 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Low VS	2	3	4	High VS	High–Low
Panel A. Raw Returns						
1996–1999	1.43	1.48	1.40	1.72	2.20	0.77***
						(2.69)
2000–2003	0.90	0.81	0.58	0.99	1.47	0.57**
						(2.02)
2004–2007	1.05	0.95	1.12	1.11	1.25	0.20
						(1.60)
2008–2012	0.34	0.53	0.45	0.58	1.14	0.80***
						(3.62)
2013–2017	1.08	1.14	1.24	1.21	1.38	0.29***
						(2.71)
Full sample	0.97	0.99	0.98	1.13	1.48	0.51***
						(5.51)
Panel B. Benchmark-Adjusted Returns						
1996–1999	−0.05	−0.07	−0.11	0.28	0.92	0.97***
						(3.91)
2000–2003	0.31	0.46	0.46	0.59	0.77	0.47*
						(1.97)
2004–2007	−0.02	0.04	0.23	0.30	0.33	0.36**
						(2.37)
2008–2012	−0.11	0.19	0.03	0.13	0.55	0.66***
						(3.31)
2013–2017	0.24	0.18	0.14	0.05	0.21	−0.03
						(−0.27)
Full sample	−0.05	0.16	0.15	0.25	0.52	0.44***
						(5.08)

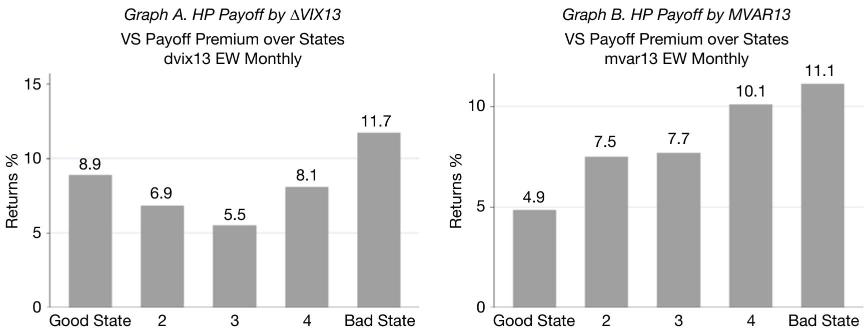
2013–2017. This result is particularly interesting because the hedge portfolio appears to generate the highest returns during the 2008–2012 subperiod, consistent with the predictability varying rather than decreasing monotonically over time. Third, the results suggest that the VS hedge portfolio generated the largest returns between 1996 and 2003, and 2008 to 2012, both of which cover periods of high aggregate volatility. This is consistent with aggregate volatility risk as a driver of the VS hedge portfolio returns. To further illustrate this, we break down the sample and calculate the average hedge portfolio returns separately for each year in our sample period, and present these in Graph B of Figure 4.

As Graph B of Figure 4 illustrates, it appears that the VS hedge portfolio returns increased during the late 1990s until 2000–2001, decreased through the mid-2000s, and increased again in 2008. This is also consistent with the hedge portfolio returns being primarily associated with periods of high aggregate volatility or poor economic conditions. Thus, we continue by analyzing the relationship between the VS hedge portfolio returns, aggregate volatility, and macroeconomic variables that represent the economic state.

FIGURE 5

VS Payoff by States

Figure 5 presents 12-month overlapping portfolio returns (%) to the VS hedge portfolio, sorted into 5 subperiods based on the change in the implied volatility of S&P 500 index options, as a measure of the change in expected aggregate volatility, over the prior 3 months (Graph A) and the market variance over the prior 3 months (Graph B).



C. Aggregate Volatility and the Volatility Spread Payoff

We first examine this relation by sorting observations into quintiles based on measures of market volatility and forming VS hedge portfolios within each market volatility quintile period. The first measure is based on the implied volatility of S&P index options (VIX). Ang et al. (2006b) argue that changes in aggregate volatility risk represent a decline in the investment opportunities set and should be negatively priced in the cross section. An increase in expected aggregate volatility risk decreases the demand for assets with high sensitivity to volatility and drives down their contemporaneous returns while preceding an increase in the expected returns to such assets. Therefore, we expect changes in VIX to be negatively related to the contemporaneous return to the volatility spread hedge portfolio, but positively predict the future returns to the VS hedge portfolio. VIX is measured as the implied volatility of an at-the-money option on the S&P 500 index.[15] The second measure of aggregate volatility is the variance in the daily market returns over each month (MVAR) following French, Schwert, and Stambaugh (1987) and Schwert (1989).

Graphs A and B of Figure 5 present the annualized hedge portfolio returns sorted on the prior change in VIX and MVAR, respectively. We find that the returns are highly sensitive to the expected market state, with the returns in bad states substantially higher than the returns in good states.[16] This supports our prediction that the hedge portfolio returns are concentrated in bad economic times and when aggregate volatility is high.

For a more in-depth investigation of the systematic relationship between the VS hedge portfolio returns and the state of the economy, we follow Stivers and Sun (2010) and regress the VS hedge portfolio premium separately on measures of macroeconomic condition calculated over the prior 3-month period. In addition

[15]We obtain the values of the VIX index from the CBOE section of WRDS.

[16]Similar results are found for each of the other measures of variance/economic condition defined below.

to VIX and MVAR, we consider three additional measures of aggregate volatility/macroeconomic conditions. These include cross-sectional stock return dispersion (RD), the expected variance premium (EVRP), and the monthly change in the Chicago Fed National Activity Index (CFNAI).

We estimate RD each month following Stivers and Sun (2010), using the cross-sectional standard deviation of the monthly returns to 100 portfolios sorted on both size (MVE) and book-to-market (BM), which are obtained from Kenneth French's data library. Prior works support the use of this measure to capture both aggregate volatility and the state of the economy (Stivers (2003), Zhang (2005), and Stivers and Sun (2010)). Following Bollerslev, Li, and Zhao (2009), EVRP is defined as

$$\text{EVRP}_t = \text{IV}_t - E[\text{RV}_{t+1}], \tag{3}$$

where IV_t and $E[\text{RV}_{t+1}]$ represent implied variance and the expectation of the future realized variance premium. $E[\text{RV}_{t+1}]$ is measured as the one-period-ahead forecast from a simple time-series model for RV_t. VIX, MVAR, RD, and EVRP each proxy for aggregate volatility risk or the risk premium, while CFNAI has been shown to be a leading indicator of economic movement, with higher values corresponding to good economic states with higher growth potential. Therefore, we expect the VIX, MVAR, RD, and EVRP to positively predict, and the change in CFNAI to negatively predict, the VS hedge portfolio returns.

