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Risk and uncertainty in style rotation

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Abstract

The Chicago Board Options Exchange (CBOE VIX; volatility) index has been established as a leading indicator of style returns since increases in this "fear index" lead to outperformance of "value" versus "growth" stocks. This study introduces the concept of "uncertainty" as an additional indicator of returns to value, as measured by the CBOE VVIX ("volatility of volatility"). This index is considered to be a proxy for "uncertainty" in the Knightian sense. Increases in expected volatility lead to short-term positive returns to value, while increases in uncertainty lead to negative short-term returns to value. Each of these observations are especially strong during economic downturns and after decreases in the VIX index. Several macroeconomic indicators provide additional incremental information regarding these phenomena. © 2018 Academy of Financial Services. All rights reserved.

JEL classification: G1; C1; C5

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1. Introduction

This article examines equity financial market relationships among risk, uncertainty, and returns to value and growth stocks. Specifically, the analysis examines the effectiveness of the Chicago Board Options Exchange (CBOE) volatility indices as leading indicators of style returns (value vs. growth). The effectiveness of the volatility index (the CBOE VIX Index, also known as the "fear index" in the financial press) as a leading indicator of style returns is examined by Copeland and Copeland (1999), who find that increases in the VIX Index lead to the outperformance of value-based indexes relative to growth-based indexes. Boscaljon,

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Filbeck, and Zhao (2011) find that these effects have diminished over time and are more recently only observable over longer return horizon periods. The theoretical underpinnings of both of these papers postulate that investors gravitate towards “value” in times of expected market turbulence (increased volatility and therefore increased risk). This supposition is first proposed by Merton (1980) and French, Schwert, and Stambaugh (1987), who suggest a positive relationship between the market risk premium and expected future volatility that is related to the asymmetric volatility phenomenon, or, alternatively, the “leverage effect.” Hence, lower beta value stocks perform better as stock prices fall in the face of expected increases in future volatility. The converse applies to higher beta growth stocks.

To explore these issues further, precise definitions of risk and uncertainty are necessary. One generally accepted definition of risk is described as being exposed to a set of possible outcomes that may be observed under an objective expected probability distribution. However, many economists posit that this measure of risk does not capture the effect of “uncertainty,” which describes the effect of “unknowns” as a distinction between risk (volatility defined by an expected probability distribution of outcomes) and “unmeasurable uncertainty” (Knight, 1921, p. 245) that is defined by expected outcomes over an unknown probability distribution. In contrast to the generally accepted definition of risk, uncertainty is defined by *subjective* assessments of possible probability distributions determined by market participants. Therefore, expected volatility is time-varying and heterogeneous among market participants. First proposed by Knight (1921) and supported by Keynes (1921) and Ellsberg (1961), this concept is often referred to as “Knightian uncertainty,” suggesting a distinction between risk (volatility that can be measured using probabilities) and “unmeasurable uncertainty” (Knight, 1921, p. 245).

Baltussen, Van Bekkum, and Van Der Grient (2017)) propose an intuitive proxy for uncertainty in equity markets that is constructed from variations in the implied volatilities of single stock options that they denote as “volatility of volatility,” or “vol-of-vol.” They calculate the monthly average standard deviation of implied volatilities of at-the-money single stock options and demonstrate that “stocks with high uncertainty about risk… robustly underperform stocks with low uncertainty about risk: (p. 1). At the aggregate market level, the CBOE provides a “volatility of volatility” index (VVIX) that is constructed using implied volatilities of VIX Index options. Therefore, this measure is an explicitly forward-looking measure of the potential future distribution of returns of the S&P 500 index, reflecting the expectations of market participants, and not prior implied volatility information. Further details regarding the construction of the VVIX index can be found in a CBOE white paper (CBOE, 2012). This measure is examined recently by Aboura and Arisoy (2017) in a study of portfolio style returns, who find that “due to their negative uncertainty betas, uncertainty-averse investors demand extra compensation to hold small and value stocks” (p. 3217). The present analysis offers a similar explanation of the size and value anomalies in highly liquid Exchange Traded Funds (ETFs; as opposed to individual stock portfolios), and the results are obtained on a lead-lag, as opposed to a contemporaneous, basis. Thus, this study may more directly reflect the future performance of “style” based investing based on investor perceptions of uncertainty. In sum, the results of the present study indicate that increases in expected volatility lead to short-term positive returns to value, but increases in uncertainty lead to negative short-term returns to value. Each of these observations are especially strong during economic downturns and following decreases in the VIX index, and these observations should spur further research into the behavior of investors that expands the traditional mean-variance framework. In support of this observation, Talukdar, Daigler, and Parhizgari (2017), posit that "behavioral theories explain the return–volatility relation better than the fundamental theories" (p. 698). Mayfield and Wooten (2009) propose that investor decisions are influenced by their personality type, a further indication of potential investor heterogeneity. Additionally, Below, Kiely, and Prati (2009) demonstrate the advantages to frequent rebalancing across equity "styles" to achieve above-average performance.

Although the evidence from the behavioral finance literature is still being developed and contradictory results have been obtained because of differentials in the information under study (time frames, sample selection, etc.), it is not for a lack of effort. The relationships among future stock returns and proxies for uncertainty are examined relative to economic policy by Brogaard and Detzel (2015), who find a positive relationship between economic policy uncertainty and future excess market returns. However, Ko and Lee (2015) find a negative relationship between these variables using wavelet analysis on a contemporaneous basis. Su, Fang, and Yin (2017) investigate "news-based" uncertainty that predicts future market volatility. The results of these studies indicate varying relationships between uncertainty and returns, and the conflation of contemporaneous and predictive results makes it difficult to disentangle the issue. Additional studies find positive relationships between differing proxies for uncertainty and future stock returns. For example, Bekaert, Engstrom, and Xing (2009) and Bali, Brown, and Caglayan (2014) examine the conditional correlations of fundamental equity characteristics and macroeconomic variables, respectively. Each of these studies find positive lead-lag relationships between their proxies for uncertainty "betas" and stock returns and hedge fund returns, respectively. Krause (2018) finds similar results using the VVIX index as a proxy for uncertainty.

This study examines the effectiveness of the two CBOE volatility indices as leading indicators of style returns (value vs. growth), and the results of the analysis indicate that the CBOE VVIX index provides significant incremental information regarding the interaction of returns, volatility, and uncertainty on a lead-lag basis. The initial analysis of the VIX index relative to style returns is consistent with Boscaljon, Filbeck, and Zhao (2011) because it finds largely insignificant short-term effects of the VIX index on returns to value. However, innovations in the VVIX index indicate significant negative returns to value. The inclusion of several macroeconomic factors provides additional explanatory information since the VIX index indicates positive returns to value under certain conditions. The main contribution to the literature of this paper is the introduction of the additional concept of "uncertainty" into the returns to value analysis using highly liquid ETFs. The availability of these products, and their recent exponential growth, provides an opportunity to examine the relation of expected volatility and uncertainty to growth and value using similar, easily tradable and low-cost instruments. The results stand in contrast to prior studies that examine MSCI BARRA and/or S&P 500 value and growth portfolios that may be costly and or difficult to implement. Also, short sale constraints are virtually nonexistent for the ETFs under study. The presence of short sale constraints may limit the effectiveness of other studies that examine portfolios of single stocks, as posited by Shleifer and Vishny (1997). Therefore, the use of ETF return time series' allows for a more practical analysis of the data. The study also contributes to the literature by examining macroeconomic variables that contribute to the explanatory power of econometric models with robust standard errors.

Several studies demonstrate that forward-looking implied volatility measures such as the VIX index provide predictive evidence regarding future realized volatility and returns. Ammann, Skovmand, and Verhofen (2009) find a positive relation between implied volatility and future realized volatility in single stock options, while both Anderson, Bollerslev, Diebold, and Labys (2003) and Blair, Poon, and Taylor (2001) find a similar relationship for S&P 100 index options. These studies examine the implied volatility of equity options as an indicator of investor expectations regarding future equity volatility. The results of early studies are somewhat mixed. but most recent studies confirm a generally positive relationship between implied volatility and future realized volatility. In early work, Canina and Figlewski (1993) demonstrate that implied volatility of the S&P 100 Index is a poor predictor of future realized volatility. Additionally, Jiang and Tian (2005) examine the relation between past realized volatility and future realized volatility in S&P 500 Index options, finding it to be a more reliable indicator than implied volatility. Chan, Jha, and Kalimipalli (2009) find that historical volatility is not a reliable predictor of future implied volatility for S&P 500 index options. However, in more recent studies, both Guo and Whitelaw (2006) and Bali and Peng (2006) find a positive relation between the VIX index and future stock returns. Sarwar (2005) finds a positive relation between implied volatility and options trading volume in S&P 500 Index options. DeMiguel, Plyakha, Upal, and Vilkov (2013) find that implied volatility is a useful factor to consider in the selection of efficient mean-variance portfolios, since single stock implied volatility is useful in forecasts of both future volatility and returns of S&P 500 component stocks on a daily and intraday basis. Similarly, Giot (2005) finds a positive relationship between the VIX Index and future stock returns, confirming the results of Copeland and Copeland (1999) and Boscaljon, Filbeck, and Zhao (2011) that are partially supported by the results in this article. An, Ang, Bali, and Cakici (2014) finds a positive relation among in increases in call implied volatilities and future stock returns, and additional evidence on this topic is provided by Bali, Cakici, and Chabi-Yo (2015), and Brous, Ince, and Popova (2009). These studies confirm the positive relation between expected returns and volatility that is first proposed by Markowitz (1952).

This study considers "risk" to be defined as the volatility of the expected return probability distribution (the proxy is the VIX index), consistent with the traditional approach to mean-variance analysis. Similarly, "uncertainty" is defined as the volatility of this volatility, and the proxy is the VVIX index. As noted in a CBOE white paper (CBOE, 2012), the VVIX measures the implied volatility of options on the 30-day forward price of the CBOE VIX index. While this index measures expected risk in the future distribution of returns, the VVIX index measures variability in expectations regarding this distribution. Thus, similar to the study of Baltussen, Van Bekkum, and Van Der Grient (2018), it is a natural proxy for uncertainty about the future distribution of returns that may not conform to a pure mean-variance framework.

There remain considerable differences of opinion regarding the theoretical and empirical evidence on the relations among stock returns and uncertainty. Baltussen, Van Bekkum, and Van Der Grient (2018) explore this issue relative to single stocks using a proxy for uncertainty that is similar to the VVIX index ("vol of vol" in single stocks) to find a negative

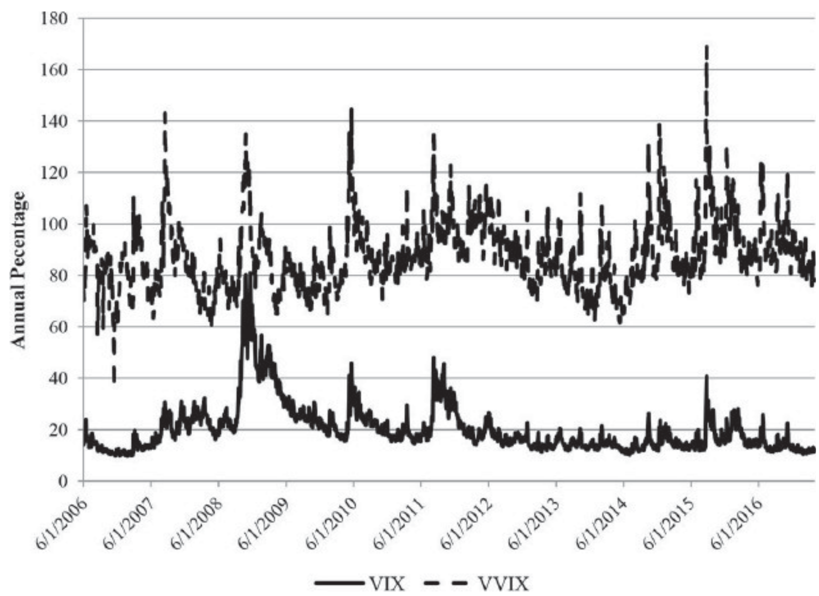

Fig. 1. This graph presents values of the VIX and VVIX index over the past decade (in percentage). Overall, the graph indicates a generally positive correlation over the sample period although there are significant deviations from this observation, especially during financial crises.

relation between uncertainty and single stock returns, an indication of uncertainty-avoiding behavior. Brenner and Izhakian (2012) find similar results for the SPDR S&P 500 ETF using intraday data, although they use a slightly different measure of uncertainty. Aboura and Arisoy (2017) provide some theory supporting the idea that uncertainty is a significant part of the equity risk premium and should be related to expected returns. The authors also conduct an empirical study of the contemporaneous returns of single-stock portfolios sorted on various characteristics relative to the VVIX index on a contemporaneous basis. The research supports the supposition that stock portfolios reflect negative "uncertainty betas" (p. 3214) that are sensitive to market capitalization.