We then regress the VS hedge portfolio premium separately on each of these measures of macroeconomic condition calculated over the prior 3-month period. Specifically,

$$\text{HP}_{t,t+s} = \gamma_0 + \gamma^S S_{t-1,t-3} + \text{C}_{t-1}\Gamma' + \varepsilon_{t,t+s}, \tag{4}$$

where HP is a cumulative payoff from the VS hedge portfolio over the next 1, 3, 6, 9, or 12 month period, and $S_{t-1,t-3}$ is the lagged 3-month moving average of the state variables described above. We also include controls (untabulated) for the lagged 3-year market return, the dividend yield (the difference between market return with and without dividends), the default spread (the difference between Baa and Aaa spreads), and the term-spread (the difference between 10-year and 1-year T-bonds). We estimate variations of model 4 based on overlapping portfolios and report t-statistics corrected for heteroskedasticity and auto-correlation using the Newey–West estimator with 12 lags.[17] The results are presented in Table 4.

We find that the VS hedge portfolio payoff is significantly related to measures of market volatility and economic state. Specifically, we find that ΔVIX, ΔRD, and EVRP positively predict the VS hedge portfolio returns for the next 12 months, while ΔCFNAI negatively predicts the VS hedge portfolio returns for 9 months.[18] We also find that MVAR positively predicts the hedge portfolio returns for 3 months. These results support our prediction of a counter-cyclical and predictable VS hedge

[17]Results are also similar if we follow Newey and West (1994) to automatically select the number of lags.

[18]Results are similar if we calculate RD based on individual stocks returns and account for market effects (relative RD), or use the CFNAI Diffusion Index or the St. Louis Fed's Leading Index for the United States.

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TABLE 4

Time-Series Predictive Regressions

Table 4 presents predictive regressions of the VS hedge portfolio premium over 1, 3, 6, 9, and 12 months on the lagged measures of macroeconomic conditions calculated over the prior 3-month period. We consider five measures of aggregate volatility/macroeconomic condition: i) VIX is the implied volatility of S&P 500 index options, ii) MVAR is the monthly variance in daily market returns, iii) RD is the cross-sectional stock return dispersion, iv) EVRP is the expected variance risk premium, and v) ΔCFNAI is the change in the Chicago Fed National Activity Index as defined in the text. Included additional controls (untabulated) are: i) the lagged 3-year market return, ii) the difference between market return with and without dividends, iii) the difference between Baa and Aaa spreads as a measure of the default spread, and iv) the difference between 10-year and 1-year T-bond yields as a measure of the yield spread. *t*-statistics in parentheses are corrected for heteroscedasticity and auto-correlation using the Newey–West estimator with 12 lags. The sample period is from Jan. 1996 to Dec. 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	1	3	6	9	12
γ^{VIX13}	0.31***	0.50***	0.46***	0.47**	0.51***
	(3.18)	(3.41)	(2.63)	(2.47)	(2.88)
γ^{MVAR13}	0.33***	0.45***	0.32	0.37	0.27
	(3.84)	(2.80)	(1.26)	(1.52)	(1.15)
γ^{RD13}	0.08*	0.11	0.24***	0.31***	0.32***
	(1.69)	(1.34)	(2.89)	(4.14)	(3.54)
γ^{EVRP13}	0.14*	0.43***	0.26**	0.24**	0.28***
	(1.74)	(5.00)	(1.98)	(2.14)	(2.62)
$\gamma^{\Delta CFNAI13}$	−0.15**	−0.20**	−0.19**	−0.16*	−0.11
	(−2.48)	(−2.32)	(−2.01)	(−1.68)	(−1.35)

portfolio return and provide further evidence consistent with the results presented in Figure 4. This is also consistent with the prediction that the VS hedge portfolio premium is driven in part by the sensitivities of the underlying stocks to aggregate volatility and the state of the economy.

D. Abnormal Returns and Aggregate Volatility Risk Factors

If aggregate volatility risk is a determinant of the VS hedge portfolio returns, benchmark return models accounting for this risk should dramatically reduce the observed abnormal performance of the VS hedge portfolio. As a baseline, we begin with the benchmark model used by Cremers and Weinbaum (2010).

$$(5)\quad R_t^e = \alpha + \beta^{\mathrm{MKT}}\mathrm{MKT}_t + \beta^{\mathrm{SMB}}\mathrm{SMB}_t + \beta^{\mathrm{HML}}\mathrm{HML}_t + \beta^{\mathrm{UMD}}\mathrm{UMD}_t + \beta^{\mathrm{CSK}}\mathrm{CSK}_t + \varepsilon_t,$$

where MKT_t is the market excess return, SMB_t and HML_t are size and value factors (Fama and French (1993)), UMD_t is momentum (Carhart (1997)), and CSK_t is a coskewness factor following Harvey and Siddique (2000).

Prior works suggest that this model cannot explain the performance of the VS hedge portfolio. Therefore, we test whether aggregate market volatility can explain a portion of the hedge portfolio returns by augmenting this model with aggregate volatility factors. First, we include FVIX, which is designed to capture the aggregate volatility risk of the market. We construct the FVIX factor similar to Ang et al. (2006b) and Barinov (2012). Specifically, we create a factor-mimicking portfolio that tracks daily changes in the VIX index. We regress innovations in the VIX index on the excess returns of 6 size and book-to-market portfolios on a daily basis.[19] The

[19]The portfolios are obtained from Kenneth R. French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/).

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estimated beta coefficients are multiplied by the corresponding portfolio returns to acquire the daily FVIX factor. We compound daily values of FVIX to obtain the monthly FVIX factor.

The results from our theoretical examples show that VS is informative about time-varying volatility in an asymmetric way. That is, VS are more informative about future volatility in the down state than the up state.[20] This suggests that VS are likely to asymmetrically capture an underlying relation between aggregate volatility and returns. Furthermore, extant literature, such as Bollerslev, Li, and Zhao (2017), suggests that the impact of volatility risk on stock returns is unlikely to be symmetric. Delisle et al. (2011), following the evidence of Dennis et al. (2006) and a number of works documenting an asymmetric relation between volatility and stock returns, suggest that FVIX has an asymmetric impact on stock returns depending on whether FVIX is high or low. Arisoy (2014) finds that the difference in sensitivity to aggregate volatility risk between small and large firms differs substantially during high and low volatility periods, consistent with Petkova and Zhang (2005), who document time-varying risk in value and growth stocks that is correlated with the state of the economy. Campbell and Hentschel (1992) argue that volatility and stock returns will have a nonlinear relation because large pieces of both positive and negative news increase volatility, but positive news has an offsetting impact while negative news has a reinforcing effect. In a related vein, Ang, Chen, and Xing (2006a) find that upside and downside risk (a stock's relation to the market when the market return is high and low, respectively) are priced asymmetrically in the cross section. Additionally, our results coupled with the findings of Berk et al. (1999), Zhang (2005), and Anderson and Garcia-Feijoo (2006) suggest that the relationship between the hedge portfolio premium and aggregate volatility may be asymmetric across market states, as aggregate volatility is correlated with the state of the economy (Barinov (2012), (2013)).[21]