The present study sheds some new light on the topic since the relation between uncertainty and returns for the sample of ETFs is examined in light of important macroeconomic variables. The distinction between volatility and uncertainty is illustrated in Fig. 1. Although the two measures are positively correlated (Pearson correlation coefficient of 0.71 over the sample period) and generally move together, that is not always the case. As shown in the graph, uncertainty increased significantly in 2014 without a concurrent increase in volatility. Additionally, the indexes diverge significantly during the financial crisis of 2007–2009 and during the European debt crisis of 2010–2012. The literature regarding the use of the volatility measures to enhance asset allocation decisions is well-documented in Boscaljon, Filbeck, and Zhao (2011). Additionally, Goldwhite (2009) demonstrates that the VIX index is a useful indicator for investors with different levels of risk aversion, because he examines the relationships among volatility and the returns to value and growth stocks. Puttonen and Seppä (2006) further document the value added by an active approach to investing in value and growth stock indexes. Finally, Talukdar, Daigler, and Parhizgari (2017) find that the VVIX index is an important driver of the VIX index and its relation to future stock returns.

Table 1 Exchange Traded Fund (ETF) descriptions, as of March 31, 2017

ETF	Symbol	Net assets ($)	Average daily trading volume ($)	Annual mgmt. fee	Beta	Inception date
iShares S&P Small-Cap 600 Value ETF	IJS	4.69B	23.4M	0.25%	1.59	07/24/00
iShares S&P Small-Cap 600 Growth ETF	IJT	4.21B	21.1M	0.25%	1.68	07/24/00
iShares S&P Mid-Cap 400 Value ETF	IJJ	5.62B	19.7M	0.25%	1.31	07/24/00
iShares S&P Mid-Cap 400 Growth ETF	IJK	5.48B	23.0M	0.25%	1.34	07/24/00
iShares S&P 500 Value ETF	IVE	13.60B	78.8M	0.18%	1.09	05/22/00
iShares S&P 500 Growth ETF	IVW	17.47B	96.6M	0.18%	1.02	05/22/00

Data is reported by Morgan Stanley & Co., LLC and BlackRock Investments, LLC. Average daily trading volume is for the prior 30 days as of March 31, 2017.

2. Data sample and methodology

The CBOE provides daily closing levels for the VVIX index beginning on June 1, 2006, so daily VIX and VVIX closing levels are collected from June 1, 2006 to March 31, 2017. Daily total return data (including dividends) for six iShares value and growth ETFs (large-, mid-, and small-cap) are obtained from Bloomberg Professional for the same time period. Summary statistics are provided for the volatility indexes and the six style-based ETFs in Table 1. As is evident, each of these ETFs has been in existence for over 15 years, and they are all large, liquid instruments available to easily implement style-based trading strategies, with limited short sale constraints, as opposed to the previously examined MSCI BARRA value and style indices. Copeland and Copeland (1999) argue that the value and growth S&P futures been have available since 1997, making them easily tradeable, but that does not obviate the fact that their analysis is based on index, not futures, data. The illiquid futures contracts based on these indices are only available for the S&P 500 (large-cap) index, and they never really caught on as liquid trading products. As of May 26, 2017, the open interest in the S&P 500 index value contracts was just twenty-six contracts while the trading volume on that day was zero. Boscaljon, Filbeck, and Zhao (2011) also utilize cash indices for their analysis, which are not easily tradeable at a reasonable cost. For instance, there are currently 1,808 constituents in the MSCI U.S.A. Small-Cap Index. However, the present analysis explicitly examines lead-lag relationships among highly liquid ETFs that are easily tradeable. As seen in Table 1, the relatively newly available and liquid ETFs are similar in terms of total net assets and trading volume (the average daily trading volume figures in the table are the most recent three-month average as of March 31, 2017). One exception to this generalization is IVW, the large-cap growth ETF, which is significantly larger than the others.

Table 2 provides summary statistics for the data, where the figures for the volatility indices are daily closing levels and the ETF data are daily returns. Over the sample time period, each of the ETFs experiences similar returns, although standard deviations decline monotonically as market capitalization rises, because the larger capitalization stocks experience lower levels of volatility. A correlation matrix for daily changes in the variables is provided in Table 3, and the first item of interest is the same positive relation between the VIX and VVIX (Pearson correlation coefficient of 0.71) that is present in Fig. 1. Aboura and Arisoy (2017)

Table 2 Summary statistics

Variable	Symbol	n	Mean (%)	Standard deviation	Skewness	Kurtosis	Min.	Max.
Volatility index	VIX	2,728	20.10	9.60	2.38	10.49	9.89	80.86
Vol of vol index	VVIX	2,728	87.22	13.14	0.86	4.67	36.14	168.75
Small value	IJS	2,728	0.044	0.0162	−0.17	8.31	−0.12	0.09
Small growth	IJT	2,728	0.047	0.0015	−0.23	7.80	−0.10	0.09
Mid value	IJJ	2,728	0.043	0.0146	−0.20	10.89	−0.11	0.11
Mid growth	IJK	2,728	0.046	0.0140	−0.38	8.61	−0.10	0.09
Large value	IVE	2,728	0.034	0.0133	−0.17	11.50	−0.09	0.11
Large growth	IVW	2,728	0.043	0.0119	−0.14	12.61	−0.09	0.11

This table presents summary statistics for the variables under study. The volatility indexes are presented as levels while the return data is presented as daily changes.

and Talukda, Daigler, and Parhizgari (2017) also use the VVIX index as a proxy for uncertainty in a different empirical framework using stock portfolios sorted on various characteristics and as a determinant of changes in the VIX index, respectively. As noted previously, as in others, their studies examine contemporaneous rather than lead-lag relationships. In Table 3, the usual negative relation is observed between the VIX index and contemporaneous returns during the financial crisis, a result of the well-known asymmetric volatility phenomenon, or leverage effect (correlations approximating −0.70 for each of the ETFs). Additionally, for all six of the ETFs, this negative relation is near −0.50 for the VVIX index, suggesting that it too may provide information regarding future payoffs to value and growth in addition to the VIX index. Finally, with one exception, all of the correlations among ETF pairs are above 0.90, suggesting, ex ante, that it may be difficult to use volatility and/or uncertainty information to forecast differential returns to style. Despite this difficulty, the following empirical analysis is designed to disentangle these relationships.