This suggests that the relation between returns and volatility risk should be nonlinear as the volatility risk premium will itself change with the level of risk.[22] FVIX is effectively a linear function of ΔVIX and captures both the level of risk and the risk premium but does not allow for the nonlinearity between VS, volatility risk, and returns. Thus we account for this potential nonlinearity by allowing FVIX betas to vary for high and low levels of volatility risk, and create a conditional volatility factor (CFVIX) that is designed to capture this effect. Specifically,

[20]Additional results suggest that VS can be informative about up- or down-state volatility when the firm pays dividends and both the call and put options are potentially subject to early exercise. Although a detailed analysis is outside the scope of this article, conceptually this should lead VS to proxy for the net effects of the changes in volatility in the up and down states, depending on which effect dominates. For sensible parameterizations of our model extended to dividends, the down volatility effect still dominates. This suggests that VS will be informative primarily for the up- or down-state volatility, but not both.

[21]Similarly, Chernov and Ghysels (2000) show that in an option pricing model with stochastic volatility, such as Heston (1993a), the price of volatility risk will be a (nonlinear) function of the level of volatility and the asset risk premium is a decreasing function of volatility.

[22]In untabulated tests, we examine the relation between returns and VIX in pooled regressions. The results confirm that returns are asymmetrically related to lagged VIX (and ΔVIX), depending on whether volatility is high or low.

$$\text{CFVIX}_t = I_t \times \text{FVIX}_t, \tag{6}$$

where I_t is an indicator function that takes a value equal to 1 during periods when the value of the FVIX factor is below the median, and 0 otherwise. In other words, CFVIX should efficiently capture any asymmetric effect of the FVIX during periods when the aggregate volatility risk between periods of unexpectedly high and low volatility and the beta associated with CFVIX should be insignificant if there is no asymmetric effect. To avoid a look-ahead bias, we use a recursive procedure that takes into account only the information that was available prior to time t, the period that we are attempting to classify.[23] For example, to classify Jan.1996, we use the data from Jan.1986 to Dec. 1995. We repeat this procedure until all periods are classified.[24]

Furthermore, Cremers et al. (2015) find that both aggregate jump and volatility risks are priced in the cross section of stock returns. Cremers et al. (2015) create factors to capture these risks (JUMP and VOL) based on the returns to two portfolios of S&P 500 index futures options: a vega-neutral straddle and a gamma-neutral straddle, respectively. The authors further show that these factors are positively correlated with the change in VIX, with correlations between 0.3 and 0.5. This suggests that each of these empirical measures proxies for a portion of the aggregate volatility and jump risks, but each may also capture distinct facets of these risks as well. Thus, in addition to FVIX and CFVIX, we include JUMP and VOL in the model to explain the returns to the VS hedge portfolio.[25]

To test aggregate volatility risk as an explanation for the hedge portfolio performance, we analyze the abnormal returns from the following benchmark model:

$$R_t^e = \alpha + \mathbf{B}'\mathbf{X} + \beta^{\text{FVIX}}\text{FVIX}_t + \beta^{\text{CFVIX}}\text{CFVIX}_t + \beta^{\text{JUMP}}\text{JUMP}_t + \beta^{\text{VOL}}\text{VOL}_t + \varepsilon_t, \tag{7}$$

where $\mathbf{X}$ includes factors in equation (5) and all factors are as defined above. The abnormal performance of the portfolios is measured by the amount that is not explained by the model and should be captured by the α coefficient. If our proposition is correct, we should observe a decrease in the hedge portfolio α when using this updated benchmark model.

[23] Delisle, Doran, and Peterson (2011) note that the relation between FVIX and stock returns may be asymmetric for positive and negative values of FVIX. We chose above/below median values of FVIX as a more general test; however, results are unchanged if we define the factor based on periods when FVIX is positive/negative. This robustness check also reinforces that our results are not driven by a look-ahead bias in defining CFVIX.

[24] We confirm that the aggregate volatility factors (FVIX and CFVIX) are negatively and significantly priced in our sample. We followed the procedure in Ang et al. (2006b) we use 25 $\beta_{\text{MKT}} \times \text{VS}$ portfolios as base assets and we then estimate the risk premiums associated with each factor following the 2-step Fama and MacBeth (1973) procedure. We also confirm that CFVIX is priced separately from FVIX in the cross section of asset portfolios. Note that the pricing of the aggregate volatility factors may vary over time and it also depends on the sample composition (Detzel, Duarte, Kamara, Siegel, and Sun (2023)).

[25] For more detail, please see Cremers et al. (2015). For this analysis, our sample ends with the available JUMP and VOL factors in 2011. We thank Martijn Cremers for providing us with the factor data.

TABLE 5

Factor Model Regressions

Table 5 presents the results of VS hedge portfolios returns (HP) regressed on benchmark return models. Column 1 presents the results from the benchmark model used by Cremers and Weinbaum (2010), based on a Fama and French (1993) 3-factor model plus momentum and coskewness (Harvey and Siddique (2000)). Columns 2–6 include the standard benchmark model plus factors designed to capture aggregate volatility risk and jump risk. FVIX is the aggregate volatility risk factor following Ang et al. (2006b), CFVIX is a factor defined to capture any nonlinear impact of FVIX between high and low FVIX states, and JUMP and VOL are jump and volatility factors based on option straddles following Cremers et al. (2015). *t*-statistics in parentheses are corrected for heteroskedasticity and auto-correlation using the Newey-West estimator with 3 lags. The sample period is from Jan. 1996 to Dec. 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	HP	HP	HP	HP	HP	HP
	1	2	3	4	5	6
α	0.51***	0.39***	0.11	0.46***	0.62***	0.14
	(5.57)	(4.33)	(0.90)	(3.99)	(5.63)	(0.88)
MKTRF	−0.01	−0.51***	−0.53***	−0.55***	−0.02	−0.59***
	(−0.43)	(−4.41)	(−5.75)	(−4.88)	(−0.61)	(−6.56)
SMB	−0.03	0.01	0.02	−0.00	−0.05	0.01
	(−0.63)	(0.29)	(0.54)	(−0.11)	(−0.97)	(0.11)
HML	0.06	−0.01	−0.01	−0.04	0.04	−0.04
	(1.41)	(−0.25)	(−0.20)	(−1.04)	(0.87)	(−1.03)
MOM	0.01	0.02	0.02	0.02	0.01	0.02
	(0.33)	(0.66)	(0.86)	(0.63)	(0.23)	(0.85)
CSK	−0.03	−0.05	−0.06	−0.06	−0.04	−0.07
	(−0.60)	(−1.12)	(−1.30)	(−1.31)	(−0.76)	(−1.38)
FVIX		−0.47***	−0.42***	−0.51***		−0.46***
		(−4.63)	(−4.75)	(−5.13)		(−5.31)
CFVIX			−0.16**			−0.16**
			(−2.47)			(−2.16)
JUMP				−0.00	−0.00	−0.01
				(−0.31)	(−0.25)	(−0.56)
VOL				0.00	−0.00	−0.01
				(0.11)	(−0.03)	(−0.33)
N	263	263	263	194	194	194
R^2	0.03	0.09	0.12	0.11	0.03	0.13