Following Copeland and Copeland (1999) and Boscaljon, Filbeck, and Zhao (2011), the first examination of the data are to model several different future return windows as a function of changes in the VIX and VVIX indexes. One deviation from their approach is that standard errors are now estimated with heteroskedasticity- and autocorrelation-consistent (HAC) errors, using the robust procedure of Newey and West (1987) with five lags to represent one week of trading activity. The following robust OLS equations are estimated:

Table 3 Correlation matrix of volatility variables and Exchange Traded Fund (ETF) returns

Variable	Symbol	VIX	VVIX	SM VL	SM GR	MD VL	MD GR	LG VL	LG GR
Δ Volatility index	VIX	1.0000							
Δ Vol of vol index	VVIX	0.7142	1.0000						
Small value	IJS	−0.6794	−0.4381	1.0000					
Small growth	IJT	−0.7053	−0.463	0.9745	1.0000				
Mid value	IJJ	−0.6996	−0.4577	0.964	0.9549	1.0000			
Mid growth	IJK	−0.7215	−0.4769	0.936	0.9616	0.9657	1.0000		
Large value	IVE	−0.7238	−0.4762	0.9182	0.9026	0.9493	0.9160	1.0000	
Large growth	IVW	−0.7511	−0.5043	0.8871	0.9095	0.9243	0.9389	0.9427	1.0000

This table provides a correlation matrix of the primary variables under study in this article.

$$RET\ (Value_{i,t+n} - Growth_{j,t+n}) = \alpha + \beta_1 \Delta VIX_t + \varepsilon_{i,j,t} \tag{1}$$

where $RET\ (Value_{i,t+n} - Growth_{j,t+n})$ represents the relevant time period return (from n equals one to 60 days in discrete increments) for a long position in the value ETF i (e.g., IVE, the iShares S&P 500 Value ETF) and an equal short position in the growth ETF j (e.g., IVW, the iShares S&P 500 Growth ETF) for each of the three size-based ETF classifications. ΔVIX_t represents daily changes in the levels of the VIX index on Day 0. This equation is identical to the specifications of Copeland and Copeland (1999) and Boscaljon, Filbeck, and Zhao (2011) for MSCI BARRA size and value indices. Additionally, a second equation is estimated that adds daily changes in the VVIX index as a proxy for uncertainty to determine whether it possesses further explanatory power for future returns to value:

$$RET\ (Value_{i,t+n} - Growth_{j,t+n}) = \alpha + \beta_1 \Delta VIX_t + \beta_2 \Delta VVIX_t + \varepsilon_{i,j,t} \tag{2}$$

where $\Delta VVIX_t$ represents daily changes in the levels of the VVIX index on Day 0. The standard errors of these estimations are also estimated using the Newey and West (1987) procedure with five lags to represent one week of trading activity.

3. Empirical results

3.1. Initial estimations

The results of the estimations of Eq. (1) for the large-cap ETFs are presented in Panel A of Table 4. The coefficients in Panel A for the large-cap ETFs present the returns to value from one-day changes in the VIX. These estimations report continued declines in the return-to-value predictability for the VIX Index over the years, since there are no significant coefficients for the large-cap ETFs, and it is clear that positive returns to value are not observable for these highly liquid and efficient liquid ETFs over the past decade. It seems that the "returns to value" strategies presented in Copeland and Copeland (1999) and Boscaljon, Filbeck, and Zhao (2011) would likely not be profitable with these highly efficient and liquid ETFs. Additionally, only one of the coefficients for returns to value from the VIX index (the two-day time return window) are statistically significant for the small- and midcap indexes, respectively. These coefficients are negative, which is a counterintuitive result given the expected and documented positive relation between risk and return.

To further explore the returns to value from uncertainty as proxied by the VVIX index, in Table 5, changes in the VVIX index are included in the estimations of Eq. (2) as a potentially further explanatory, independent variable. In this estimation, there is one indication of the potential returns to value from volatility in conjunction with uncertainty. In Panel A, for the large-cap ETFs, the results for five-day returns to value are significantly positive for changes in the VIX index (volatility) at the five percentage level, although some other coefficients (10- and 20-day) are significant at the 10% level. Additionally, the coefficients are significant and negative for changes in the VVIX index (uncertainty) over five- to 30-day time periods (the 20-day coefficient is marginally significant) at the five percentage level. The coefficients

Table 4 Newey and West (1987) regressions of one-day value minus growth Exchange Traded Fund (ETF) returns against changes in the VIX index

Panel A—Large cap VIX only

Day(s) ahead return	1	2	5	10	20	30	40	50	60
Δ VIX	−0.053	−0.046	0.241	0.152	0.292	−0.188	0.034	−0.082	0.004
	(−0.38)	(−0.29)	(1.14)	(0.52)	(0.68)	(−0.39)	(0.06)	(−0.13)	(0.01)
Constant	−0.009	−0.018	−0.047	−0.094*	−0.183**	−0.267**	−0.354***	−0.444***	−0.533***
	(−1.06)	(−1.13)	(−1.32)	(−1.67)	(−2.19)	(−2.53)	(−2.83)	(−3.14)	(−3.47)
Observations	2,728	2,727	2,724	2,719	2,709	2,699	2,689	2,679	2,669
Adjusted R^2	0.001	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Panel B—Mid cap VIX only

Day(s) ahead return	1	2	5	10	20	30	40	50	60
Δ VIX	−0.155	−0.349**	−0.286	−0.230	−0.324	−0.518	−0.125	0.301	0.153
	(−1.455)	(−2.617)	(−1.356)	(−0.912)	(−0.966)	(−1.178)	(−0.266)	(0.542)	(0.248)
Constant	−0.003	−0.006	−0.019	−0.040	−0.076	−0.113	−0.153	−0.203	−0.255*
	(−0.441)	(−0.529)	(−0.706)	(−0.898)	(−1.122)	(−1.321)	(−1.506)	(−1.771)	(−2.027)
Observations	2,728	2,727	2,724	2,719	2,709	2,699	2,689	2,679	2,669
Adjusted R^2	0.001	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Panel C—Small cap VIX only

Day(s) ahead return	1	2	5	10	20	30	40	50	60
Δ VIX	−0.109	−0.257*	−0.210	−0.361	−0.512	−0.598	−0.344	−0.254	−0.264
	(−1.019)	(−1.991)	(−1.031)	(−1.538)	(−1.494)	(−1.415)	(−0.700)	(−0.454)	(−0.443)
Constant	−0.003	−0.007	−0.019	−0.042	−0.083	−0.127	−0.171	−0.223*	−0.281*
	(−0.436)	(−0.567)	(−0.754)	(−0.992)	(−1.304)	(−1.545)	(−1.732)	(−1.987)	(−2.283)
Observations	2,728	2,727	2,724	2,719	2,709	2,699	2,689	2,679	2,669
Adjusted R^2	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000

This table presents the results of estimations of Eq. (1). The dependent variable is daily returns to a portfolio that contains a long position in the value ETF and an equal short position in the growth ETF for each for each size category. For ease of interpretation, all of the coefficients have been multiplied by 100. Thus, for example, if the coefficient is 1.00, a one percentage increase in the VIX index leads to a one basis point return differential over the relevant time frame.

*Significant at the 5% level. **Significant at the 1% level. The standard errors are estimated using five lags to account for one week of trading activity autocorrelation and heteroskedasticity (Newey and West, 1987).

Table 5 Newey and West (1987) regressions of one-day value minus growth Exchange Traded Fund (ETF) returns against changes in the VIX and VVIX indices

Panel A—Large cap VIX and VVIX

Day(s) ahead return	1	2	5	10	20	30	40	50	60
Δ VIX	−0.015	0.189	0.725**	0.886*	1.165*	0.961	1.107	0.337	−0.058
	(−0.077)	(0.836)	(2.200)	(1.770)	(1.704)	(1.164)	(1.186)	(0.333)	(−0.053)
Δ VVIX	−0.075	−0.452*	−0.932**	−1.417**	−1.686*	−2.218**	−2.071*	−0.809	0.120
	(−0.354)	(−1.653)	(−2.165)	(−2.102)	(−1.924)	(−1.995)	(−1.652)	(−0.605)	(0.081)
Constant	−0.009	−0.018	−0.047	−0.094*	−0.183**	−0.267**	−0.353***	−0.444***	−0.533***
	(−1.055)	(−1.127)	(−1.322)	(−1.665)	(−2.191)	(−2.534)	(−2.827)	(−3.137)	(−3.470)
Observations	2,728	2,727	2,724	2,719	2,709	2,699	2,689	2,679	2,669
Adjusted R^2	0.001	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Panel B—Mid cap VIX and VVIX

Day(s) ahead return	1	2	5	10	20	30	40	50	60
Δ VIX	0.046	−0.369	−0.240	−0.107	0.032	0.046	0.458	0.681	0.426
	(0.245)	(−1.795)	(−0.847)	(−0.303)	(0.066)	(0.073)	(0.677)	(0.895)	(0.515)
Δ VVIX	−0.585**	0.039	−0.089	−0.238	−0.687	−1.089	−1.127	−0.733	−0.527
	(−2.602)	(0.156)	(−0.260)	(−0.532)	(−1.099)	(−1.321)	(−1.275)	(−0.756)	(−0.469)
Constant	−0.007	−0.006	−0.019	−0.040	−0.076	−0.113	−0.153	−0.203	−0.255*
	(−0.561)	(−0.529)	(−0.706)	(−0.897)	(−1.120)	(−1.320)	(−1.505)	(−1.770)	(−2.026)
Observations	2,728	2,727	2,724	2,719	2,709	2,699	2,689	2,679	2,669
Adjusted R^2	0.001	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Panel C—Small cap VIX and VVIX

Day(s) ahead return	1	2	5	10	20	30	40	50	60
Δ VIX	0.045	0.046	0.126	0.115	0.106	0.259	0.434	0.587	0.238
	(0.268)	(0.245)	(0.433)	(0.315)	(0.211)	(0.415)	(0.612)	(0.767)	(0.298)
Δ VVIX	−0.298	−0.585**	−0.647	−0.918	−1.194	−1.655	−1.502	−1.625	−0.967
	(−1.492)	(−2.602)	(−1.777)	(−1.948)	(−1.812)	(−1.944)	(−1.580)	(−1.580)	(−0.884)
Constant	−0.003	−0.007	−0.019	−0.041	−0.083	−0.127	−0.171	−0.223*	−0.281*
	(−0.430)	(−0.561)	(−0.751)	(−0.990)	(−1.303)	(−1.544)	(−1.730)	(−1.986)	(−2.282)
Observations	2,728	2,727	2,724	2,719	2,709	2,699	2,689	2,679	2,669
Adjusted R^2	0.001	0.003	0.001	0.001	0.001	0.001	0.000	0.000	0.000

This table presents the results of estimations of Eq. (2). The dependent variable is daily returns to a portfolio that contains a long position in the value ETF and an equal short position in the growth ETF for each for each size category. For ease of interpretation, all of the coefficients have been multiplied by 100. Thus, for example, if the coefficient is 1.00, a one percentage increase in the VIX or VVIX indexes leads to a one basis point return differential over the relevant time frame. The standard errors are estimated using five lags to account for one week of trading activity autocorrelation and heteroskedasticity (Newey and West, 1987).

*Significant at the 5% level. **Significant at the 1% level.

in Tables 4 through 9 are multiplied by 100 for ease of interpretation. Specifically, for example, a one percentage daily increase in the VIX index leads to a marginal 0.725 basis point increase in returns to the large-cap value ETF over the following five-day period as opposed to its large-cap growth counterpart. On an annualized basis, that translates to a 3.720% excess return to the value ETF over the growth ETF.

Thus, over five-day time periods at least, investors are rewarded for investing in value stocks when expected volatility increases. This can be explained by the fact that increases in the VIX index are normally accompanied by contemporaneous negative stock returns as investors demand an additional risk premium that is "repaid" over future periods more quickly for value stocks, as in Merton (1980) and French, Schwert, and Stambaugh (1987). However, the short-term returns to value are negative and significant for several periods for the proxy for uncertainty, which is consistent with the recent empirical results of Brenner and Izhazian (2012) for the S&P 500 ETF, and Baltussen, Van Bekkum, and Van Der Grient (2017) for single stocks. Incrementally, for two- to forty-day periods, large-cap value-based ETFs marginally underperform growth-based ETFs when the VVIX index increases. For example, a one percentage increase in the VVIX ("uncertainty") index leads to a 2.218 basis point return decline over a 30-day window for large-cap value versus their growth counterparts. This represents an annualized 1.879% excess return. For the five-day return window, the equivalent annual excess return is 4.807%. Thus, it seems that as investors observe increased uncertainty in the marketplace, they sell growth stocks in disproportionate amounts relative to their value counterparts, and subsequently growth stocks experience higher future returns. This result is consistent with the "uncertainty-avoiding" hypothesis that is analyzed by Aboura and Erisoy (2017), Baltussen, Van Bekkum, and Van Der Grient (2017), and Brenner and Izhazian (2012). Panels B and C of Table 5 provide similar but significantly weaker results for the midcap and small-cap ETFs. Therefore, in the interest of brevity, the focus of the remaining discussion will center solely on the large-cap ETF results, although results for the other ETFs are available upon request.

3.2. Additional explanatory variables

The results of the previous section provide strong evidence that returns to value are driven by investor expectations regarding future risk and potential uncertainty. These results do not, however, explain the fact that overall market implied volatility and uncertainty are not constant over time. This section of the analysis examines some of the macroeconomic factors that may enhance the prior results and analyze the variations observed in the data to better explain the true drivers of the value versus growth return anomaly.