Table 5 presents the results of this test for portfolios held for 1 month following portfolio formation to determine the model's explanatory power.[26] We start by examining the alpha from a standard Fama and French (1993) model plus momentum and coskewness, following Cremers and Weinbaum (2010). Using this model, we find a monthly abnormal return of 51 bps (*t*-stat. of 5.57). However, this result changes dramatically when we include factors to capture aggregate volatility risk. After augmenting the model with FVIX and CFVIX, the results no longer suggest that the hedge portfolio earns an abnormal return – the alpha decreases to a statistically insignificant 11 bps (*t*-stat. of 0.90) in model 3. We find that the hedge portfolio returns (VS5–VS1) load negatively and significantly on both FVIX and CFVIX.[27] We also find that the hedge portfolio returns load negatively but insignificantly on JUMP and VOL, with little impact on the estimated alpha in our

[26]We also examine portfolios held for 1 day or 1 week post-formation, as discussed in a later section.

[27]Results are similar if we split FVIX into two factors representing the returns when volatility risk unexpectedly increases or decreases, or if we replace FVIX with the natural log of the FVIX factor (plus a small constant so that all values are defined) further supporting the nonlinear nature of the relation between the hedge portfolio returns and aggregate volatility risk. Untabulated tests confirm that CFVIX and ln(FVIX) are each priced in the cross section. If we split FVIX into separate factors for high and low-value periods, we find the factor is only significantly priced during low-value periods.

sample (models 4–6). Furthermore, the adjusted R^2 increases from 0.03 to 0.12–0.13, verifying that the alpha is not simply being driven to zero by adding irrelevant variables to the model. These results suggest that the aggregate volatility risk factors are negatively and significantly related to the hedge portfolio performance as predicted, and, more importantly, explain its abnormal returns.[28] Untabulated tests further show that hedge portfolio returns load significantly on macro variables representing shocks to aggregate volatility and market states, consistent with the factor regression results. Because hedge portfolio returns do not load consistently on JUMP and VOL and these factors are only available for a portion of our sample period, we present our remaining analysis using only FVIX and CFVIX to capture aggregate volatility risk, but note that our results are substantively similar if we also include JUMP and VOL.

Interestingly, we find that the coefficient on CFVIX is negative, meaning that FVIX has a more pronounced impact on the VS hedge portfolio returns when FVIX is low. This is consistent with volatility feedback: any large news (positive or negative) increases volatility but with asymmetric effects (Campbell and Hentschel (1992)). This is also consistent with the asymmetric relation between VS and volatility in our theoretical examples, as changes in volatility have a greater impact on VS in down states.[29] Thus, our results support a risk-based explanation for the VS-stock return predictability. Individual firm VS appear to capture both the firm's sensitivity to volatility risk and the market's expectations regarding future aggregate volatility. This leads firms in VS5 to have higher required returns, and appear to outperform firms in VS1.

E. Related Anomalies

If VS captures the firm's sensitivity to changes in aggregate volatility risk, we might also expect aggregate volatility to have explanatory power for stock return predictability using other measures of implied volatilities. Thus, we investigate whether aggregate volatility can explain the performance of stock portfolios created based on both VS and changes in VS, relative changes in implied volatilities, and implied volatility smirks. The advantage of analyzing these alternative measures of option market information is that they are not perfectly correlated and may or may not be driven by the same underlying concerns.[30]

Cremers and Weinbaum (2010) document greater predictability when sorting stocks on a combination of VS and changes in VS. To examine whether this can be explained by aggregate volatility risk, we perform a double-sorting procedure and

[28]We repeat the same analysis using value-weighted portfolios using NYSE breakpoints and value-weighted portfolios based on the log of the market value of equity, and the results are robust to these alternatives.

[29]Additional tests show that the VS hedge portfolio is less sensitive to FVIX when the CFNAI is high (up state) than when the CFNAI is low (down state).

[30]In untabulated FM regressions, the smirk and changes in implied volatilities do not subsume the VS-stock return predictability (or vice versa), suggesting that these are at least partially distinct anomalies. The VS hedge portfolio is highly correlated with the portfolio formed using both VS and changes in VS (0.80), but less so with the change in implied volatility hedge portfolio (0.17) and the smirk hedge portfolio (0.02). The smirk appears to be more heavily correlated with the changes in VS and implied volatilities (0.20–0.25).

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form a hedge portfolio with a long position in firms in the highest quintile of both the level of and changes in VS (5,5), and a short position in firms in the lowest quintile in both (1,1). The relative changes in implied volatilities are defined as the change in the implied volatilities of at-the-money call options minus the change in implied volatilities in at-the-money put options (An, Ang, Bali, and Cakici (2014)). A similar argument could be made for a link between aggregate volatility risk and changes in implied volatilities. However, a potentially confounding issue for the changes in implied volatilities is that, unlike the volatility spread and smirk, sorting on the changes does not necessarily equate to sorting firms on a measure of the volatility spread or the level of expected aggregate volatility. We again sort firms into quintiles and form a hedge portfolio with a long position in the highest quintile and a short position in the lowest quintile.

Finally, the volatility smirk is defined as the difference in implied volatilities between an at-the-money call option and an out-of-the-money put option (Xing et al. (2010)).[31] While our theoretical results focus on the relation between time-varying volatility and VS, the spreads are generated by differences in early exercise across otherwise identical calls and puts. Thus, time-varying volatility may also contribute to a divergence of implied volatilities between an at-the-money call and an out-of-the-money put. Consistent with this, nonconstant volatility has been shown to explain a portion of the differing values of options across moneyness levels that could lead to a volatility smirk (Bakshi et al. (1997)). We then sort firms into quintiles based on the volatility smirk and form a hedge portfolio with a long position in the highest quintile and a short position in the lowest quintile.