To analyze the time-varying aspects of risk and uncertainty, one-day returns of the large-cap value minus growth ETFs are regressed against prior day changes in the VIX and VVIX indexes over rolling one-year periods (252 trading days). The results of these estimations provide daily point estimates for the effect of each of the slope coefficients on future one-day returns, and they are summarized in Fig. 2. Notably, as seen in this graph, in recent years the coefficient values reflect the 0.71 positive correlation between the VIX and VVIX indexes (see Table 3), although there are significant deviations, especially during the global financial crisis of 2007–2009 and the European debt crisis from 2010–2012. The

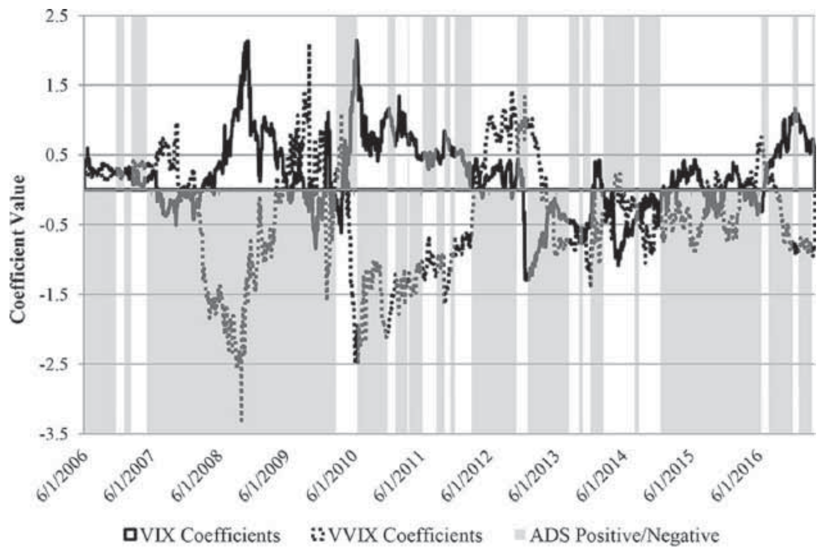

Fig. 2. This figure presents rolling regression coefficients (252-day) for the one-day ahead return estimations of large-cap value minus large-cap growth Exchange Traded Funds (ETFs) using changes in VIX and VVIX as independent variables. The time-varying effects of risk and uncertainty, one-day returns of the large-cap value minus growth ETFs are regressed against prior day changes in the VIX and VVIX indexes over rolling one-year periods (252 trading days). Notably, as seen in this graph, in recent years the coefficient values reflect the 0.71 positive correlation between the VIX and VVIX indexes (see Table 3), although there are significant deviations, especially during the global financial crisis of 2007–2009 and the European debt crisis from 2010–2012. Shaded areas identify whether the ADS business conditions index is positive or negative for that particular time frame.

shaded areas of the graph represent time periods when the ADS index of business conditions (Aruoba, Diebold, and Scotti, 2009) is positive or negative. Further implications of the differing time periods are explored in the analysis that follows. The implications of this graph are interesting because the coefficients for the proxy for uncertainty (VVIX) reach their lowest levels during crisis periods, while the coefficients on the risk index (VIX) reach their highest levels. Thus, it seems that especially during these periods, over a one-day return horizon, investors buy value stocks that are depressed during periods of increased volatility that subsequently outperform.

Potential explanatory variables that may identify how investors view risk and uncertainty are provided by Bali (2008) and Bali and Engle (2010). Their analyses demonstrate that the Moody’s Baa-Aaa corporate bond default spread and the TED spread (Eurodollar over Treasuries) are priced in the time-series and cross-section of equity portfolios. In their study of economic conditions and the effect on future stock returns, Aruoba, Diebold, and Scotti (2009) postulate that their business conditions index (the Aruoba-Diebold-Scotti, or ADS Index) determines “good” and “bad” states of the economy. This index is reported by the Philadelphia Federal Reserve Bank and “is designed to track real business conditions at high frequency.” Its underlying (seasonally adjusted) economic indicators (weekly initial jobless claims; monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales; and quarterly real GDP) blend high- and low-frequency information and stock and flow data.”[1] Summary statistics for these additional variables are not presented in the interest of brevity, but a correlation matrix is provided in Table 6. It is clear that these variables are correlated to a certain degree with each other, but

Table 6 Correlation matrix of additional explanatory variables

Variable	Symbol	VIX	VVIX	ADS	TED	Baa-Aaa
Δ Volatility index	VIX	1.0000				
Δ Vol of vol index	VVIX	0.7142	1.0000			
ADS index	IJS	−0.0035	0.0053	1.0000		
TED spread	IJT	0.0157	0.0027	−0.6374	1.0000	
Baa-Aaa spread	IJJ	−0.0160	−0.0155	−0.8221	0.5249	1.0000

ADS = Aruoba-Diebold-Scotti. This table provides a correlation matrix of the additionally explanatory variables under study in this article.

their correlation to the VIX and VVIX indexes are minimal; thus, they may shed further light on the relationships among risk, uncertainty, and returns to value if they are significant when included in regressions of returns to value.

These variables are added to the right-hand side of Eq. (2), and the results of these estimations are provided in Table 7 for the large-cap ETFs. The results are quite similar to the initial results of the previous section in Panel A of Table 5, in that the coefficient signs for the risk and uncertainty indexes are similar in direction and magnitude. Also, the additional explanatory variables contribute to the model fit since all of the Adjusted R^2 values are higher, especially over longer time frames. The coefficients for the VIX and VVIX Indexes are similar to the original specification. The coefficients for the ADS Index are not statistically significant (although they are uniformly positive and some are significant at the 10% level), but the TED Spread variable is negatively related to future returns to value for the longer time frames. Each of these results is consistent with future returns being positively related to business conditions (positive ADS Index and lower TED Spread). The Baa-Aaa credit spread is not significant in these regressions over any time frame.

Table 8 provides a similar, but more informative, analysis to Table 7 in that it includes the additional explanatory variables, but the two panels distinguish between "bad" and "good" states of the economy as specified by the ADS Index (Aruoba, Diebold, and Scotti, 2009). In Panel A for "bad" states of the economy ($ADS < 0$), the previously reported and expected coefficients for the VIX and VVIX variables are observed, although they are uniformly higher (in absolute value) and stronger in significance than those observed in Table 7. The TED spread coefficients remain negative and are stronger than those in Table 7 as well, while the corporate bond spread remains insignificant. Thus, the results of this subsample support the initial inferences made regarding the variables' relationships in Table 7.

However, in Panel B that contains the results for "good" states of the economy ($ADS > 0$), the coefficients for the VIX and VVIX indexes are uniformly insignificant. This behavior from investors may be viewed through the lens of the "mental accounting" framework of Kahneman and Tversky (1984), who posit that individuals feel better about avoiding losses than they feel about making gains ("loss aversion"). In this case, where the state of the economy is "good," investors may purchase growth stocks (or be indifferent and not sell them) even when volatility rises, giving rise to the insignificant results. In this specification, the TED spread coefficients become insignificant, while the corporate bond spread is positively related to future returns over the 20- to 60-day horizons. Thus, as corporate bond quality declines in a "good" state of the economy, investors prefer to invest in value rather

Table 7 Large-cap estimations with additional explanatory variables

Day(s) ahead return	1	2	5	10	20	30	40	50	60
Δ VIX	−0.040	0.158	0.701*	0.887	1.256	1.129	1.375	0.709	0.421
	(−0.213)	(0.702)	(2.164)	(1.772)	(1.839)	(1.390)	(1.520)	(0.738)	(0.414)
Δ VVIX	−0.046	−0.416	−0.896*	−1.397*	−1.712	−2.287*	−2.174	−0.977	−0.100
	(−0.221)	(−1.542)	(−2.115)	(−2.089)	(−1.948)	(−2.060)	(−1.778)	(−0.763)	(−0.072)
ADS index	0.045	0.085	0.191	0.339	0.510	0.602	0.617	0.503	0.277
	(1.448)	(1.439)	(1.565)	(1.793)	(1.811)	(1.862)	(1.880)	(1.532)	(0.845)
TED spread	0.019	0.025	0.038	0.001	−0.239	−0.630*	−0.957**	−1.473**	−2.144**
	(0.562)	(0.415)	(0.342)	(0.005)	(−0.919)	(−2.050)	(−2.710)	(−3.763)	(−4.980)
Baa-Aaa Corp. spread	0.039	0.078	0.172	0.306	0.466	0.668	0.746	0.799	0.832
	(0.887)	(0.950)	(1.001)	(1.169)	(1.313)	(1.657)	(1.690)	(1.605)	(1.554)
Constant	−0.045	−0.087	−0.190	−0.314	−0.402	−0.487	−0.497	−0.435	−0.317
	(−1.043)	(−1.069)	(−1.124)	(−1.206)	(−1.133)	(−1.231)	(−1.114)	(−0.842)	(−0.549)
Observations	2,699	2,698	2,695	2,690	2,680	2,670	2,660	2,650	2,640
Adjusted R^2	0.000	0.002	0.008	0.016	0.033	0.052	0.061	0.076	0.104

ADS = Aruoba-Diebold-Scotti. This table presents the results of estimations of Eq. (2) with additional explanatory factors used as independent variables. The dependent variable is daily returns to a portfolio that contains a long position in the value Exchange Traded Fund (ETF) and an equal short position in the growth ETF for each for each size category. For ease of interpretation, all of the coefficients have been multiplied by 100. Thus, for example, if the coefficient is 1.00, a one percentage increase in the VIX or VVIX indexes leads to a one basis point return differential over the relevant time frame. The standard errors are estimated using five lags to account for one week of trading activity autocorrelation and heteroskedasticity (Newey and West, 1987).

*Significant at the 5% level. **Significant at the 1% level.

Table 8 Large-cap estimations with states of Aruoba-Diebold-Scotti (ADS)

Panel A: Bad state (ADS < 0)

Day(s) ahead return	1	2	5	10	20	30	40	50	60
Δ VIX	0.033	0.235	1.063**	1.411*	2.108*	2.092*	2.528*	1.669	1.242
	(0.151)	(0.836)	(2.683)	(2.262)	(2.476)	(2.106)	(2.287)	(1.422)	(1.018)
Δ VVIX	−0.026	−0.623	−1.236*	−1.902*	−2.425*	−3.029*	−2.960*	−1.437	−0.536
	(−0.108)	(−1.923)	(−2.371)	(−2.273)	(−2.195)	(−2.182)	(−2.002)	(−0.953)	(−0.340)
TED spread	0.001	−0.008	−0.040	−0.132	−0.444*	−0.882**	−1.220**	−1.684**	−2.261**
	(0.017)	(−0.150)	(−0.393)	(−0.954)	(−2.167)	(−3.521)	(−3.933)	(−4.866)	(−6.029)
Baa-Aaa Corp. spread	−0.013	−0.020	−0.048	−0.094	−0.169	−0.113	−0.102	−0.003	0.182
	(−0.358)	(−0.285)	(−0.314)	(−0.393)	(−0.467)	(−0.239)	(−0.191)	(−0.005)	(0.341)
Constant	0.004	0.004	0.018	0.067	0.237	0.340	0.425	0.492	0.551
	(0.096)	(0.053)	(0.117)	(0.272)	(0.648)	(0.708)	(0.772)	(0.826)	(0.929)
Observations	2,010	2,010	2,010	2,010	2,002	1,992	1,982	1,972	1,962
Adjusted R^2	0.000	0.000	0.003	0.007	0.025	0.049	0.064	0.088	0.128

Panel B: Good state (ADS > 0)

Day(s) ahead return	1	2	5	10	20	30	40	50	60
Δ VIX	−0.221	−0.295	−0.685	−1.143	−1.885	−2.332	−2.453	−2.046	−1.757
	(−0.690)	(−0.894)	(−1.342)	(−1.621)	(−1.807)	(−1.938)	(−1.798)	(−1.485)	(−1.139)
Δ VVIX	−0.093	0.498	0.753	1.032	1.807	1.441	1.650	1.216	1.852
	(−0.277)	(1.042)	(0.986)	(0.938)	(1.184)	(0.812)	(0.755)	(0.555)	(0.720)
TED spread	−0.020	−0.022	−0.114	−0.547	−1.253	−1.750	−1.676	−2.309	−3.578
	(−0.237)	(−0.142)	(−0.314)	(−0.850)	(−1.218)	(−1.343)	(−1.107)	(−1.396)	(−1.871)
Baa-Aaa Corp. spread	0.088	0.173	0.367	0.860*	1.613**	2.168**	2.774**	3.777**	4.803**
	(1.456)	(1.562)	(1.540)	(2.262)	(2.848)	(3.039)	(3.377)	(4.089)	(4.501)
Constant	−0.072	−0.146	−0.303	−0.632	−1.171*	−1.626**	−2.270**	−3.124**	−3.914**
	(−1.416)	(−1.569)	(−1.512)	(−1.946)	(−2.293)	(−2.591)	(−3.321)	(−4.247)	(−4.723)
Observations	689	688	685	680	678	678	678	678	678
Adjusted R^2	0.004	0.004	0.012	0.033	0.047	0.054	0.070	0.105	0.132

This table presents the results of estimations of Eq. (2) with additional explanatory factors used as independent variables over differing states of the ADS business conditions index. The dependent variable is daily returns to a portfolio that contains a long position in the value Exchange Traded Fund (ETF) and an equal short position in the growth ETF for each for each size category. For ease of interpretation, all of the coefficients have been multiplied by 100. Thus, for example, if the coefficient is 1.00, a one percentage increase in the VIX or VVIX indexes leads to a one basis point return differential over the relevant time frame. The standard errors are estimated using five lags to account for one week of trading activity autocorrelation and heteroskedasticity (Newey and West, 1987).

*Significant at the 5% level. **Significant at the 1% level.

than growth stocks. But overall, the results indicate that value style investors are not penalized to exposures to risk or uncertainty "good" states of the economy, although it should be noted that the number of observations for "good" states of the economy are only about one quarter of the total observations in the sample.