In each case, we calculate the returns to the resulting hedge portfolio over the month following portfolio formation. We then analyze the ability of aggregate volatility risk to explain the returns to each of these hedge portfolios. The results are presented in Table 6. We first examine we examine whether aggregate volatility risk can explain the returns to a (5,5) minus (1,1) hedge portfolio created from an independent double-sorting procedure using both VS and the change in VS, similar to Cremers and Weinbaum (2010). In the standard benchmark model, we find that the hedge portfolio earns a statistically significant alpha of 53 bps per month (*t*-stat. of 4.21). When the aggregate volatility risk factors are included, we find that the hedge portfolio returns are significantly related to both FVIX and CFVIX, and the alpha is reduced by up to 92% to a statistically insignificant 10 bps (*t*-stat. of 0.59). This provides further evidence that VS captures aggregate volatility risk, leading to the observed stock return predictability.

We next examine the returns to a hedge portfolio based on relative changes in the implied volatilities of call and put options. When the standard benchmark model is used, we find that the hedge portfolio earns a statistically significant 55 bps per month. Adding FVIX and CFVIX leads to a decrease in abnormal returns to 31 bps (*t*-stat. of 2.16), and the hedge portfolio returns are significantly related to CFVIX. Consistent with the results documented above for VS, this also suggests that

[31] We use this measure, which is the reverse of the measure used by Xing et al. (2010) (OTM put minus ATM call), for ease of comparison with our other tests. Because we effectively multiply the Xing et al. (2010) measure by -1, we expect the hedge portfolio to earn a positive rather than a negative abnormal return.

TABLE 6

Alternative Measures of Option-Implied Volatility

Table 6 presents the results of the VS hedge portfolios returns (HP) regressed on benchmark return models for three alternative measures of option-market information: the levels of VS coupled with changes in VS (ΔVS&VS columns 1 and 2), the relative changes in implied volatilities for ATM calls and ATM puts (ΔC-ΔP columns 3 and 4), and the difference between the implied volatilities of ATM call and OTM put options (SKEW columns 5 and 6). Columns 1, 3, and 5 presents the results from the benchmark model used by Cremers and Weinbaum (2010), based on a Fama and French (1993) 3-factor model plus momentum and coskewness (Harvey and Siddique (2000)). Columns 2, 4, and 6 include the standard benchmark model plus FVIX is the aggregate volatility risk factor following Ang et al. (2006b), and CFVIX is a factor defined to capture any nonlinear impact of FVIX between high and low FVIX states. All results are estimated using the monthly returns for a monthly-rebalanced quintile 5 minus quintile 1 hedge portfolio, with the exception of columns 1 and 2, which are based on the returns to a (5,5) minus (1,1) double-sort on both the level of and changes in VS. *t*-statistics in parentheses are corrected for heteroskedasticity and auto-correlation using the Newey–West estimator with 3 lags. The sample period is from Jan. 1996 to Dec. 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	ΔVS&VS		ΔC-ΔP		SKEW	
	HP	HP	HP	HP	HP	HP
	1	2	3	4	5	6
α	0.53***	0.10	0.55***	0.31**	0.18*	0.10
	(4.21)	(0.59)	(5.58)	(2.16)	(1.71)	(0.63)
MKTRF	0.06	−0.37**	0.02	−0.16*	0.16***	0.46*
	(1.36)	(−2.03)	(0.92)	(−1.71)	(4.66)	(1.74)
SMB	−0.02	0.02	−0.00	0.02	0.16***	0.14***
	(−0.46)	(0.57)	(−0.04)	(0.86)	(4.64)	(4.07)
HML	−0.01	−0.06	−0.01	−0.03	−0.39***	−0.34***
	(−0.17)	(−1.28)	(−0.25)	(−0.94)	(−6.99)	(−4.71)
MOM	0.01	0.03	0.01	0.02	0.08***	0.08***
	(0.34)	(0.73)	(0.67)	(0.88)	(3.37)	(3.46)
CSK	−0.02	−0.05	−0.02	−0.04	0.01	0.02
	(−0.43)	(−0.93)	(−0.72)	(−1.13)	(0.21)	(0.34)
FVIX		−0.32*		−0.12		0.32
		(−1.94)		(−1.36)		(1.45)
CFVIX		−0.18**		−0.11*		−0.08
		(−2.03)		(−1.78)		(−1.21)
N	262	262	262	262	263	263
R^2	0.02	0.07	0.01	0.04	0.53	0.54

aggregate volatility risk has significant explanatory power for the performance of hedge portfolios created based on option implied volatilities.[32]

Finally, we examine the relation between aggregate volatility risk and the returns to volatility smirk hedge portfolios. When the standard benchmark portfolio is used, we find that the hedge portfolio earns a statistically significant 18 bps per month (*t*-stat. of 1.71). When we include FVIX and CFVIX, we find that the hedge portfolio return alphas decrease to 10 bps per month and become insignificant (*t*-stat. of 0.82), but returns do not significantly load on FVIX and CFVIX. This suggests that the smirk predictability is not robust to controlling for aggregate volatility risk.[33] Taken together, our results support the prediction that the

[32]As an alternative, we sort firms using the change in VS and form associated Q5–Q1 hedge portfolios. We find that the alpha is positive and significant in the 5-factor model, is significantly related to CFVIX, and the alpha is driven to 0 once CFVIX is included in the model.

[33]In untabulated tests, we analyze the anomalies while using the full benchmark model including JUMP and VOL. In each case, our conclusions are unchanged. We find only a small difference in abnormal returns that may be due in part to the difference in sample periods, as these factors are only available through 2011.

asymmetric pricing effects of nonconstant volatility can generate differences in the implied volatilities of call and put options that capture aggregate volatility risk.

V. Additional Analysis and Robustness

A. Differing Sensitivities to Aggregate Volatility Through Growth Options

Our results suggest that the VS hedge portfolio returns are correlated with aggregate volatility. While our predictions are made irrespective of why firms may have differing sensitivities to aggregate volatility, further examination of the underlying reason may also be of interest. One potential explanation is that the firms in each portfolio have differing mixes of growth options and assets-in-place. Theoretical and empirical evidence suggests that assets-in-place have greater sensitivity to economic states and aggregate volatility (Berk et al. (1999), Zhang (2005), and Anderson and Garcia-Feijoo (2006)). In particular, Barinov ((2012), (2013)) argues that increases in aggregate volatility cause the expected returns to high-growth-option (assets-in-place) firms to decrease (increase), and shows that this can help explain sensitivity to aggregate volatility risk and the small growth anomaly, the new issues puzzle, and the analyst disagreement effect. This also leads to different loadings on FVIX. Thus, the mix of assets-in-place versus growth options may also differ across the VS portfolios, and help to explain the link between aggregate volatility risk, VS, and the underlying stock returns.

We analyze differences in asset growth, capital expenditures, employee growth, cash sales growth, and external financing growth as measures of the exercise of growth options. We measure asset growth (ATGR) as the percentage change in total assets, capital expenditures as total capital expenditures scaled by net property plant and equipment (PPENTGR), employee (EMPGR), and cash sales growth (CSGR) as the percentage change in total employees and cash sales, respectively, and external financing growth (XFINPGR) as the change in equity and debt minus net income, scaled by total assets (Zhang (2007)). We use multiple measures of growth to take advantage of their differing characteristics.[34]

The evidence presented in Table 7 shows that firms with higher VS have relatively fewer growth options: Firms in the high volatility spread portfolio (VS5) have significantly lower growth than firms in low volatility spread portfolio (VS1) across the five measures of growth. On average across the measures, we find that firms in VS5 exhibit a growth rate 5% lower than firms in VS1, suggesting significantly lower growth options for firms in VS5. While this may not be the sole link between aggregate volatility and VS, it presents a plausible explanation that may help to explain why firms in VS5 and VS1 have different sensitivities to aggregate volatility.

[34]Asset growth measures the total growth of the firm, regardless of asset type. Capital expenditures capture growth in tangible, fixed assets. Employee growth and external financing growth capture the activities that the firm must take to support growth through financing and expanding its employee base, while cash sales growth captures the growth in the firms' outcomes from its operating activities.

TABLE 7

Volatility Spreads and Growth Options

Table 7 presents the average firm growth options for each of the volatility spread quintile portfolios. Following Zhang (2007), asset growth (ATGR) is the percentage change in total assets, capital expenditures is total capital expenditures scaled by net property plant and equipment (PPENTGR), employee (EMPGR), and cash sales growth (CSGR) are the percentage change in total employees and cash sales, respectively, and external financing growth (XFINPGR) is the change in equity and debt minus net income, scaled by total assets. Also presented is the difference in firm growth options for the VS5 and VS1 portfolios, with *t*-statistics in parentheses. The sample period is from Jan. 1996 to Dec. 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	VS1	VS2	VS3	VS4	VS5	VS5–VS1
ATGR	0.22***	0.20***	0.19***	0.18***	0.18***	−0.04***
						(−12.11)
PPENTGR	0.04***	0.04***	0.04***	0.04***	0.03***	−0.01***
						(−13.11)
EMPGR	0.14***	0.12***	0.11***	0.11***	0.11***	−0.03***
						(−11.35)
SCGR	0.20***	0.19***	0.17***	0.17***	0.18***	−0.02***
						(−5.68)
XFINPGR	0.16***	0.11***	0.09***	0.09***	0.11***	−0.05***
						(−14.08)

B. Moneyness and Informed Trading

An alternative explanation for our results is that aggregate volatility risk explains the returns to stocks with low levels of informed trading, leading to decreased abnormal performance *on average* in our sample. This explanation, however, would not preclude firm-specific information as a driver of the VS hedge portfolio performance for certain subsets of stocks in which informed trading is more likely to occur, such as OTM puts, which are more likely to be the focus of traders with firm-specific information (Xing et al. (2010)).

To examine this alternative, we sort options into levels of moneyness and construct hedge portfolios based on three groups of paired options: i) OTM (out of the money) puts and ITM (in the money) calls, ii) ATM (at the money) puts and ATM calls, and iii) ITM puts and OTM calls.[35] We follow Xing et al. (2010) and use the ratio of the strike price to the stock price (X/S) to define moneyness, where i) OTM is defined as a ratio lower than 0.95, ii) ATM is defined as a ratio between 0.95 and 1.05, and iii) ITM is defined as a ratio above 1.05. Under the informed trading explanation, we would expect the predictability to be concentrated in hedge portfolios created using the VS of OTM puts and ITM calls and to remain after controlling for aggregate volatility risk. Table 8 presents the results from this analysis estimating the alphas for the hedge portfolios using a standard benchmark model as well as a benchmark model accounting for aggregate volatility risk.

In contrast to prior works, we find that the predictive ability is not concentrated in any one type of option. In each case, we find a significantly positive alpha for the hedge portfolio when the standard benchmark model is used. Benchmark models that account for aggregate volatility risk show a different result: portfolio returns load significantly on FVIX and CFVIX, alphas decrease in magnitude for all

[35]We analyze these three groups because our measure (VS) assumes that the put and call under consideration each have the same strike price, which creates one of these three relationships between the put and call moneyness levels by definition.

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TABLE 8

Moneyness

Table 8 presents the results of VS hedge portfolios returns regressed on benchmark return models for three sets of paired options: OTM puts and ITM calls (columns 1 and 2), ATM puts and ATM calls (columns 3 and 4), and ITM puts and OTM calls (columns 5 and 6). Columns 1, 3, and 5 present the results from the benchmark model used by Cremers and Weinbaum (2010), based on a Fama and French (1993) 3-factor model plus momentum and coskewness (Harvey and Siddique (2000)). Columns 2, 4, and 6 include the standard benchmark model plus FVIX and CFVIX, as defined in Table 4 and in the text. All results are estimated using the monthly returns for a monthly-rebalanced VS5–VS1 hedge portfolio. *t*-statistics in parentheses are corrected for heteroskedasticity and auto-correlation using the Newey-West estimator with 3 lags. The sample period is from Jan. 1996 to Dec. 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	TYPE 1		TYPE 2		TYPE 3	
	HP	HP	HP	HP	HP	HP
	1	2	3	4	5	6
α	0.49***	0.15	0.50***	0.24*	0.47***	0.12
	(5.42)	(1.25)	(5.55)	(1.91)	(4.85)	(0.96)
MKTRF	−0.00	−0.40***	−0.02	−0.36***	−0.00	−0.48***
	(−0.13)	(−3.65)	(−0.55)	(−3.39)	(−0.17)	(−3.94)
SMB	0.04	0.09***	−0.01	0.02	−0.06	−0.02
	(1.22)	(2.59)	(−0.25)	(0.54)	(−1.11)	(−0.36)
HML	0.12***	0.06	0.01	−0.04	−0.05	−0.11***
	(2.66)	(1.52)	(0.25)	(−0.74)	(−1.18)	(−3.26)
MOM	0.07**	0.08***	−0.05	−0.04	−0.04	−0.02
	(2.38)	(3.05)	(−1.37)	(−1.05)	(−1.25)	(−0.83)
CSK	−0.01	−0.03	−0.08*	−0.10**	−0.03	−0.05
	(−0.25)	(−0.81)	(−1.83)	(−2.43)	(−0.60)	(−1.29)
FVIX		−0.32***		−0.28***		−0.40***
		(−3.12)		(−2.86)		(−3.34)
CFVIX		−0.14**		−0.10*		−0.13**
		(−2.56)		(−1.72)		(−2.05)
N	263	263	263	263	263	263
R^2	0.09	0.15	0.04	0.09	0.04	0.10

moneyness levels and become statistically indistinguishable from zero for OTM/ITM options. Furthermore, the updated benchmark model explains the majority of the abnormal performance of the hedge portfolio in each subgroup. This is inconsistent with informed trading as a primary driver of our results.