One final analysis examines potentially "asymmetric" responses to changes in the VIX index. The sample is divided into days when the change in the VIX index is negative or positive, respectively. The results of this analysis are presented in Table 9, and the results for prior day decreases in the VIX index are presented in Panel A. These results are largely consistent with the previous results in Table 7 and Panel A of Table 8. Decreases in the VIX index lead to future positive returns to value while changes in the VVIX index are negatively related to future returns. Increases in the TED spread are related to future negative returns. However, the returns to value in Panel B for the volatility indices are almost wholly insignificant. Only two of the negative coefficients for the TED spread are statistically significant, and any consideration for changes in the VIX and VVIX indexes are fully ignored. Investors do not seem to be concerned with changes in these variables on days that the VIX index rises, or perhaps they simply choose not to trade in this environment, thus the new information regarding risk and uncertainty is not impounded into ETF prices. However, when the VIX declines, investors are rewarded for exposures to value stocks, although the effects are mitigated given a concurrent increase in the VVIX index. Panel B of Table 9 does not provide further insight into these issues.

To summarize, the most consistent results of the paper are presented in Table 7 and each Panel A of Tables 8 and 9. In all of these estimations, one-day changes in the VIX index (the proxy for risk) are positively related to returns to value, while the opposite is true for the VVIX index (the proxy for uncertainty). Adding macroeconomic variables to the analysis increases the models' explanatory power, and the results are intuitive. The results are strongest during periods when the ADS index is in a "good" state and when the change in the VIX index is negative.

4. Conclusion

The results of this article examine time-varying returns to risk and uncertainty in various market states dependent on macroeconomic variables, using extremely liquid ETFs. In contrast to the findings of Boscaljon, Filbeck, and Zhao (2011), where these differences have disappeared over all but the longest time frames, the inclusion of a proxy for uncertainty and macroeconomic variables provides economically significant results. When these results are evaluated in conjunction with the VVIX Index, there are still returns to value in the evaluation of the VIX index under certain conditions. These returns are also incrementally larger when considering information from the VVIX index that provides a proxy for uncertainty. The inclusion of the VVIX index and proxies for economic conditions in the analysis of the VIX effect on returns to value for inexpensive and easily-traded ETFs is informative, since it is straightforward and cost-effective to implement style-based trading strategies with these highly liquid securities.

Table 9 Large-cap estimations with VIX positive/negative

Panel A: Negative changes in VIX index

Day(s) ahead return	1	2	5	10	20	30	40	50	60
Δ VIX	0.278	0.622	2.442**	2.885*	4.908**	4.277*	2.999	1.178	0.707
	(0.733)	(1.193)	(3.012)	(2.299)	(3.230)	(2.344)	(1.600)	(0.539)	(0.302)
Δ VVIX	−0.339	−0.816*	−1.421*	−2.481*	−2.113	−2.122	−1.964	0.235	1.460
	(−1.250)	(−2.173)	(−2.127)	(−1.971)	(−1.289)	(−0.990)	(−0.933)	(0.107)	(0.633)
ADS index	0.097*	0.131	0.225	0.406	0.576	0.735*	0.703	0.600	0.420
	(2.404)	(1.875)	(1.594)	(1.619)	(1.598)	(1.740)	(1.592)	(1.367)	(0.967)
TED spread	0.018	−0.008	−0.041	−0.096	−0.345	−0.562	−1.129*	−1.629**	−2.296**
	(0.439)	(−0.139)	(−0.369)	(−0.493)	(−1.169)	(−1.425)	(−2.303)	(−2.898)	(−3.798)
Baa-Aaa Corp. spread	0.116*	0.141	0.241	0.441	0.573	0.709	0.750	0.813	0.975
	(2.241)	(1.535)	(1.302)	(1.400)	(1.282)	(1.337)	(1.297)	(1.267)	(1.429)
Constant	−0.106*	−0.114	−0.145	−0.326	−0.278	−0.352	−0.298	−0.280	−0.301
	(−2.026)	(−1.237)	(−0.786)	(−1.063)	(−0.642)	(−0.684)	(−0.510)	(−0.413)	(−0.402)
Observations	1,443	1,442	1,439	1,439	1,434	1,428	1,423	1,417	1,411
Adjusted R^2	0.006	0.010	0.020	0.031	0.054	0.060	0.083	0.089	0.113

Panel B: Positive changes in VIX index

Day(s) ahead return	1	2	5	10	20	30	40	50	60
Δ VIX	−0.316	−0.350	−0.405	−0.597	−0.794	−0.201	−0.181	0.279	0.184
	(−0.974)	(−1.038)	(−0.860)	(−0.936)	(−0.767)	(−0.156)	(−0.132)	(0.183)	(0.111)
Δ VVIX	0.241	0.130	−0.049	−0.030	−0.670	−1.988	−1.185	−1.117	−0.785
	(0.810)	(0.366)	(−0.089)	(−0.038)	(−0.586)	(−1.553)	(−0.771)	(−0.663)	(−0.396)
ADS index	−0.009	0.036	0.166	0.273	0.465	0.479	0.525	0.393	0.115
	(−0.206)	(0.502)	(1.250)	(1.268)	(1.169)	(1.052)	(1.173)	(0.907)	(0.261)
TED spread	0.027	0.064	0.145	0.132	−0.081	−0.671	−0.802	−1.359**	−2.032**
	(0.585)	(0.791)	(1.096)	(0.673)	(−0.220)	(−1.601)	(−1.754)	(−2.740)	(−3.752)
Baa-Aaa Corp. spread	−0.041	0.019	0.112	0.167	0.382	0.681	0.813	0.835	0.699
	(−0.627)	(0.169)	(0.589)	(0.525)	(0.773)	(1.251)	(1.280)	(1.152)	(0.855)
Constant	0.031	−0.042	−0.147	−0.196	−0.312	−0.461	−0.620	−0.552	−0.247
	(0.486)	(−0.378)	(−0.772)	(−0.599)	(−0.618)	(−0.882)	(−0.978)	(−0.742)	(−0.282)
Observations	1,244	1,244	1,244	1,239	1,234	1,230	1,225	1,221	1,217
Adjusted R^2	0.000	0.000	0.003	0.006	0.019	0.045	0.039	0.062	0.094

ADS = Aruoba-Diebold-Scotti. This table presents the results of estimations of Eq. (2) with additional explanatory factors used as independent variables over differing changes in the VIX index. The dependent variable is daily returns to a portfolio that contains a long position in the value Exchange Traded Fund (ETF) and an equal short position in the growth ETF for each for each size category. For ease of interpretation, all of the coefficients have been multiplied by 100. Thus, for example, if the coefficient is 1.00, a one percentage increase in the VIX or VVIX indexes leads to a one basis point return differential over the relevant time frame. The standard errors are estimated using five lags to account for one week of trading activity autocorrelation and heteroskedasticity (Newey and West, 1987).

*Significant at the 5% level. **Significant at the 1% level.

Note

1 *Source:* https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index.

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