C. Contemporaneous Returns

Our results are consistent with a risk-based explanation for the VS-stock return predictability. If this is correct, firms in VS5 require higher future returns to compensate investors for aggregate volatility risk. To earn the higher required return in the month following portfolio formation, the same stocks would need to experience a price decrease during the month of portfolio formation, generating a *negative* contemporaneous VS-return relation. To test this, we calculate the returns to the VS hedge portfolio during the month of portfolio formation. Consistent with our predictions, we find a negative and significant contemporaneous relation. In particular, VS5 firms experience a price decrease, and the hedge portfolio returns are negative and significant throughout our sample period. Further discussion and tabulated results are provided in Table A1 in the Supplementary Material.

D. Short-Term Predictability

Informed trading could also contribute more to predictability over shorter windows. To further examine informed trading as a potential driver of predictability, we examine the returns to the VS hedge portfolio over 1 day and 1 week post-formation. We find that aggregate volatility risk is also a significant determinant of the returns to weekly and daily rebalanced portfolios. In each case, the abnormal return is reduced by more than 40% relative to the abnormal return when the standard benchmark model is used. For weekly returns, the portfolio loads significantly on FVIX and CFVIX, and the alpha is reduced from 22 (*t*-stat. of 9.53) to 13 bps (*t*-stat. of 4.11) per week, or approximately 41%. For daily returns, the hedge portfolio loads significantly on FVIX, CFVIX, and JUMP, and the alpha decreases from 8 bps (*t*-stat. of 15.32) to 3 bps (*t*-stat. of 1.85) per day, or approximately 63%. For comparison, the explanatory power of aggregate volatility risk is very similar to that found by Barinov (2013), who shows that the market premium and aggregate volatility risk can explain 50% to 90% of the analyst disagreement anomaly. Further analysis shows that the remaining weekly alpha is driven by the first 2 days of returns post-formation, and daily alphas are insignificant beyond the first 2 days. This suggests that the remaining predictability dissipates quickly. Taken together, these results are consistent with hedge portfolio returns driven largely by exposure to aggregate volatility risk. However, it does appear that a portion of the stock return predictability remains over the short-term, consistent with the conclusions of Cremers and Weinbaum (2010).

E. Implied Volatilities Versus Option Volume

Next, we examine the ability of aggregate volatility risk to explain the performance of hedge portfolios created based on option volume. Option volume has been argued to capture informed trading-based demand pressure, leading to stock return predictability. Our theoretical analysis makes no such prediction for a relation between volume and aggregate volatility. Thus, we would not expect aggregate volatility to the volume–return relation. However, if our results were driven by the time-varying value of information, we would expect similar results when analyzing option volume.

We follow Pan and Poteshman (2006) and define the information from option volume as the ratio of put option volume to the total of put and call option volume for the options written on each individual stock. However, because OptionMetrics does not provide information to separate the volume into categories by type of transaction, we cannot limit this to trades by non-market-makers opening new option positions.[36] Thus, we base this measure on all option trading volume for individual options. In untabulated results, we find that a volume-based hedge portfolio generates a statistically significant alpha that is unaffected by aggregate volatility risk factors. This suggests that option volume, which might reflect demand for options based on informed investors trading on new firm-specific information (Garleanu, Pedersen, and Poteshman (2009)), is distinct from the other anomalies related to implied volatilities. It also suggests that our results are not

[36]Results are similar if we construct the hedge portfolio based on open interest rather than volume.

driven by time-varying value of information, as this should also impact the volume–return predictability. An important caveat is that our data does not provide trade-level information or daily aggregated volume by transaction type.

F. Additional Alternate Explanations

We also consider whether informed trading or liquidity can explain the volatility spread-stock return relationship. Using Fama and MacBeth (1973) characteristics regressions estimated on each monthly cross section, we regress future monthly excess returns $R^e_{i,t+1}$ on the firm's implied volatility spread $\mathrm{VS}_{i,t}$, measures of informed trading or liquidity, and other characteristics representing firm risk measured at time t. These include market beta from a 48-month rolling regression (β^{MKT}), market value of equity (MVE), market-to-book ratio (MB), and cumulative stock returns over the last 6 months (MOM). Specifically,

$$R^e_{i,t+1} = \alpha_0 + \alpha_1 \mathrm{VS}_{i,t} + \alpha_2 A_{i,t} + \alpha_3 \mathrm{VS}_{i,t} \times A_{i,t} + \mathbf{C}_t \Gamma' + \varepsilon_{i,t+1}, \tag{8}$$

where $A_{i,t}$ captures the alternative explanations. We consider eight alternate measures that may potentially explain our results: i) stock PIN, ii) analyst coverage, iii) option volume, iv) stock volume, v) relative option-to-stock volume, vi) option illiquidity, vii) stock illiquidity, and viii) relative option-to-stock illiquidity. In each case, we interact the measure of informed trading with the firm's implied volatility spread to attempt to determine whether the observed VS-stock return relationship is explained by informed trading. Each of the measures of informed trading and liquidity is described in detail in the Supplementary Material.

If firm-specific informed trading or liquidity is the primary driver of this relationship, we would expect the direct relation between VS and subsequent firm stock returns to be insignificant, and the VS-stock return relation should only be found for the interaction terms. As shown in Table A2 in the Supplementary Material, our results do not support this. In each specification, VS remains positive and significant, and no interaction term is significant. This does not support informed trading as a driver of the VS-stock return predictability.

As an analog to the above test, we analyze the impact of aggregate volatility by estimating VS-stock return predictability conditional on the level of volatility. We follow a similar procedure to Mashruwala, Rajgopal, and Shevlin (2006) and estimate FM regressions with interactions between VS and (separately) the decile rank of macro variables VIX, RD, MVAR, and EVRP. This allows us to examine whether the impact of VS differs across periods of high and low volatility. Contrary to the results for informed trading/liquidity, we find that the volatility interaction coefficients are positive and significant in each case. Moreover, VS does not have significant independent predictive ability during low volatility periods when VIX, RD, or MVAR is used to measure aggregate volatility. This provides further evidence that VS captures some aspect of aggregate volatility, leading to the observed predictability. Full details and tabulated results are provided in Table A3 in the Supplementary Material.

A related concern is that the VS-return predictability is an artifact of persistence in VS and stock returns leading to a spurious correlation between the two (Wei

(2014)). To address this possibility, we repeat the base specification FM regression described above, but control for 3 months of lagged stock returns, the "difference in returns" over the 3-month period, or both (Wei (2014)). The untabulated results show that the VS-return predictability is robust to each alternate specification. Alternately, we orthogonalize VS to the three lagged stock return differences following Wei (2014), and form a hedge portfolio using the portion of VS unrelated to past returns. We find that the returns to the hedge portfolio are nearly identical to those for the full sample in Table 3. Taken together, these tests help to rule out persistence as the underlying cause of the VS-return predictability.

Similarly, Muravyev et al. (2018) show that option implied volatilities are correlated with stock borrowing fees and that removing expensive-to-short stocks reduces the predictability of stock returns from VS, implied volatility skews, and option volume.[37] Specifically, excluding difficult-to-short stocks reduces the 1-week predictability associated with VS and skew, and the 1-month predictability using option volume. This provides complementary evidence to our results, as we find that the 1-month predictability associated VS and skew is economically and statistically insignificant after removing the effects of aggregate volatility, while shorter-term predictability and the predictability using option volume (as discussed in the prior subsection) persist. Thus, while volatility and short-sale constraints are correlated (Barinov and Wu (2013)) and may be impossible to fully disentangle empirically, these explanations need not be mutually exclusive. In fact, each appears to contribute to explaining a different portion of the predictability.

To ensure that our results do not simply reflect difficult-to-short stocks, we perform a number of additional tests. First, we perform a double-sorting procedure, first sorting firms into quintiles based on short-interest[38] and then by VS. In untabulated tests, we find that VS predicts stock returns in all but the lowest short-interest quintile. Second, similar to the tests for informed trading, we repeat the FM regression described above, but control for short interest and an interaction between short interest and VS. We include the results in Table A2 in the Supplementary Material. If short sale constraints were the primary driver of the predictability in our sample, we would expect the interaction to be significant, and this should subsume the direct effect of VS. However, we find that VS remains significant, and while short interest has a negative and significant direct effect as expected, the interaction is insignificant. This suggests that, while short sale constraints have a significant impact on stock returns, they do not explain the VS-return predictability in our sample.

Third, we exclude all stocks in the lowest decile of short interest, similar to Muravyev, Pearson, and Pollet's (2018) exclusion of difficult-to-short stocks, and repeat the tests in Tables 2 and 5. We find that VS continues to predict stock returns across firm-level volatility quintiles, but only when aggregate volatility is high, the

[37]The authors establish a theoretical link between implied volatilities and borrowing fees with the assumption that OptionMetrics' American option implied volatilities are a reasonable approximation of Black–Scholes European option implied volatilities. Our results demonstrate that this is unlikely to hold when volatility is nonconstant, potentially complicating the relation between implied volatilities and borrowing fees.

[38]We use short interest as a proxy for short-sale constraints, as we do not have the Markit borrowing fee data used by Muravyev et al. (2018).

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VS hedge portfolio loads significant on FVIX and CFVIX, and the hedge portfolio's alpha is meaningfully reduced after these factors are included. These results are available in Tables A4 and A5 in the Supplementary Material, respectively. While these results demonstrate that our findings do not simply capture short-sale constraints, we note that our goal is not to rule out short-sale constraints contributing to the predictability, but to show that this does not drive our results. Thus, short-sale constraints and aggregate volatility could both contribute to the predictability in meaningful ways.

A related concern is that capital constraints increase during poor economic times, reducing the ability of investors to trade and keep a stock's price closer to fundamental value, leading to predictability during bad times. However, this would not explain why the volatility spread is correlated with the sensitivity to aggregate volatility or the mix of assets-in-place and growth options at the underlying firms, or why this would impact these firms' returns more than others. This is also inconsistent with the results in Table A2 in the Supplementary Material. If constraints were the primary driver of predictability, we would expect VS to become an insignificant predictor of returns when we control for illiquidity and volume, which are likely to be highly correlated with capital constraints.

Similarly, informed traders could possess information that is valuable during specific periods. This could explain the significance of CFVIX if the information has greater value during low FVIX periods. To address this possibility, we conduct additional tests where, in addition to the factors included in Table 5, we include an indicator variable that takes a value of 1 during low FVIX periods, and 0 otherwise. If CFVIX is simply capturing the time-varying value of information, we would expect the coefficient on the indicator variable to be positive and significant, and for CFVIX to no longer have a significant relation with the hedge portfolio returns. Although not reported in a table, this test shows that the indicator variable is not significant and does not affect the significance of CFVIX. This is inconsistent with CFVIX capturing time-variation in the value of information.[39]

Finally, we consider the possibility that our results are driven by the financial firms during the recent financial crisis. To address this concern, we repeat the analysis presented in Table 4 excluding all financial firms (firms with SIC codes between 6000 and 6999). However, we continue to find a significant positive alpha when the standard benchmark model is used, and an insignificant monthly alpha in our updated benchmark model. Thus, our results are not driven by financial firms that experienced large shifts in value during the financial crisis. Taken together, these tests continue to support aggregate volatility risk as an explanation for the observed VS-return predictability.

VI. Conclusion

This article examines the apparent deviations from put-call parity captured by implied VS and offers an alternative explanation for why these spreads occur. VS may occur for American options in cases when volatility is nonconstant due to differences in optimal early exercise between call and put options and between

[39]We thank an anonymous referee for suggesting this test.

constant and nonconstant volatility cases. Furthermore, the ability of VS to predict stock returns is the result of sensitivity to aggregate volatility that drives both the underlying stock returns and VS. We show theoretically that VS are related to the state-dependent nature of volatility when volatility is time-varying and options have American-style exercise. Empirically, we find that the performance of volatility spread hedge portfolio (VS5-VS1) is higher if it was formed during periods with high aggregate volatility and among stocks with high firm-level volatility. Robustness checks reasonably rule out firm-specific information-based trading and liquidity as explanations for these results.

Our study makes a number of interesting contributions. First, we contribute to the theoretical understanding of VS, and how these can arise without violating put-call parity conditions when volatility is time-varying and options can be exercised early. Second, we contribute to the empirical literature on individual option implied VS by showing that VS appears to proxy for expected aggregate volatility and the firm's sensitivity to this risk. Finally, we show that empirical factors designed to capture volatility and jump risk have nonlinear effects, may each be relevant for explaining stock returns, and are not perfectly interchangeable.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109023000182, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4384496, or https://drive.google.com/file/d/1s7p5Qi7uZvOP9NvXaTEAmvLGCv-zTRZ7/view.

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